Managing Residential Water Demand: An Applied Econometric Analysis

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RESUMEN (en español)

Esta tesis está formada por tres ensayos que muestran un análisis integrado de la demanda de agua residencial y las herramientas de gestión de la misma. Este es un tema de gran interés debido a la creciente escasez de agua causada por la actividad económica, el crecimiento de la población y el cambio climático. Los tres ensayos en esta tesis se centran en: el análisis de la demanda de agua en presencia de preferencias heterogéneas para poder valorar la efectividad de las políticas de gestión de la demanda, un estudio sobre la relación entre la adopción de tecnologías eficientes de uso de agua y los hábitos correspondientes a las mismas, y un análisis semiparamétrico de la eficiencia en el consumo de agua que permite calcular los ahorros de agua potenciales.

Esta tesis utiliza microdatos de panel relativos a la demanda residencial de agua y algunas características de los hogares. La base de datos ha sido obtenida al combinar información de una encuesta a 1.465 usuarios domésticos en la ciudad de Granada con datos sobre consumo bimensual y precios proporcionados por la empresa de abastecimiento de agua en esta ciudad para el periodo 2009-2011.

En el primer capítulo “Respuestas al cambio en la estructura de tarifas de agua a nivel residencial: un análisis de clases latentes a nivel hogar en Granada” se modelizan las demandas heterogéneas de agua residencial utilizando modelos de clases latentes. Entre los problemas metodológicos abordados en este ensayo, destaca el de la endogeneidad del precio en un modelo no lineal, que se ha solucionado mediante el uso de un enfoque denominado función de control. Se han identificado cuatro perfiles distintos de consumidores de agua residencial en Granada para el periodo 2009-2011 en base a las similitudes de sus preferencias inobservables, en lugar del único perfil asumido por enfoques de una única ecuación. Además, esta estimación nos permitió observar cuatro reacciones distintas a cambios en los precios, implicando que algunos grupos de consumidores no son sensibles al precio, por lo que otros instrumentos alternativos al precio deberían ser utilizados a fin de promover la conservación del agua. La probabilidad de pertenencia a cada clase es parametrizada, permitiendo a los reguladores de agua caracterizar los distintos hogares para poder hacer un diseño de políticas de gestión de demanda adaptado a consumidores heterogéneos.

El capítulo de esta tesis titulado “Adopción y uso de tecnologías eficientes a nivel residencial; análisis desagregado en el sector del agua“ analiza los determinantes de la adopción de dispositivos eficientes en el uso de agua y los presencia de hábitos responsables en el uso de dichas tecnologías. En este sentido, se diferencia entre distintos tipos de tecnologías según necesiten energía eléctrica para su funcionamiento o no. Esta distinción se debe no solo a las diferencias en las características técnicas de los dispositivos analizados sino también a que estos han sido objeto de distintas políticas públicas. Al analizar estas decisiones, se estudia

también la relación entre la adopción de tecnologías eficientes de agua y hábitos, ya que podría existir un mal uso de estas tecnologías que condujera a pérdidas de eficiencia en agua. Para llevar a cabo este análisis, se utiliza un probit recursivo semi-ordenado para modelizar conjuntamente la elección de cada tecnología y su hábito correspondiente. Los resultados muestran que existen diferencias en los determinantes de las decisiones estudiadas. Además, la relación entre tecnologías eficientes y hábitos también es distinta según el tipo de tecnología, existiendo una relación negativa entre dispositivos eficientes no eléctricos y los hábitos asociados a dichas tecnologías, es decir, los hogares que disponen de este tipo de tecnologías eficientes no están haciendo un uso adecuado de las mismas.

Por último, el ensayo titulado “El impacto del comportamiento medioambiental en la eficiencia en el consumo residencial de agua”, mide el nivel de eficiencia en el consumo de agua y analiza el efecto de distintos comportamientos medioambientales en el mismo. Para llevar a cabo este análisis, se estima una función frontera de demanda de agua usando un modelo semiparamétrico de frontera estocástica denominado smooth-coefficient stochastic frontier model. Esta metodología permite no solo analizar el efecto de estos factores medioambientales en el término de ineficiencia, pero también incluir estas variables en la función principal, es decir, los coeficientes estimados en la función principal también son funciones de los comportamientos medioambientales. Los resultados nos permiten apreciar que, a pesar de los elevados índices de eficiencia, los ahorros de agua pueden ser importantes si se aumenta el número de electrodomésticos eficientes en los hogares y mejoran los hábitos de ahorro de agua.

RESUMEN (en Inglés)

This thesis is formed by three essays that carry out an comprehensive analysis of residential water demand and water demand management tools. It is a topic of critical importance as there is a growing need to analyze water demand due to the increasing water stress caused by economic activity, increasing population and climate change. The three essays of my thesis elaborate on: 1) the analysis of water demand under heterogeneous preferences to better understand the effectiveness of demand management policies; 2) a study of the relationship between the adoption of efficient water-using technologies and user habits corresponding to these technologies; and 3) a semiparametric study on efficiency in water consumption that allows us to compute potential water savings.

The thesis exploits household-level panel data on residential water demand and consumers' characteristics obtained by combining information from a survey of 1,465 domestic users in the city of Granada and bimonthly price and consumption data supplied by this city's water supplier from the period 2009-2011.

The essay entitled “Responses to changes in domestic water tariff structures: a Latent Class Analysis on household-level data from Granada (Spain)” studies heterogeneous residential water demand by implementing latent class models. Among the methodological issues addressed in this essay, we have dealt with price endogeneity in a nonlinear model, which has been treated using a Control Function approach. Four different residential water consumer profiles in Granada for the period 2009-2011 are identified based on the similarity of their unobservable preferences, rather than the common profile assumed by single equation approaches. Moreover, this estimation allowed us to observe four distinct price responses, implying that some groups of consumers are price insensitive so that non-pricing policies should be implemented in order to foster water conservation. The probability of belonging to each class is parameterized, allowing water regulators to characterize the households in each class in order to tailor water demand management policy to heterogeneous users.

The second essay in this thesis named "Adoption and use of efficient technologies at residential level: a disaggregated analysis in the water sector" analyzes the determinants of the adoption of water-efficient appliances and habits, disaggregating each type of behavior since households may choose to purchase some of those efficient appliances or adopt habits because of the resulting energy savings, with water savings being a secondary consideration due to the lower price of water. When analyzing these decisions, the relationship between the adoption of water-efficient equipment and habits is also examined, as there could be an inappropriate use of the technologies that could lead to water efficiency losses. In order to do so, a recursive semi-ordered probit model is proposed to jointly model choices about the adoption of different technologies and water conservation habits. Our results show that there are differences in terms of the determinants of each decision. Furthermore, the relationship between efficient water-using technologies and habits differs depending on the type of technology. This relationship is found to be negative in the case of non-electrical efficient devices and the corresponding habits, implying that households with this type of technology are not making an appropriate use of it.

Finally, the essay entitled "The impact of environmental behavior on the efficiency in residential water consumption" measures the level of efficiency in water demand and analyzes the effect of different environmental behaviors on efficiency in residential water consumption. In order to do so, a water demand frontier function is estimated using a semiparametric smooth-coefficient stochastic frontier model. This methodology allows us not only to analyze the effect of the environmental factors on the unobserved inefficiency term but also to include these variables into the main regression function. In doing so, the intercept and the slope coefficients are expressed as unknown functions of these environmental factors. This methodology allows us to compute potential water savings associated with different environmental behaviors. Despite obtaining high efficiency scores, there is still room for water savings, which may be enhanced by promoting water efficient appliances and water conservation habits.

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Chapter 1

Introduction

Water is one of the most essential elements on Earth, and all forms of life depend on it. Moreover, water has played a fundamental role in the development of civilizations since the origin of humankind, as humans have usually settled close to sources of water. For example, Mesopotamia (from Ancient Greek: *Μεσοποταμία* "land between rivers") is an area geographically located between the Tigris and Euphrates rivers, Ancient Egypt emerged at the lower reaches of the Nile river, and the Chinese civilization originated in the Yellow and Yangzi river basins. The rise of these civilizations went hand in hand with an improvement in managerial capabilities for waterworks in order to supply water to inhabited areas. This has fostered sanitary systems and health conditions, and with increasing populations and the development of agriculture, water needs increase, leading to shortages. Thus, water shortages have been common throughout history. There has been a long history of attempts at solving the problem. For example, in Ancient Egypt, one of the tributaries of the Old Nile was dredged around 2100 B.C. after 40 years of falls in water levels. [Hassan, 2003]. However, such attempted solutions to obtain water security did not achieve long-lasting results, leading to a gradual increase in water demand [Hassan, 2003].

In more recent times, the Industrial Revolution generated greater demand for water since it was not only used for agriculture and domestic uses, but also as a source of energy and as an input for the industrial sector. Moreover, the Industrial Revolution brought improvements in medicine and living standards, resulting in a population explosion that reached 6.1 billion people at the start of the 21st century.

Water availability issues have been aggravated by policy failures that allowed countries to use more water than is sustainable according to the rate of replenishment [Watkins, 2006], generating an important water-based ecological debt that will be suffered by future generations. Moreover, climate change may transform the hydrological cycles that determine water availability [Watkins, 2006]. Among the potential impacts of this phenomenon are temperature rises and rainfall declines, rapid glacial melt and rising sea levels resulting in reduction in freshwater. Finally, behavioral changes related to climate change, such as increases in the demand for heating and cooling, may also impact water availability [Olmstead, 2010].

When tackling the problem of water scarcity, water resource management has been generally thought of as an engineering problem rather than an economic one [Olmstead and Stavins, 2007]. Consequently, supply enhancement has been the dominating approach towards responding to water scarcity. However, fresh water sources are physically limited, so traditional forms of augmenting supply lead to withholding water from future generations. Moreover, the rise in infrastructure costs due to stricter environmental regulation would make supply enhancement difficult to implement, especially in the current context of public funding constraints [Grafton, 2014]. An alternative supply-side option is desalination of sea water. However, high energy costs may prevent poor countries from doing so [Watkins, 2006].

As a consequence, there has been an increased focus on water demand policies. Water demand management is considered a "no-regrets" option to cope with water scarcity [IPCC, 2008], where a "no regret" policy is defined as one that would generate net social benefits even in the absence of climate change impacts. There are two categories of demand management policy instruments: price and non-price policies. Water price demand management policies need to reflect the value of water. However, the development of competitive water markets is not desirable from an economic point of view due to the low sensitivity of residential water demand to water prices and to the special characteristics of water resources that make them difficult to manage through ordinary markets [Olmstead and Stavins, 2007]. Instead, non-price demand management policies are preferred. These include water rationing, subsidies for the adoption of efficient technologies, or information and educational campaigns. It is important to identify the determinants of water demand behaviors so that supply managers and policy makers can understand the ways in which urban water consumption can be reduced. Furthermore, it is also crucial to examine the level of efficiency in residential water consumption and its determinants for a better understanding of the potential water savings that could be achieved through price and non-price policies.

Water demand is the focus of this thesis. In particular, the thesis centres on various aspects of residential water demand where econometric techniques are used to estimate empirical models whose purpose is to provide insights into water consumption behavior. This in turn will allow interesting policy conclusions to be drawn. The three chapters of the thesis focus on different but related aspects of residential water demand. In particular, these chapters comprise an analysis of residential water demand focusing on demand side management tools. As water availability issues have been increasing, several policies aiming at reducing water demand have been implemented. Therefore, it is of interest to understand the effect of these policies on the behavior of residential consumers. Moreover, heterogeneity in consumers' preferences may affect the effectiveness of these policies depending on the composition of the targeted population, so taking into account consumers' heterogeneity may improve the design of water demand management policies.

The essays in the thesis use data from the city of Granada, in the South of Spain which is an area particularly affected by water scarcity. Concretely, the empirical work exploits household-level panel data on residential water demand and consumers' characteristics obtained by combining information from a survey of 1,465 domestic users in the city of Granada and bimonthly price and consumption data supplied by this city's water supplier from the period 2009-2011. This database is further explained in the next chapter. The three remaining chapters of my thesis elaborate on the topics discussed above.

The chapter titled *Responses to changes in domestic water tariff structures: a Latent Class Analysis on household-level data from Granada (Spain)* studies heterogeneous residential water demand since we believe that a common demand function is unlikely to represent the behavior of all users. We use a Latent Class Model to classify consumer into different groups and estimate water demand functions for each of the four groups identified. Among the methodological issues addressed in this paper, we account for price endogeneity in a nonlinear model, using a Control Function approach. Four different residential water consumer profiles in Granada for the period 2009-2011 are identified based on the similarity of their unobservable preferences, rather than the common profile assumed by single equation approaches. Since this estimation allows us to observe four distinct price responses, these results should be of interest to regulators who would like to tailor water demand management policy to heterogeneous users. Of particular interest is our finding that some groups of consumers are price-insensitive, implying a more prominent role for non-pricing policies in order to foster water conservation.

The chapter *Adoption and use of efficient technologies at residential level: a disaggregated analysis in the water sector*, analyses the determinants of the adoption of water-efficient appliances and corresponding water-conservation habits disaggregating each type of behavior since households may choose to purchase some of those efficient appliances or perform habits because of the resulting energy savings, with water savings, due to the lower price of water, being a secondary consideration. When analyzing the adoption of water-efficient equipment and habits, the possibility that consumers' habits adjust to the adoption of the water efficient equipment is tested, as there could be a so-called "rebound effect" of the type found in the energy conservation literature. In order to do so, a recursive multivariate probit model is proposed to jointly model choices about different technologies adoption and conservation habits. This is an original contribution, since this is the first attempt in the literature to analyze this issue in a disaggregated way and it yields interesting conclusions regarding the effectiveness of public policies in the context of the Europe 2020 strategy proposed by the European Commission to reach a resource-efficient and greener economy.[1]

Finally, the last chapter in this thesis, *The impact of environmental behavior on the efficiency in residential water consumption*, measures the level of effi-

[1]See http://ec.europa.eu/europe2020/index$_e n.htm$ for more detailed information about the Europe 2020 strategy.

ciency in residential water consumption and analyzes the effect of different pro-environmental behaviors (that are considered environmental factors) on efficiency. In order to do so, a water demand frontier function is estimated using a semiparametric smooth-coefficient stochastic frontier model. This methodology allows us not only to analyze the effect of the environmental factors on the unobserved inefficiency term but also to include these variables in the main regression function. In doing so, the intercept and the slope coefficients are expressed as unknown functions of these environmental factors. The latter can then shift the frontier non-neutrally. The results show that households with efficient electrical appliances are indeed more water-efficient. However, those households with efficient non-electrical devices show increases on water consumption. This may be caused by the lack of uniform labelling on non-electrical devices, that is, consumers are not properly informed about their devices' water saving potential, and the low price of water as opposed to the price of energy that may affect the correct use of efficient electrical appliances, as could be inferred from the previous chapter. Despite obtaining relatively high efficiency scores, there is still room for substantial water-savings. These savings may be enhanced by promoting water-efficient electrical appliances and the design of educational campaigns that may affect water conservation habits and provide more information about the appropriate use of efficient devices. Furthermore, a simulation of scenarios shows the effects of changes in the efficient technology and water conservation habits and the quantity of water that could be saved by promoting these environmental behaviors.

In summary, this thesis comprises a systematic analysis of the effect of demand side policies on consumers' water behavior. The empirical estimations show that pricing policies are not effective in reducing water consumption for all types of consumers. Regarding non-pricing policies, our results indicate that the promotion of the adoption of efficient technology has not led to a reduction in water consumption for some type of devices. Therefore, further efforts must be made in terms of information campaigns and educational programmes to raise awareness of the increasing levels of water scarcity. Finally, some policy recommendations are derived from the three essays included in this thesis.

The three main chapters in this thesis are adaptations of articles that have been sent to academic journals or are being prepared for this purpose. It should be noted that Chapter 3 is a version of a paper forthcoming in *Environmental and Resource Economics*, coauthored with my co-director, Dr María Ángeles García Valiñas of the University of Oviedo, and Prof. Roberto Martínez-Espiñeira of the Memorial University of Newfoundland.

Chapter 2

Context and data

2.1 Context

2.1.1 Brief overview

Spain is the most semi-arid country in the EU Lopez-Gunn et al. [2012], and it is increasingly affected by water scarcity problems. These are expected to worsen due to climate change. Estimated resource availability of water in Spain is now 3000 m^3/person/year, for a demand of 2000 m^3/person/year. However, at the end of the 21^{st} century, water availability is expected to be reduced to just 450 m^3/person/year, with demand expected to be slightly higher than at present IPCC [2007].

In this context, international and national regulators are playing a crucial role in the management of water resources. The European Union has been paying more and more attention to the balance between water demand and availability, and has legislated to address this issue and promote efficient technologies and water conservation habits. The usual procedure is that the European Union (EU) establishes some general requirements, sets out environmental regulations which should be incorporated into national legislation by each EU member. The Spanish Ministry of Environment is responsible for identifying strategic objectives for certain environmental issues, defining specific objectives and setting targets. The regional and local governments are responsible for implementing the plans. EU legislation has established the Water Framework Directive (EU

Directive 2000/60/CE) as the overriding legislation concerning water resource management. In turn, Spanish national law has stressed the importance of water as a public good and of water management as a public service. The Revised Water Law (Texto Refundido de la Ley de Aguas) lays down the basic national principles about the public property of water, the river basins and the importance of hydrological planning. The Local Regime Law (1985) specifies that water services are public services under the control of the municipalities that provide these services. However, water services management may involve not only the municipalities but also the regions (Autonomous Communities). Here, water services include water supply, which comprises collection, treatment and distribution of water resources; sewage, which includes the process to drive wastewater from the start of the sewer line to the wastewater treatment plant; and wastewater treatment, which comprises physical, chemical and biological processes to minimize the level of water pollution so it can be discharged into another body of water or reused. The regulation of water supply and sewage services can be local or regional, depending on the municipality. However, wastewater treatment is mainly regulated by the regions due to the high costs, and the synergies and economies of scale of this service [Ruiz Cañete and Dizy Menéndez, 2009].

Moreover, according to the Local Regime Regulation Law (1985) art. 25 and 26, water services are directly assigned to the municipalities. However, there are different forms of water services as shown in Table 2.1. Indirect management, including private companies, mixed companies and other types, is the most prevalent in Spain, accounting for more than 50% of the population served.

The EU Water Framework Directive indicates that water prices should be based on the cost recovery principle in order to ensure sustainability in the use of water resources. In Spain, the Autonomous Community may control water tariffs through a Regional Committee. However, as seen in Table 2.2, not all Spanish municipalities are subject to these Committees. In particular, in most municipalities with less than 20,000 inhabitants, the City Council can independently establish water prices [Ruiz Cañete and Dizy Menéndez, 2009].

This lack of homogeneity in the financial control of water tariffs in Spain leads to different pricing schemes. However, the most common one is Increasing Blocks with a fixed charge, as shown in Table 2.3. As discussed by Garrido et al.

Table 2.1: Water management regimes in Spain
(% of inhabitants)

	Management modalities
% of inhabitants	
Public Company	39 %
Town Council	8 %
Private Company	36 %
Mixed Company	13 %
Other	4 %

Source: Spanish Association of Water Supply and Sewage (AEAS) 2012

Table 2.2: Water pricing regulation
(% of municipalities)

	Water supply		Sewage	Wastewater treatment
	> 20,000 inhabitants	< 20,000 inhabitants		
Committee on Prices & Full City Council	37 %	51 %	11 %	4 %
Committee on Prices	25 %	1 %	28 %	33 %
Full City Council	22 %	46 %	58 %	27 %
Other	16 %	2 %	3 %	36 %

Source: Spanish Association of Water Supply and Sewage (AEAS) 2004

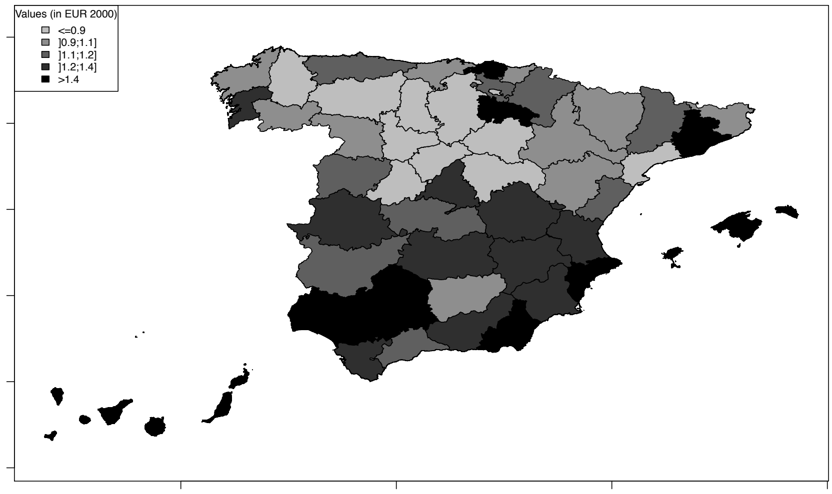
[2015], Increasing Block tariffs are preferred from an environmental perspective. However, they may have undesirable consequences in terms of equity, such as large families paying higher average prices. In order to address this, some municipalities in Spain establish a discount on the first blocks of consumption for such families, whereas other municipalities adapt the size of the blocks to the number of family members.

Table 2.3: Water price schemes in Spain
(% of inhabitants)

	Supply	Sewerage	Wastewater treatment
Fixed charge + increasing blocks	90 %	76 %	79 %
Fixed charge + constant price	2 %	8 %	8 %
Free allowance	4 %	5 %	3 %
Constant price	3 %	9 %	8 %
Flat fee	1 %	2 %	2 %

Source: Spanish Association of water supply and sewage (AEAS) 2012

Figure 2.1 illustrates the geographical distribution of the average water price in Spain. The light (dark) color represents the lowest (highest) quantile average water price. As it might be expected, the provinces located on the North of Spain have the lowest average price and the provinces in the South of the country register higher water prices, reflecting the higher level of water scarcity. It is also worth noting that the Canary and Balearic Islands, Murcia and some provinces in Catalonia belong to the highest quantile, since they have implemented desalinization techniques to increase the water supplied [Garrido et al., 2015] with the consequence that the costs of water services are higher in these provinces.



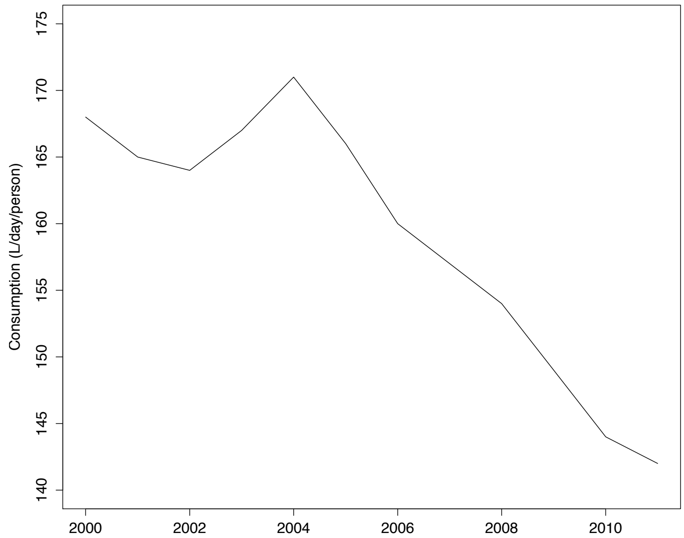
Source: Author own elaboration from the Spanish Association of Water Supply and Sewage (AEAS) 2012

Figure 2.1: Residential average price for water in Spain

Non-pricing policies are also implemented in order to promote reductions in water consumption. Policies promoting water-efficient behaviour differ depending on whether they are focused on efficient electrical or non-electrical water-using technologies. On the one hand, there are some efficient electrical appliances, such as washing machines and dishwashers, which could generate significant water savings at residential level. These appliances are identified by labelling schemes, which form part of the policies aimed at providing information to help consumers understand the potential savings of different devices. Furthermore, there is a subsidy program (*Plan Renove*) to promote investment in efficient electrical appliances. On the other hand, the installation of non-electrical water-using devices is also promoted by subsidy programs providing incentives to renew housing equipment.

Regarding policies promoting water conservation habits, information campaigns to encourage water savings have been designed at European, national and municipal levels. For example, an ambitious program named Generation Awake was launched by the European Commission's Directorate-General for the Environment in 2011 to reduce waste and the use of resources such as water, energy, wood and metals. Non-pricing policies in Spain are further discussed in Chapter 4.

The greater intensity of water demand management policies that have been implemented in Spain in the past years seems to have affected consumers' awareness of the problem, and as shown in Figure 2.2, residential water consumption has been slowly but constantly decreasing in Spain.



Source: Author own elaboration from http://www.ine.es

Figure 2.2: Evolution of residential water consumption

In light of the above, it is clear that pricing and non-pricing policies aiming at reducing water consumption are already in place. Provinces where water is scarcer generally exhibit higher average water prices and make more intense use of non-price mechanisms, and the analysis of water demand at the household level in these provinces could give us a sense of the behavioral response of households to these policies and of households' awareness of the water scarcity problem.

2.1.2 The case of Granada

The data for this study were collected from a survey carried out in the city of Granada, which is part of the region of Andalusia, located in the South of Spain and one of the most water-stressed regions in Europe.The city had a population of more than two hundred thousand people in 2014 [INE, 2014]. Its climate is Mediterranean-Continental with cool winters and very hot and dry summers. The city of Granada is located at the foot of Sierra Nevada mountains and water availability has been historically regulated by the snowmelt from these mountains. However, due to climate change and increasing pressure on water resources, nowadays reservoirs are also necessary.[1] Moreover, this situation is expected to intensify over time as the Sierra Nevada Global Change Observatory predicts an increase of over 4.8°C by at the end of the 21^{st} century in Sierra Nevada [Pérez-Luque et al., 2012]. Therefore, the predictions for Granada are more unfavorable than predictions at global level that forecast a general increase between 1.5°C and 4.5°C [IPCC, 2007]. Moreover, rainfalls could suffer a slight decrease over time, with heavy and torrential rainfalls alternating with long periods of droughts. It is also worth noting that there is an increasingly negative trend in snow duration that may worsen the freeze-thaw cycle [Pérez-Luque et al., 2012]. Aquifers are another source used to ensure water supply in the city of Granada. However, a decreasing trend in the aquifer replenishment is observed as a consequence of the change in land use from crops to urban settlement, whereas discharges from the aquifer have not decreased [Calvache et al., 2013]. Therefore, the sustainability of the aquifer is also at risk.

As water becomes increasingly scarce in the South of Spain, water supply managers are already implementing pricing and non-pricing policies as water conservation tools. In Granada, prices for water are set by EMASAGRA, the company in charge of water supply and sewage collection in the city. This company's ownership is divided between the city municipality (51%) and private interests (49%)[2], and it supplies water services to 15 municipalities in the metropolitan

[1] See http://www.emasagra.es/ESP/152.asp for detailed information about the regulation of the hydrologic cycle in Granada.

[2] The private companies that own 49% of the company in charge of water supply and sewage collection in Granada are Aquadom, Concesiones Ibéricas S.A., Agbar, Unicaja Banco

area of Granada with a population of almost four hundred thousand people.[3]

The water pricing structure in the city of Granada is based on increasing block prices (IBP): the tariff includes a fixed water service fee that must be paid regardless of the level of use and a variable cost that depends on the amount of water consumed and that increases as the latter becomes larger.[4] The fixed component of the tariff includes a water supply fee, a sewage collection fee, a treatment fee and, in 2009 and 2010, a drought surcharge. Additionally, starting in 2011 a water tax collected on behalf of the Andalusian regional government was incorporated into the tariff. Water bills are sent every two months, but prices refer to monthly water consumption. The evolution of the prices in each block is shown in Table 2.4 (in real terms calculated using the province-level Consumer Price Index with base 2011).

Table 2.4: Evolution of prices in €(in US$) 2009-2011

Year	P. Block 1	P. Block 2	P. Block 3	P. Block 4	P. Block 5
2009	0.9798	1.9130	1.9310	2.4451	2.7356
2010	1.0318	1.9365	1.9545	2.5411	2.9137
2011	0.9731	1.3536	2.3534	3.4347	-

Table 2.5 shows the structure of water prices in Granada. This structure remained unchanged between 2009 and 2010. However, it was altered in 2011 by changing the size of blocks. The water tariff in Granada is reviewed annually. Block prices were adjusted upwards from 2009 to 2010 but, as mentioned above, the price structure remained unchanged. However, in 2011 the price schedule was also changed. Table 2.5 shows the cubic meters per block in each price schedule.

and CajaGranada.

[3]See http://www.emasagra.es/ESP/86.asp for a description of the areas for a description of the areas covered by the service.

[4]The tariff also includes discounts to those who are unemployed, retired, or have a certain minimum number of dependents.

Table 2.5: Evolution of the size of pricing blocks

Blocks	2009-2010	2011
Block 1	0-8 m^3	0-2 m^3
Block 2	8-10 m^3	2-10 m^3
Block 3	10-16 m^3	10-18 m^3
Block 4	16-30 m^3	>18 m^3
Block 5	>30 m^3	-

Regarding non-pricing policies, apart from the strategies discussed above there have been several initiatives to improve people's awareness of the water scarcity problem. At regional level, an information campaign to encourage all type of consumers to reduce water consumption was set up. At provincial level, the Municipality Network on Sustainability from Granada (Red GRAMAS) has designed an educational campaign focused on water as an essential resource for life and financed by the European Regional Development Fund (ERDF). Finally, at local level the Fundación Agua Granada (Water Granada Foundation) has initiated a set of information campaigns and activities to raise awareness about water conservation. Among the activities are educational visits to the wastewater treatment plant or school-based educational programs to promote sustainable water consumption.

2.2 Database

The dataset used in this thesis is an unbalanced panel of bimonthly observations corresponding to 1,465 households in the city of Granada covering the period 2009 to 2011. The data come from two sources. The first source of information consists of water consumption and water tariffs data on a random sample of urban households in four different districts in the city of Granada, provided by EMASAGRA, the company in charge of water supply and sewage collection in Granada. The sample is representative of a population in the city center whose water consumption is mainly indoors and who live in older houses, therefore, decisions on the adoption of efficient electrical appliances are generally made by the household, as opposed to newer buildings that have efficient technology by default.The second one is a 2011 survey of these households. A person in each of the households was questioned about socioeconomic characteristics (occupation, household size), housing characteristics (size, equipment), attitudes towards the environment, and conservation habits.

Data on water consumption and water tariffs were merged with survey data. Since the survey was carried out at the beginning of 2011[5], we only have information related to socioeconomic characteristics from that year. However, since the variables considered in the survey can plausibly be considered time-invariant in the short and medium term, we consider them applicable to the period 2009-2011.

Figure 2.3 shows the evolution of the average bimonthly household water consumption and total bill for the period 2009-2011. There was a slight increase in both average water consumption and the total bill in 2010. However, after the change in the price structure in 2011, average water consumption decreased whereas the average total bill increased.

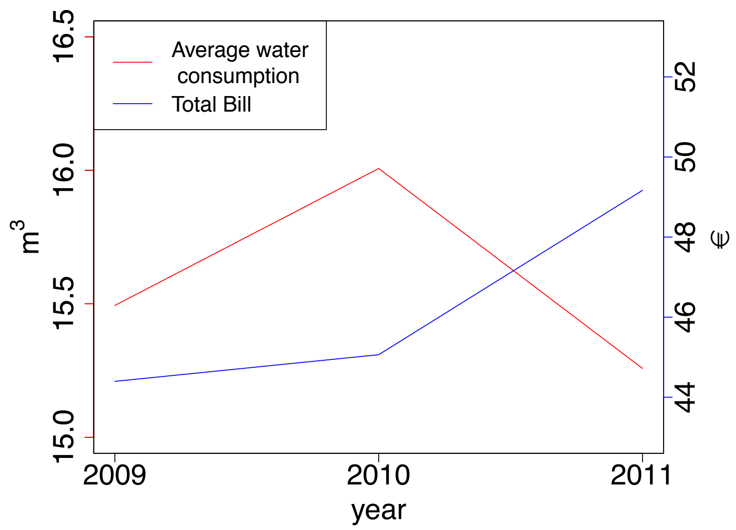


Figure 2.3: Residential average residential water prices and total bill in Granada (2009-2011)

Table 2.6 presents the definitions of the variables used in this thesis. Detailed descriptive statistics are provided in the following chapters.

[5]Information from a pretest that took place at the end of 2010 is also considered in the database.

Table 2.6: Definition of variables used in this thesis

Data on water consumption	
W	average bimonthly water consumption per year (m^3)
AvP	average price (€/m^3)
Std. Dev	standard deviation in water consumption within a year
Data from the survey	
Socioeconomic variables	
Members	number of people in the household
Highincome	= 1 if the household income is over 2700€per month, 0 otherwise
Education	=1 if the head of the household has higher education, 0 otherwise
Age	age of the head of the household
Gender	=1 if the head of the household is male, 0 otherwise
Young16	proportion of household members younger than 16
Old65	proportion of household members over 65
Owner	=1 if the house is owned by one of the household members, 0 otherwise
Tariffinfo	=1 if the household members have knowledge of tariff structure, 0 otherwise
Housing characteristics	
Electappl	number of electrical appliances in the household
Bathrooms	number of bathrooms in the household
Electeff	number of efficient electrical appliances
Noelecteff	=1 if the household is equipped with water saving devices, 0 otherwise
Home-age	Age of the house
Remodel	=1 if there were renovation works in the house in the previous five years, 0 otherwise
New pipes	=1 if 1 if there were renovation works in the water infrastructure in the five years prior the survey, 0 otherwise
Attitudinal factors	
Habits	index of water conservation habits based on responses to survey questions
Elect-habits	=1 if the household runs fully loaded dishwasher and washing machine, 0 otherwise
Noelect-habits	the sum of scores of water saving habits
Enviro	index of environmental concern based on responses to survey questions
Campaign	=1 if the person has knowledge of any water conservation campaign, 0 otherwise

The representative household in the sample has an average size of just under three members, where the head of the household is around 50 years old and male. Almost a quarter of the households in our sample are in the highest income bracket, and around a third of the households have higher education. More than half of the surveyed households are aware of some educational campaign and on average the respondents are seriously concerned about environmental problems. Most of the respondents declare that they are not aware of the price structure or their level of water consumption. This is a common issue in Spain and it is mainly due to the complexity of water tariffs in the country. Regarding housing characteristics, around two thirds of the sample live in houses that are more than 15 years old, so it is unlikely that those households have efficient technologies installed by the builder. The main tenancy regime is ownership, though the average ownership rate is lower than in Spain because there is a high number of university students in this city. Only a small proportion of the households carried out some renovations.

In terms of pro-environmental behaviors, almost half of the households are equipped with efficient water-using non-electrical devices, whereas the average number of efficient electrical appliances is around one. The average number of water-conservation habits is relatively high, with almost half of the households indicating that they have more than six water-conservation habits. However, it is important to note that the variables describing habits are self-reported, so respondents could overstate the household environmental behavior.

Chapter 3

Responses to changes in domestic water tariff structures: a Latent Class Analysis on household-level data from Granada, Spain

3.1 Introduction

Demand for water is expected to increase in future years as the world population is also predicted to grow from 6.9 billion in 2009 to 8.3 billion in 2030 and 9.1 billion in 2050 [UNDESA, 2009]. This population growth and the increasing trend towards urbanization will lead to a higher water demand and, at the same time, compromise the ability of ecosystems to provide conventional and cleaner supplies [The World Bank, 2012]. Although there are different types of strategies to deal with imbalances between water supply and demand, the use of demand-side policies has emerged as a preferred option during the last decades. Among these, pricing policies have become a particularly attractive option since they may result in lower levels of efficiency losses than other rationing alternatives [Roibás et al., 2007]. In this sense, accurate estimates of price elasticity of water demand are crucial for policy decision-making, since they make it possible for water policy designers to understand how strongly water consumption will react to changes in price. However, due to the characteristics of the good, pricing policies are often constrained by regulation [Olmstead and Stavins, 2007], so water suppliers also use non-price conservation programs to induce water reductions.

In the past, the neoclassical approach assumed that "tastes neither change capriciously nor differ importantly between people" and it was limited "to searching for differences in prices and incomes to explain any differences or changes in behavior" [Stigler and Becker, 1977, p.76]. However, there may be great heterogeneity in water consumption even amongst individuals who are similar in observable characteristics. Therefore, when analyzing the estimation of residential water demand using microdata, addressing unobserved heterogeneity is a critical issue since the demand functions are influenced by unobservable heterogeneous preferences.

During the last few years, the problem of unobserved heterogeneity has received special attention and has been addressed in two main ways. One approach confines unobserved heterogeneity in an individual-specific effect, as in linear panel data models such as fixed-effects and some random-effects models, while assuming that the marginal response to the demand determinants is the same across individuals. A more flexible approach based on the use of random coefficient models assumes instead that the regression parameters vary randomly across individuals according to some distribution and identifies the mean and the standard deviation for these parameters [Cameron and Trivedi, 2005, p. 9-10]. Another common strategy in the water demand literature has been to group individuals *a priori* according to observable characteristics that are assumed to be proxies for unobserved preferences and tastes.

The approach adopted here differs from the previous literature in that we use a Latent Class Model (LCM) to control for heterogeneity in preferences. It allows us to identify a finite number of consumer "classes" and hence different water demand functions. This methodology consists of estimating a model of two equations simultaneously. One involves estimating the main function, in this case water demand, and the other estimates the probability that each consumer belongs to a given class. By sorting individuals based on the similarity of their unobserved component, the LCM accommodates unobserved heterogeneity, while tractability and theoretical consistency are preserved in terms of the so-called

Ockham's razor. That is, water use would be perfectly explained with a model in which each consumer had a different water demand function. However, that model would be practically intractable and useless for predicting water consumption. Instead, the LCM groups consumers into the minimum number of classes that is consistent with common preferences.

The LCM has several advantages over the techniques discussed above. Compared to the first approach (using linear panel data models, such as fixed-effects and random-effects) it also accounts for slope heterogeneity across different groups of consumers, instead of confining unobserved heterogeneity to an individual-specific effect and constraining all consumers to have the same marginal effects. The second approach (the random coefficient model) assumes that the coefficients are different for each consumer. On the other hand, the LCM identifies consumer profiles that may be more easily managed when it comes to effecting water conservation policies. The LCM does not require making an *ad hoc* selection regarding the membership, which could be highly sensitive to arbitrariness, since it segments consumers endogenously into different groups. Moreover, the LCM identifies classes and allows flexible modelling of the probability of belonging to a certain group (within which unobservable preferences are similar) as a function of a set of (potentially) observable covariates. Therefore, it provides information about the size of each group and a description of the type of consumer belonging to them. This information can be very useful for the design of water management policies, as long as information about the factors that affect class membership can be obtained at a reasonable cost.

Our application exploits the panel dataset from Granada (Spain) that contains information on water consumption and prices for the period 2009-2011, as well as on socioeconomic variables and self-reported water conservation habits from a household survey carried out in 2011, which can be useful to control for individual heterogeneity. Recalling the discussion in the previous chapter, this data set is of particular interest for two reasons. First, Spain is the most semi-arid country in the European Union [Lopez-Gunn et al., 2012] and the South of Spain, where the city of Granada is located, is regularly affected by droughts and other water availability issues. Thus, it is important to understand residential water demand in order to improve water management. Second, there was a change in the price structure in the city of Granada in 2011, which makes it possible for us to consider not only changes in price levels but also changes in the size and number of price blocks when analyzing consumer responses to the water tariff. Our findings provide potentially useful information for regulators by identifying four different residential water consumer profiles. We also derive some rather informative conclusions from the analysis of the change in the price structure effected in 2011. Additionally, a sensitivity analysis is carried out to compare the results obtained using the LCM with those obtained using an alternative grouping technique. This analysis illustrates the superiority of LCMs for identifying homogeneous groups of consumers.

The chapter has the following structure. In Section 3.2, we discuss different methods that previous literature has applied to deal with heterogeneity issues. Section 3.3 presents the econometric model. Section 3.4 describes the tariff structure in the city of Granada, paying special attention to the change in the structure in 2011. Section 3.5 describes the data. Estimates from the LCM and sensitivity analysis are presented in Section 3.6. Finally, Section 3.7 concludes summarizing the main results.

3.2 Background

Understanding residential water demand is essential for the effective management of water resources. Consequently, the literature on residential water demand is vast, as revealed by the many studies that have surveyed the estimation of water demand. For example, Arbués et al. [2003] focus on different modeling approaches and data sets; Dalhuisen et al. [2003] include a meta-analysis of price and income elasticities; Worthington and Hoffman [2008] provide a survey of model specification and results; and Nauges and Whittington [2010] review the literature analyzing household residential demand in developing countries.

As mentioned in Section 3.1, it is important to account for heterogeneity, particularly when analyzing the effect of a change in the price structure. Differences in terms of price elasticities may be due to the underlying heterogeneity among regions and even households. Thus, an increasing number of studies aim to control for the presence of unobserved individual heterogeneity in residential water demand. However, the common methods to address heterogeneity seem to perform relatively poorly under certain circumstances. We will discuss the problems associated to each technique, providing additional arguments to support the use of Latent Class Analysis.

A frequently adopted approach is to control for unobserved household heterogeneity through the inclusion of household fixed effects. For example, Pint [1999] uses a fixed-effects model and an ordinary least squares (OLS) model to estimate household responses to water price structure changes in California, finding the fixed-effects model to be preferable to the OLS model. However, none of these estimations considered instrumental variable (IV) specifications, resulting in upward-sloping water demand at high prices. Worthington et al. [2009] analyze residential water demand in several councils in Queensland by estimating *common-effects* (whereby they assumed that water consumption was homogeneous across local councils), fixed-effects, and random-effects models. Their results show that the fixed-effects model outperforms the others for that particular case. Coleman [2009] develops dynamic models of water demand in Salt Lake City estimated using fixed-effects and compares them with static models obtained using pooled, fixed-effects and random-effects models. Polebitski and Palmer [2010] estimate pooled, fixed-effects and random-effects models to analyze single-family residential water demand for over 100 census tracts for the period 1991-2005, and the Hausman test indicates that the fixed-effects model is preferred over the random-effects model. Nataraj and Hanemann [2011] include household and year fixed-effects into a regression discontinuity model to account for heterogeneity across the treatment and control households in a natural experiment to determine whether consumers react to an increase in marginal price.

As previously discussed, another way to handle heterogeneity is through the estimation of Random-Coefficient Models (RCM). This methodology has not been widely used in the water demand literature, likely due to its difficult interpretation as a tool to identify groups of individuals with relatively similar responses to changes in dependent variables. This is because the RCM assumes a continuous distribution of random individual-specific regression parameters and only identifies the mean and the standard deviation of each of these distributions. This limits its usefulness in a case like ours. As far as we are aware, Miyawaki et al. [2010] is the only study that applies this methodology in this field. They conduct an analysis of Japanese residential water demand estimating a random parameters model and an autoregressive of order one error component model, obtaining similar results from both estimations.

An alternative approach consists of including dummy variables in the demand function to indicate socioeconomic and demographic characteristics that can capture differences in individual's preferences. Renwick and Green [2000] incorporated irrigation dummy variables into the demand equation to account for differences in outdoor water use. Krause [2003] investigated consumer heterogeneity in water demand using a set of experiments and a survey. First, they included group dummy variables interacted with the parameters in the demand function and then computed disaggregated demand functions for three consumer types considered in the experiment and surveys: students participants, workforce participants and retired participants. Therefore, the ability of this technique to control for heterogeneity is clearly limited.

Some studies identify different groups of consumers according to observable characteristics that may be related to the consumers' unobserved preferences. Renwick and Archibald [1998] analyze the effect of demand side policies by clustering groups of consumers in terms of income. Ruijs et al. [2008] estimate a linear demand function in the Metropolitan Region of Sao Paulo for the period 1997-2002 and evaluate welfare and distribution effects for five income groups. Mansur and Olmstead [2012] divide the sample into four sub-groups based on income and lot size in order to compare different price elasticities for indoor and outdoor water demand. However, these techniques make an *ad hoc* selection to the membership, which is highly sensitive to arbitrariness.

LCMs have attracted increased attention lately since, as we will see in the following section, this technique presents significant advantages. Among these advantages, we exploit the fact that it makes it possible to generate homogeneous groups of consumers without setting any *a priori* criteria. A number of studies use this methodology to analyze demand in other economic fields such as health economics [Ayyagari et al., 2013; d' Uva, 2006; Deb and Trivedi, 2002; Hyppolite and Trivedi, 2012], cultural economics [Boter et al., 2005; Fernandez-Blanco et al., 2009; Grisolía and Willis, 2012] or transport [Greene and Hensher, 2013; Hensher and Greene, 2003; Hess et al., 2011; Shen, 2010; Shen et al., 2006].

There are several applications of the LCM in environmental economics. For example, Scarpa et al. [2005] compare the use of the mixed logit random parameter model with the use of Latent Class Analysis to model the choice of water utility by the consumer. Patunru et al. [2007] implement this methodology to investigate the willingness-to-pay for the clean-up of hazardous waste by homeowners in Waukegan, Illinois. Scarpa et al. [2007] study different groups in the demand for hiking in the eastern Italian Alps, arguing that it is fundamental to assess heterogeneity when analyzing expected consumers surplus, predicted visitation, and response to access fees. Campbell et al. [2011] identify heterogeneous groups of respondents that were asked about the willingness-to-pay for improvements in four rural landscapes in the Republic of Ireland. However, to our knowledge, there have been no applications as yet to residential water demand functions.

Another typical concern identified in the residential water demand literature is about price endogeneity, especially in the presence of nonlinear prices. As detailed by Olmstead [2009], there are two types of estimation approaches that have been used in the literature to control for this problem: reduced-form approaches, such as IV, and structural approaches, such as discrete/continuous choice models (DCC). The IV approach is often undertaken in water demand analysis along with fully parametric or semiparametric methodologies as two-stage least squares (2SLS) or Generalized Method of Moments (GMM)[1]

In DCC models, a consumer's utility maximization problem is solved in two steps. First, the consumer selects the block given the price of each block and then decides the level of consumption that maximizes her utility. These models have been used by relatively few papers in the literature. Hewitt and Hanemann [1995] develop a DCC model of residential water demand using household level data from Denton (Texas) for the period 1981-1985, obtaining price elasticities in the range of -1.57 to -1.63, which are much higher than those obtained in the literature based on IV techniques. Apart from the models described above, Pint [1999] applies DCC models obtaining relatively low price elasticities. Olmstead [2009]

[1]See for instance, Agthe et al. [1986] in IV, Nieswiadomy and Molina [1988, 1989] in 2SLS or García-Valiñas [2005] for GMM.

compares IV and DCC estimates of water demand under increasing-block pricing using a Monte Carlo experiment finding that both models exhibit significant bias in the simulations. Strong and Smith [2010] criticize DCC models, as Bockstael and McConnell [1983] stated that the Marshallian "prices as parameters" demand function does not exist with a nonlinear budget constraint and, therefore, applied welfare analysis is problematic in this case. Moreover, this model is based upon marginal prices, which assumes that consumers are aware of the price structure.[2] There is no general theory recommending how to control for endogeneity in LCMs. Nevertheless, we use a two-stage control function approach (explained in the Appendix A) because it performs better on nonlinear models.

3.3. **Methodology**

From a methodological viewpoint, LCMs are proposed to identify different groups of consumers. This methodology may perform well in estimating residential water demand for two main reasons. First, water demand functions are related to utility functions, which are based on consumers' unobservable preferences and tastes that may differ across consumers. Therefore, LCMs allow us to identify groups of consumers who have similar unobservable preferences about how to change their water use in response to changes in a certain set of observable explanatory variables, since it sorts individuals based on the similarity of their conditional distributions. Second, from a statistical point of view, Figure 3.1 shows that the distribution of residential water consumption is asymmetric in our sample. Therefore, this distribution may be better approximated by a mixture of several normal distributions rather than a single normal (and symmetric) distribution.

In LCMs, we assume that the sample of individuals is drawn from a population that is a finite mixture of C distinct subpopulations [Cameron and Trivedi, 2005]. The density of the dependent variable (residential water consumption) y, for observation i conditionally on some parameters (β, π) and on some explanatory

[2]However, this assumption does not hold for our sample, since only 34.62% of the households know the price schedule they face.

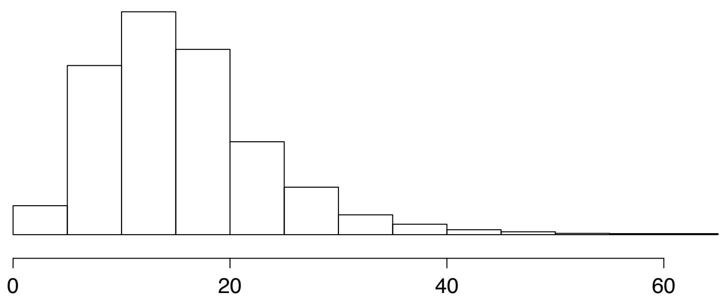


Figure 3.1: Distribution of residential water demand in Granada 2009-2011 (m[3)

variables x can be written as:

$$f(y_i|x_i;\beta,\pi) = \sum_{j=1}^{C} \pi_j f_j(y_i|x_i\beta_j) \qquad i = 1, ..., n \tag{3.1}$$

where π_j is the probability of choice j of individual i ($\sum_{j=1}^{C} \pi_j = 1$ and $\pi_j \geq 0$ $j = 1, ..., C$).

If any potential sources of heterogeneity are observed, the probability that consumer i belongs to class j can be parameterized as a function of covariates assuming that the latent variable follows a multinomial probability that yields a multinomial logit model:

$$\pi j = \frac{exp(\gamma_j' z_i)}{\sum_{j=1}^{J}(\gamma_j' z_i)}, \quad j = 1, ..., J \tag{3.2}$$

where γ_i is a vector of parameters to be estimated and z_i is a vector of observable characteristics and self-reported valuations that may be considered proxies for the underlying utility preferences [Fernandez-Blanco et al., 2009].

Therefore, if we consider a normal mixture, the log-likelihood is defined as the sum of C log-likelihood normal distributions weighted by the probabilities of class membership:

$$\mathfrak{L}(\beta, \gamma) = \sum_{j=1}^{C} P_{ij} \frac{1}{\sqrt{2\pi\sigma_j^2}} exp(-\frac{1}{2\sigma_j^2}(y_i - x_i\beta_j^2)) \tag{3.3}$$

One of the key issues in the application of the LCM is how to correctly determine the number of classes. Although LCMs with additional numbers of classes are considered nested models, it is not possible to identify the correct model using a likelihood ratio test (LRT), because regularity conditions are not met [Nylund et al., 2007]. The usual way to proceed is to estimate models with increasing numbers of classes in a stepwise fashion and compare the results using likelihood-based information criteria such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC). However, since these criteria do not share the same properties, they may yield contradictory verdicts. Nylund et al. [2007] analyzed the performance of these information criteria using Monte Carlo simulations and found that the Bayesian Information Criterion outperforms the others in correctly identifying the optimal number of classes.

Once the model is estimated, we use the parameter estimates to compute the posterior probabilities of belonging to each latent class:

$$Pr[y_i \epsilon c | x_i; y_i; \theta] = \frac{\pi_c f_c(y_i | x_i; \theta_c)}{\sum_{j=1}^{C} \pi_j f_j(y_i | x_i; \theta_j)} \qquad c = 1, ..., C \tag{3.4}$$

3.4. Residential Water Tariffs in Granada

As explained in Chapter 2, the water pricing structure in the city of Granada is based on increasing block prices (IBP). The tariff includes a fixed water service fee that must be paid regardless of the level of use and a set of increasing block prices. The fixed component in the tariff includes a water supply fee, a sewage collection fee, and a treatment fee and, in 2009 and 2010, a drought surcharge. Additionally, in 2011 a water tax collected on behalf of the Andalusian regional government was incorporated into the tariff. The tariff also includes some discounts in order to solve issues in terms of equity. As shown in Chapter 2 (see Table 2.5), the price structure in Granada remained unchanged between 2009 and 2010 but in

2011 the size of the pricing blocks was altered.

As explained in Chapter 2, the tariffs in Granada were reviewed annually, with the block prices slightly adjusted upwards from 2009 to 2010. In 2011 the rate schedule was also changed. [3]

As water becomes increasingly scarce in the South of Spain, water supply managers are using price as a water conservation tool. As stated above, Granada experienced a change in the price structure that resulted in a decrease in average water consumption but also an increase in the average total bill (Table 3.1).

Table 3.1: Evolution of the average total bill and the average quantity of water consumed

	2009	2010	2011
Water consumed* (m^3)	15.4939	16.0069	15.2579
Total bill (€)	44.3969	45.0625	49.1680

* Water consumed per household every two months

3.5. Data

The data used in this chapter is the unbalanced panel of bimonthly observations corresponding to households in the city of Granada covering the period 2009 to 2011, as described in the previous chapter. However, several alterations were performed since the average price is the only time-varying explanatory variable in our specification. As explained in Section 3.4, the pricing structure is based on IBP and, therefore, we must consider the price endogeneity generated by the simultaneous determination of the price level and the level of consumption that determines the price block. When addressing this issue, we face the problem that both water consumption and average price change within a given year in our dataset but we cannot observe a set of exogenous instruments that also vary

[3] To the best of our knowledge, there is only one previous work which deals with a change in the price structure similar to the one exploited in this research. Martínez-Espiñeira and Nauges [2004] study residential water demand in Seville (Spain) for the period 1991-1999, where the block size changed slightly in 1996. Water demand is modeled using Stone-Geary utility function that allows identifying a threshold of water that is insensitive to price, though the change in the block is not directly analyzed.

within each year. Therefore, in order to address the endogeneity problem, it was necessary to aggregate water consumption by year, which made it possible to use the set of marginal prices per block, which change yearly, as instruments. Furthermore, after this transformation, we also excluded from the sample those individuals who were not observed for the entire year 2011, because of the possible bias introduced by seasonality in their water consumption.

Therefore, after the data aggregation, the dependent variable in our specification is the average bimonthly household water consumption per year, in cubic meters, which was calculated by dividing total consumption per year by the number of two-month billing periods. Regarding the price variable, there are two main issues related to price when analyzing water demand facing a nonlinear pricing scheme. First, one must face the choice between marginal and average price. In this particular case, consumers indicated that they were not well informed about the pricing scheme. Therefore, households may be more sensitive to changes in average price (AvP) than in marginal price. The second issue, as commented above, relates to the price endogeneity generated by the simultaneous determination of price and the block of consumption. In the absence of a general theory about how to handle endogenous explanatory variables in LCMs, we used a two-stage control function (CF) estimation technique [Blundell and Powell, 2003; Howard and Roe, 2013; Imbens and Wooldridge, 2007] over two-stage least squares (2SLS), because it is more appropriate for nonlinear models and, although our model is linear in parameters (since we are estimating mixtures of normal distributions), the nonlinearities arise when estimating the posterior probabilities at each maximization stage. The 2SLS approach would fail, because it implies approximating the endogenous variable with a linear transformation thereof and then using the estimated coefficients in the second stage would be used to compute the posterior probabilities. Therefore the nonlinear step in the computations of the posterior probabilities is not invariant to the use of 2SLS. A more detailed discussion of this methodology and the instruments selected can be found in the Appendix A and the results of the estimation.

In order to allow for the possibility that the price elasticity differs between the period before and after the change in the price structure, we include an interaction (labelled *AvP2011*) between the binary indicator for 2011(*Year2011*) and the average price (AvP). Following Gaudin [2006], we also incorporated an indicator capturing how well-informed users are about their water tariff in the demand equation through its effect on price elasticity. To do so, we interacted a binary variable indicating awareness of the price structure with the average price (resulting in variable *Priceinfo*).

Household income was recorded as an ordered categorical variable, with households belonging to one of the following intervals(in Euros/month): [0-1100]; [1101-1800]; [1801-2700]; [2701-3500]; [3501- $+\infty$]. It would not be appropriate to use the interval categories as if they were values of a continuous variable. Usually, one would construct a set of five binary indicators of income level and introduce four in the model. However, because we did not seem to have enough sample variability to estimate all four corresponding parameters, we simplified our original income variable into a binary indicator (*Highincome*) of relatively higher income. In particular, we create a binary variable that identifies the richer households (those falling in the two highest income categories). Additionally, and based on previous literature, there were other variables included in the demand function. Household size (*Members*) was included, following most previous studies of residential water demand. Water conservation habits (*Habits*) were included using an aggregate index based on different daily behaviors.[4] Several variables representative of housing equipment are also considered, such as the number of electrical appliances (*Electappl*) and the number of efficient water-using electrical appliances (*Electeff*). Finally, an indicator of home ownership was included since homeowners are expected to have more incentives than tenants to make investments in water-saving devices as shown by Grafton et al. [2011].

As stated in Section 3.3, individuals are sorted by the LCM into groups based on the similarity of their conditional distributions. However, the probability of belonging to a certain group can be further modeled as a function of covariates that can be considered proxies for the unobserved preferences related to water demand. That is, these variables allow us to identify household characteristics for the different water user profiles. In this sense, these variables belong in the

[4]As shown in Beaumais et al. [2010], a water habit index was constructed by calculating the mean score on the answers related to the values of water use/conservation habits that were elicited by the survey (possible answers were 1 = yes or 0 = no).

class-selection function rather than in the water demand functions. This is to say, they determine how the households' quantity demanded reacts to demand drivers, especially prices, but not the quantity demanded as such.

At this stage, water suppliers would benefit from the knowledge of the main factors determining class membership, in particular the membership to classes with some specific characteristic (for example, a particularly (in)elastic response to price changes or a particularly sensitive response to moral suasion campaigns), if combined with the availability of individual data about those variables. In practice, these variables could end up being easily observable factors (e.g. household type, presence of children, living in an apartment or not, availability of an individual meter, being a year-round versus a seasonal dweller, education levels, tenancy status, etc.) or else variables whose values would be costly for the water supplier to gather. The practical advantages provided by the application of the LCM to estimate water demand would depend on these informational requirements, apart from having the technical sophistication and computational resources to periodically estimate the LCM itself.[5] In some cases, a more *ad hoc* approach to identifying consumer groups might thus end up being more efficient, particularly in those cases in which the differences among classes in terms of the most relevant estimated parameters (such as price-elasticities) are minor.

Following Russell and Fielding [2010], we use Stern [2000] as a guide to categorize the determinants of different water demand behaviors into four types of causal variables. Attitudinal factors are one of the causes of behaviors. According to the value-belief-norm theory (VBN), "the general predisposition to act with proenvironmental intent can influence all behaviors an individual considers environmentally important" [Stern, 2000, p. 416]. Therefore, we include an environmental concern index (*Enviro*) as the general attitude towards the environment may influence preferences and, therefore, membership to a certain water use profile.

The second type of causal variables that we should take into account is personal capabilities among which we included knowledge and skills that may affect the drivers of residential water demand. In the estimation we considered a binary

[5]Fortunately, since nowadays LCM routines are available through statistical packages such as Stata, estimating them should be within the reach of most analysts.

variable related to the knowledge of the existence of an environmental campaign (*Campaign*). We also include the age (*Age*) of the head of the household, since it has been commonly considered as a determinant of environmentalism and, more specifically, water demand behavior. However, prior literature drew mixed conclusions about this effect. Kantola et al. [1983] and Scott and Willits [1994] found a negative effect on environmental behavior, whereas Gilg and Barr [2006] and Clark and Finley [2007] found that older consumers are more likely to report water conservation intentions.

Automatic processes such as habits and routines may guide behaviors. Therefore, examining the role of habits and routines is fundamental for the analysis of water demand behaviors. As people of different ages may have different habits and routines, we include variables reflecting the proportion of members over 65 years (*Old65*) and those under 16 years (*Young16*). We can expect households with a higher proportion of younger members to have a lower response to changes in the drivers of residential water demand due to the need for more frequent laundering, more frequent showers and use of water-intensive outdoor activities. On the other hand, retired people may also have a lower response since they are likely to devote more time to activities that involve water use such as gardening and spending more time at home. A water-conservation habits index (*Habits*) was also included as a covariate.

The last category of determinants of different water demand behaviors includes contextual factors such as physical infrastructure and technical facilities that are also closely related to human behavior. We used a categorical variable that accounts for the number of water-efficient electrical appliances in a household (*Electeff*).

In order to control for different consumption patterns that may have been masked by the aggregation, we included as a covariate the standard deviation in water consumption (*Std. Dev*) within a year. This variable is not included in the demand function, because it affects the water consumption profiles but not the level of water consumption.

Table 3.2 shows some descriptive statistics and descriptions for the variables included in the LCM.

Table 3.2: Summary statistics

Variable	Description	Mean	S. d.	Min.	Max.
Dependent variable					
Consumption	Average bimonthly water consumption per year (m^3)	15.699	8.084	1.167	65
Water demand covariates					
AvP	Average price (€/m^3)	1.699	0.495	0.663	8.076
AvP2011	*AvPrice*×dummy 2011 (€)	0.696	1.001	0	8.076
PriceInfo	*AvPrice*×dummy knowledge of tariff structure (€)	0.565	0.84	0	8.076
Highincome	= 1 if the household income is over 2700€	0.213	0.41	0	1
Members	household size	2.713	1.225	1	9
Owner	=1 if house is owned by a household member	0.776	0.417	0	1
Habits	Index of water conservation habits	0.618	0.159	0	1
Electappl	Number of electrical appliances in the house	2.007	0.603	1	4
Electeff	Number of efficient water-using electrical appliances in the house	0.822	0.839	0	2
Class membership covariates*					
Enviro	Index of environmental concern ranging from 0 (*not concerned*) to 2 (*very concerned*)	1.821	0.422	0	2
Campaign	=1 if respondent knows of any water conservation campaign	0.552	0.497	0	1
Young16	proportion of household members younger than 16	0.043	0.127	0	0.778
Old65	proportion of household members over 65	0.332	0.424	0	1
Age	Age of household's head	54.128	19.274	18	94
Std. Dev	Standard deviation in water consumption within a year	2.958	2.721	0.278	44.444

**Electeff* and *Habits* are also included as class membership covariates

3.6. **Results**

In order to select the model that best fits the data, we estimated several LCMs changing the number of classes and compared likelihood-based model selection criteria, such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), as explained in Section 3.3. The selection criteria, reported in Table 3.3, lead to different conclusions. The BIC suggests that the 4-class model with variable probabilities fits the distribution better but the AIC suggests that a 5-class model with variable probabilities is best. Therefore, following Nylund et al. [2007], we selected the model that minimizes the BIC, that is, the 4-class model with variable probabilities, since it provides the best fit for these data. The results confirm that the LCM outperforms the OLS model. That is, household heterogeneity is significant and that there seem to be four distinct residential water consumer profiles in Granada for the period 2009-2011, rather than the single one assumed by the conventional OLS approach, which forces all consumers to respond to the same pattern in terms of their water demand.

Table 3.3: Selection criteria for several models

	N	log -likelihood	Akaike information criterion	Bayesian information criterion
1-class, constant probability	3012	-10225.0	20472.0	20538.1
2-class, constant probability	3012	-9509.6	19069.1	19219.4
3-class, constant probability	3012	-9235.9	18547.7	18776.1
4-class, constant probability	3012	-9170.1	18442.3	18748.8
5-class, constant constant probability	3012	-9139.0	18405.9	18790.6
4-class, variable probability	2845	-8072.1	16294.2	16740.7
5-class, variable probability	2845	-8116.8	16425.5	16996.9

Moreover, as explained in Section 3.3, the distribution of residential water consumption in the city of Granada is asymmetric and, as shown in Figure 3.2, the 4-class model fits the data better than both the OLS and the random-effects models.

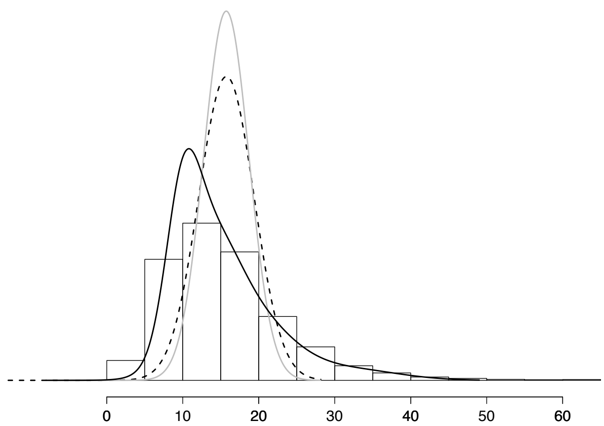


Figure 3.2: Distribution of residential water demand in Granada 2009-2011 (histogram). Distribution of the predicted value using OLS model (dashed line), random-effects model (grey line) and the 4-classes LCM with variable probabilities (black line)

Table 3.4 presents selected descriptive statistics for water consumption by class. On average, the first and the second class are the ones with the lowest and the highest average water consumption respectively. However, as explained in Section 3.3, it should be stressed that consumers are not sorted based on the values taken by the dependent variable (water consumption)[6] but instead according to the similarity of their conditional distributions of the error component, as shown by the minimum and maximum values. It is also worth noting that Class 2, the smallest (representing just over 6% of the sample), has the highest estimated standard deviation in the distribution of consumption. That is, their consumption levels within this class are the most variable. Moreover, Table 3.5 shows that most of the explanatory variables are not significant, so that it is not possible to identify a pattern in residential water consumption. As explained by Cameron and Trivedi (2005, p. 625), additional classes may be the result of the LCM grouping outliers. Therefore, considering that this is the smallest class and that we cannot identify the drivers of water demand, we may think that households

[6]The sample could be split into arbitrary intervals by modeling the inverse of the cumulative distribution function (CDF) of the dependent variable using Quantile Regression.

that belong to this class are in fact outliers whose consumption patterns cannot easily be explained by the usual determinants of the quantity of water demanded.

Table 3.4: Water consumption statistics by class

Variable	Mean	Std. Dev.	Min	Max	Classification based on posterior probability (%)
Class 1	9.8910	2.4020	4.1667	16.3333	0.2619
Class 2	33.8012	9.8352	1.1667	65	0.0692
Class 3	13.2829	3.94914	3	22.3333	0.3367
Class 4	18.9621	6.6983	1.333	38.1667	0.3322

In Table 3.5, we present the results of the 4-class model with variable probabilities. We also report the results of the OLS model, i.e., a single-class model, and a random-effects model that will be used to assess the importance of household heterogeneity.

First, the estimation of the single-class model and the random-effects model suggests that the demand is price inelastic, with the price elasticity at the sample means being -0.4368 and -0.3255 respectively as shown in Table 3.6. However, turning to the 4-class model, we find that for Classes 1 and 2, which include 26.19% and 6.92% of the observations respectively, price has no significant impact on residential water demand. Therefore, the effect of a change in price would be overestimated for those consumers in Classes 1 and 2 when using the other two models. In contrast, for the remaining classes, price is significant, but price elasticities vary across classes, with the fourth class having the most elastic water demand. This heterogeneity in terms of price elasticities is masked when estimated through a single-class model and a random-effects model. As explained in Section 3.5, in order to allow for the possibility that price elasticity differs between 2009-2010 and 2011, that is, between the period before and after the change in the price structure, we included the interaction involving a dummy variable for 2011 and the lagged average price. Table 3.6 shows that water demand becomes more inelastic in the single-equation and random-effects estimation. The 4-class models suggests that it is only consumers in Class 3 that have become more price inelastic after the 2011 change in the price structure. That is, the single-class model and random-effects model identify a shift in the demand function for all consumers, while the 4-class model identifies this shift for

Table 3.5: Estimated water demand models

	OLS	RE	LCM			
Water demand			Class 1	Class 2	Class 3	Class 4
AvP	-4.048**	-3.015***	-1.420	18.08	-2.756**	-5.297**
	(-2.32)	(-4.26)	(-0.82)	(0.54)	(-2.46)	(-2.35)
AvP11	0.740*	0.605***	0.354	-5.214	0.557**	0.704
	(1.91)	(4.13)	(0.90)	(-0.65)	(2.29)	(1.50)
Priceinfo	0.488*	0.430*	-0.0475	2.105	0.0731	0.242
	(1.85)	(1.89)	(-0.46)	(1.17)	(0.40)	(0.84)
Highincome	-0.942*	-0.734	-0.255	-4.263	-0.762***	-0.867
	(-1.88)	(-1.54)	(-1.60)	(-1.42)	(-2.62)	(-1.18)
Members	1.806***	1.907***	0.626***	3.801***	1.090***	1.828***
	(9.08)	(9.59)	(7.07)	(3.44)	(10.09)	(7.27)
Electappl	1.450***	1.403***	0.712***	4.056*	0.854***	0.958*
	(3.53)	(3.59)	(4.13)	(1.85)	(3.79)	(1.69)
Habits	-2.322	-1.677	0.0481	-22.91	-0.385	-3.362
	(-1.58)	(-1.16)	(0.06)	(-1.43)	(-0.24)	(-1.63)
Electeff	-0.467*	-0.572**	0.285***	2.290	0.372	1.114**
	(-1.86)	(-2.27)	(2.61)	(0.69)	(1.59)	(2.45)
Owner	-0.391	-0.486	-0.0409	-3.766	0.0908	-0.720
	(-0.69)	(-0.91)	(-0.21)	(-1.14)	(0.27)	(-1.00)
ControlFunction	-2.323	-0.672	-11.11***	-17.75	-8.578***	-2.297
	(-1.38)	(-1.00)	(-6.18)	(-0.74)	(-6.32)	(-1.12)
Constant	16.34***	14.23***	8.248***	1.148	12.11***	21.97***
	(5.24)	(7.83)	(2.62)	(0.02)	(4.84)	(4.44)
Latent Class Probability						
Enviro			-0.227	0.0550	0.312	
			(-0.86)	(0.14)	(1.21)	
Campaign			0.0303	0.703**	0.0439	
			(0.13)	(2.15)	(0.22)	
Electeff			0.405*	-0.930**	0.127	
			(1.75)	(-2.35)	(0.92)	
Habits			-0.389	1.049	-1.508*	
			(-0.30)	(0.65)	(-1.70)	
Young16			1.848**	0.456	1.418*	
			(2.02)	(0.34)	(1.96)	
Old65			0.976**	-0.159	0.225	
			(2.19)	(-0.27)	(0.61)	
Age			-0.0234**	0.0201	-0.0114	
			(-2.44)	(1.30)	(-1.56)	
Std. Dev			-1.805***	0.291***	-0.520***	
			(-11.34)	(5.56)	(-7.14)	
Constant			4.599***	-4.429***	2.136***	
			(4.40)	(-3.15)	(2.69)	

t statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

a specific group of consumers implying that the change in the price structure was not similarly perceived by all consumers. Furthermore, knowledge of the price structure has no significant impact on price elasticity in the 4-class model, but it has a positive and significant effect at the 10% level both in the single-class model and random-effects model. The lack of significance of this variable may be due to the fact that knowledge of the price structure, that is, that consumers know that the price structure is based on IBP, does not imply that consumers are aware of the block where they consume and the set of marginal prices per block.

Table 3.6: Price elasticities of demand

Model		Price Elasticities	
		2009-2010	2011 Effect
single-class model		-0.4368**	0.0327*
random-effects model		-0.3255***	0.0268***
	Class 1	-0.2357	0.0224
	Class 2	0.9675	-0.1221
4-class model	Class 3	-0.3419**	0.0300**
	Class 4	-0.4951**	0.0264

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Under the single-class model, we find that the high-income indicator has a negative and significant impact on the amount of water consumed. In the 4-class model, this only applies for Class 3. This negative effect may be reflective of water conservation measures resulting from the greater possibilities for investing in water-saving devices by this class of consumers. The income variable coefficients corresponding to the remaining classes are not significant. Therefore, a higher level of income is not associated with a higher demand of water for all the users in the sample.

The household size has a positive estimated effect on water consumption in all the models. For comparison purposes across models, the values of average elasticities of water demand with respect to household size from the models are presented in Table 3.7. Overall, the elasticities with respect to family size are quite heterogeneous among classes. However, the results show that, in every case, an increase in water use is less than proportional to an increase in the number of persons per household. This is consistent with other studies that have found economies of scale [Arbués and Villanúa, 2006].

Table 3.7: Elasticity of water demand with respect to family size

Model		Elasticities
single-class model		0.3121***
random-effects model		0.3289***
	Class 1	0.1571***
	Class 2	0.3185***
4-class model	Class 3	0.2257***
	Class 4	0.2731***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Electappl has a positive and significant effect in both the OLS and the random-effects models. That is, the higher the number of electrical- and water- appliances, the higher the level of water consumption. These coefficients are significant for the four classes in the LCM and differ across classes, which suggests that the effect of a higher number of appliances on water demand is heterogeneous.

The variable *Habits* does not have a significant effect on water demand in any of the models that we have estimated. Self-reported water-conservation habits may not have a significant effect on water consumption after controlling for other variables. However, the effect of this variable on water demand may also depend on the habits index used and when those habits are measured, as in Trumbo and O'Keefe [2005]. These authors measured self-reported behaviors related to water conservation across a two-year time frame, finding that self-reported water-conservation in 1998 had a significant effect on conservation intentions in 2000. That is, future intentions may be affected by past water-conservation habits.

The number of efficient electrical appliances has a negative and significant effect at the 10% level in both the single-class model and the random-effects model. However, when we estimate the 4-class model, this variable has no significant effect for Classes 2 and 3, although it does have a positive and significant effect for Classes 1 and 4. The installation of water-efficient appliances should reduce water use, although several studies have also found the opposite effect [Campbell et al., 2004; Fielding et al., 2012; Inman and Jeffrey, 2006]. Among the possible causes of this positive effect on water demand is the possibility of a so-called rebound effect, that is, smaller water savings than expected from the installation of water-efficient equipment due to behavioral changes that partially offset technical efficiency gains and the fact that investments on water-efficient appliances may be related to activities that imply higher water consumption [Fielding et al., 2012]. However, given the unstable behavior and high potential for biasedness[7] affecting the estimates associated with this variable and the habits index, we make no strong claims about their validity and the resulting conclusions should be viewed with caution.

The coefficient of the binary variable indicating home ownership is not significant in any of the models estimated, indicating that owner occupiers do not differ significantly in terms of their water demand depending on whether they own their home or not. This result could be due to the high proportion of home ownership in Granada (as in the rest of Spain), or the likelihood that many of those who do not own their homes are actually students who might make substantial proportion of their water use (for laundry, etc.) at their family home outside the city.

The lower portion of Table 3.5 presents the estimated coefficients of the covariates in the membership function, with Class 4 as the reference category. We can see that most of the covariates do not have statistically significant coefficients. That is, they seem to have very little predictive power about individuals' preferences about water demand. Therefore, if we had divided the sample into explicitly defined groups based on these observable characteristics and self-reported valuations that *a priori* we expected to be proxies for unobserved preferences about

[7]The potential endogeneity of habits or efficient electrical appliances is not considered in the empirical analysis, since we are not trying to make any type of causal inference about the impact of habits on water consumption. In the terminology of [Angrist and Pischke, 2009, p. 68], these variables can be referred to as proxy control variables, in the sense that they are included in the regression in order to serve as a measure of the observed water behavior and in order to avoid omitted variable bias. Including this variable would not generate a regression coefficient of interest but it may be an improvement over the alternative of using no control. Moreover, we test the robustness of the results by excluding these variables, finding that the other coefficient estimates (not reported but available upon request) remain qualitatively unchanged.

water consumption, we would have misclassified individuals. In this case, LCMs seem to be appropriate when some sources of heterogeneity remain unobserved.

However, there are some covariates that provide some information for identifying the different water demand profiles. *Campaign*, *Electeff*, *Habits*, *Young16*, *Old65*, *Age* and *Std. Dev* are all statistically significant. The first class has a positive and significant coefficient for *Young16* and *Old65*. Therefore, the proportion of children under 16 and adults over 65 is expected to be higher than in Class 4. Class 1 is also characterized by younger household heads and a smaller standard deviation of water consumption within the year. This class also has a positive and significant coefficient for *Electeff*, suggesting that consumers in this class have a higher number of efficient electrical appliances than those in Class 4.

Class 2 is characterized by consumers who are aware of the existence of campaigns to promote water savings and who have fewer efficient appliances compared to those in the fourth class. Moreover, consumers in Class 2 have a higher standard deviation in annual water consumption. As explained above, consumers in this group lack a clear pattern of consumption that can be explained by the standard drivers of water demand: consumers on this class have not the highest standard deviation of water consumption but also the highest within-year variation of consumption.

We estimated that Class 3 was characterized by households with a significantly lower score on the water habits index, a significantly higher proportion of children under 15, and a significantly lower standard deviation in annual water consumption relative to the fourth class.

Finally, Class 4, by implication, is defined by households with a lower proportion of children (compared to Class 1 and 3) and adults over 65 (relative to Class1). However, the head of the household is older than those in the first class. Consumers in this class are less aware of the existence of water-saving campaigns than those in the second class, have fewer water-conservation habits than consumers in the third class, and have a lower number of efficient appliances than consumers in the first class, but higher than consumers in the second class. Regarding the variability (as measured by its standard deviation) of annual water consumption, households in this class have a larger dispersion than those in Class 1 and 3, but smaller than households in the second class.

3.6.1. ***Sensitivity analysis***

We compared the LCM to an alternative model in order to show that the LCM can better capture heterogeneity in the sample. As noted in the introduction, several studies have sorted consumers into different groups based on observable characteristics such as income. In our own comparative exercise and in order to make groups comparable to those estimated using the LCM, we divided the sample into four sub-groups based on income and the standard deviation[8] and we maintained the same demand specification. As a comparison, and although the LCMs is a probabilistic model, we grouped consumers based upon their estimated modal probability. The results are shown in Table 3.8.

In the spirit of Nguyen and Rayward-Smith [2008] and Eshghi et al. [2011], we used two measures to evaluate the performance of the different grouping methodologies: the homogeneity of the observations within each group, and the heterogeneity between groups.

To measure the level of homogeneity within groups, we computed the standard deviation of the residuals in each group and then we summed the indicator across groups and divided by the number of groups.

$$s(j) = \sqrt{\frac{\sum_{i=1}^{N(j)} (\epsilon_{ij} - \epsilon_j)^2}{N(j) - 1}} \tag{3.5}$$

$$S = \sum_{j=1}^{J} \frac{s(j)}{J} \tag{3.6}$$

To measure the level of heterogeneity between groups, we considered the ratio of the difference between the observed realization of the value of the dependent and the predicted value to the difference between the observed value and the value that would be predicted for that observation if it were assigned to a different group. This indicator was computed for each group, summed across groups, and

[8] These groups are defined based on their sample average of the standard deviation in water consumption within a year and the two possible categories of the income variable.

Table 3.8: Water demand, by Income/Std. Deviation groups

	(1)	(2)	(3)	(4)
AvP	-5.866***	-0.944	-4.796	-3.925
	(-3.07)	(-0.16)	(-1.64)	(-0.66)
AvP2011	1.255***	-0.262	0.900	0.580
	(2.99)	(-0.20)	(1.36)	(0.44)
Priceinfo	-0.241	0.755	0.994**	0.913
	(-0.97)	(1.31)	(2.41)	(1.19)
Members	0.989***	1.762***	1.684***	1.902***
	(4.85)	(4.55)	(4.77)	(3.76)
Electappl	1.004***	1.137	0.998	2.424*
	(2.87)	(1.26)	(1.43)	(1.80)
Owner	-0.343	0.0156	1.198	3.569**
	(-0.63)	(0.01)	(1.13)	(1.99)
Habits	-1.412	-1.204	0.961	-4.729
	(-1.02)	(-0.38)	(0.34)	(-1.13)
Electeff	-0.113	-0.574	-0.0759	-0.772
	(-0.43)	(-1.08)	(-0.18)	(-0.92)
ControlFuntion	-1.991	-3.622	-1.193	-2.607
	(-1.05)	(-0.66)	(-0.40)	(-0.50)
Constant	19.30***	15.20	11.86*	13.43
	(5.28)	(1.56)	(1.93)	(1.15)
N	1491	872	424	225
Log-likelihood	-4610.9	-3131.8	-1279.4	-763.2
AIC	9241.8	6283.6	2578.9	1546.4
BIC	9294.9	6331.3	2619.4	1580.5

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

then divided by the number of groups.

$$\sum_{i=1}^{N(j)} \frac{(y-\hat{y}_j)^2}{(y-\hat{y}_{k\neq j})^2} \tag{3.7}$$

$$H = \sum_{j=1}^{J} \frac{h(j)}{J} \tag{3.8}$$

Table 3.9 shows the measures of homogeneity and heterogeneity calculated using the results from each methodology. These results support the conclusion that our LCM estimation provides the most homogeneous groups while it succeeds in differentiating among these groups.

Table 3.9: Measures of Homogeneity and Heterogeneity

	Homogeneity	Heterogeneity
Latent Class model	5.0241	0.1091
Grouping based Income/Std. Dev	6.5698	0.8548

3.7. Conclusions

This study provides strong evidence of unobserved heterogeneity in residential water demand in the city of Granada for the period 2009-2011. We identified four different residential water consumer profiles in Granada for the period 2009-2011 using a LCM, rather than the common profile assumed by single equation approaches, and this estimation allowed us to observe four distinct prices responses. Moreover, our sensitivity analysis shows that the LCM technique is an appropriate method to group observations homogeneously.

Water demand is found to be perfectly inelastic for two of the classes we identify. The proportion of consumers who belong to these classes, based on the posterior probabilities, exceeds 33%. The effect of a change in price would be overestimated for these two groups of consumers, which represent a substantial proportion of the sample, if price elasticities were estimated using a single-class model. The implementation of pricing policies would likely be less effective in reducing water consumption for these two groups of consumers in the future. Particularly, one of the groups that is relatively insensitive to price changes (which represents a quarter of the households) registers low average consumption levels. This result seems to be in line with those obtained estimating residential water demand functions based on a Stone-Geary utility function [Dharmaratna and Harris, 2012; Garcia-Valiñas et al., 2014; Gaudin et al., 2001; Martínez-Espiñeira and Nauges, 2004], which suggest the existence of a nondiscretionay amount of water that is not sensitive to price changes and an additional quantity devoted to discretionary uses that does respond to price variations.

Identifying different price elasticities allows regulators to more accurately predict the effect of different water conservation policies. Our analysis suggests that the focus of a water demand management policy could be tailored to the specific demand function of a particular group of consumers. Indeed, in order to reduce water consumption, pricing and non-pricing policies such as education programs, water rationing, retrofit subsidies or public information campaigns can be jointly applied to the most price-responsive groups of consumers. However, non-pricing policies should be intensified in the case of the least price-responsive consumers, especially for the class that has a low level of water consumption, likely to be mainly nondiscretionary and, therefore, hard to adjust in the short-run. Promoting water-saving habits and the installation of efficient appliances could be useful to reduce both discretionary and non-discretionary residential water consumption [Garcia-Valiñas et al., 2014]. We illustrate how the analysis of membership probabilities makes it possible to identify the characteristics of the users that belong to a given class, which should make it easier to tailor water conservation programs to best suit the response patterns of different user groups.

We have shown that the use of Latent Class Analysis shows a reasonable degree of potential as a tool to improve our understanding of residential water demand. This is, however, the first time that, to our knowledge, Latent Class Analysis has been used in the estimation of water demand functions. It would, therefore, be interesting to replicate this type of work using similar data from other jurisdictions to find out whether and to which extent our results can be generalized further.

Chapter 4

Adoption and use of efficient technologies at residential level: a disaggregated analysis in the water sector

4.1. Introduction

Water scarcity has emerged as a serious and growing environmental problem. The IPCC has predicted that "freshwater resources are vulnerable and have the potential to be strongly impacted by climate change, with wide-ranging consequences for human societies and ecosystems" [Bates et al., 2008, p. 3]. Consequently, numerous measures to promote sustainable water consumption have been established by governments. As we mentioned when describing the context of this research, both pricing and non-pricing instruments have been used to match water demand and supply at residential level.

The effect of price on residential water demand has been widely studied in the literature, as was noted in the previous chapter (see Arbués et al. [2003] and Worthington and Hoffman [2008] for comprehensive literature reviews). However, water supply managers have been often hesitant to implement pricing policies to promote reductions in water consumption due to the relatively low sensitivity of residential water demand to water prices, using instead non-pricing policies that are also more politically acceptable than other more stringent policies such as price increases or water restrictions. Among these non-pricing policies we can distinguish those aimed at affecting water-use habits, such as public information campaigns or moral suasion initiatives, and those intended to encourage the investment on water-efficient appliances, such as subsidies.

Several studies have aimed at analyzing the effect of water-saving technologies and pro-environmental habits on water demand. For example, Renwick and Archibald [1998] used data from Santa Barbara and Goleta in California to analyze the effects of certain indoor water-efficient equipment in the household, finding that the use of a low-flow toilet and showerhead decreases household water use by 10% and 8% respectively. Renwick and Green [2000] studied residential water demand using aggregate data from eight Californian water agencies for the period 1989-1996 and their results showed that voluntary measures such as public water-saving campaigns and retrofit subsidies reduced aggregate demand by 8% and 9% respectively, being larger those reductions achieved by more stringent mandatory policies. Kenney et al. [2008] use data from Colorado for the period 1997-2005 to analyze indoor water-efficient equipment and they find that water-efficient washing machines and low-flow toilets reduce household water demand by 10%.

However, the actual water savings arising from the installation of water-efficient devices and appliances may not coincide with expected savings due to behavioural changes which lead to so-called 'rebound' effects. For example, the installation of dual toilets may lead to significant increases in the number of flushes per day. Similarly, the presence of efficient washing machines or dishwashers could result in an overuse of these appliances. Studies which have analyzed the existence of a potential rebound effect in the water sector include [Bennear et al., 2011; Campbell et al., 2004; Davis, 2008; Mayer et al., 1998].The rebound effect has been classified into three types in the energy literature. There is a positive rebound effect if the percentage reduction in consumption is smaller than the expected efficiency gain. A special case known as "backfire" occurs if the rebound is higher than the expected improvement in efficiency, thereby leading to an increase in consumption [Saunders, 1992]. A negative effect or "super-conservation" [Saunders, 2008] is also possible if consumption decreases by a greater amount than the expected efficiency gain. Moreover, the European Commission (EC, 2012) alerts EU members to the water efficiency losses linked to the rebound effect in all the main water using sectors (industry, energy production, agriculture, households). The European Commission propose the application of different policies, combining both pricing and non-pricing instruments, in order to avoid the rebound effect. As a consequence, this issue has entered in the political agenda of several European contries.

In this context, the interaction between habits and technologies is crucial, as for some appliances and/or groups of people the potential rebound effect due to behavioural changes may lead to lower than expected water efficiency gains from the introduction of water-saving technologies (i.e., devices and appliances). The detection of different profiles with higher probability to show some rebound effect should be an additional feature to consider in the design of public policies. This issue is specially sensitive in some sectors where pro-environmental behaviours could be taken into account in the design of grant frameworks, creating incentives to improve environmental efficiency.

The aim of this chapter is analyze the determinants of a set of decisions on the adoption of water-efficient technology and the corresponding water conservation habits. As an original contribution, we consider two groups of water-efficient technologies, namely electrical and non-electrical appliances, identifying habits corresponding to each type of technology. From a methodological point of view, we use a recursive bivariate probit model for each pair of decisions to account for the correlation between disturbances. Moreover, the recursive model allows us to test the effect of efficient technologies on water-saving habits. Since we are using cross-sectional data, it is not possible to observe the sign of the rebound effect, but we can identify whether households with efficient technologies have a higher or lower probability of manifesting a specific water-saving habit. This analysis allows us to identify certain target groups on which public policy on residential water demand could usefully be focused.

The outline of the chapter is as follows. First of all, a brief literature review is presented, explaining the main contributions related to the rebound effect in the water sector and the determinants of water conservation habits and technology adoption. Section 4.3 describes some public policies aimed at promoting environment friendly behaviours and efficient technology adoption in Spain. The methodology is explained in Section 4.4, while Section 4.5 briefly describes the dataset used in the empirical application. Section 4.4 shows the results from the estimation of the bivariate probit model. The chapter includes with a summary of the main contributions and some policy implications.

4.2. Literature review

The analysis of the determinants of water-efficient technology adoption and the choice of water-conservation habits has received some attention in the literature. Except in one particular case [Martínez-Espiñeira and García-Valiñas, 2013], the majority of papers have analyzed these choices separately.

Water conservation activities (technology adoption and habits) are influenced by socioeconomic characteristics and attitudinal and behavioral variables. One of the socioeconomic variables that is usually considered is income and its effect on water conservation activities is not clear in the literature. Millock and Nauges [2010] study the impact of several variables on the adoption of water-efficient technology using data on 10000 households from 10 OECD countries, finding a positive and significant effect of income on the probability of installing indoor water-efficient equipments but a negative effect on the probability of buying a water tank. De Oliver [1999] analyzes the demographics of support for water conservation using municipal water consumption data from San Antonio (Texas) finding a negative correlation between high income and conservation. However, Domene and Saurí [2006] find no significant effect of income on water conservation behavior of households in 22 municipalities in the metropolitan region of Barcelona.

Regarding the impact of education, the evidence is also ambiguous. De Oliver [1999] finds a negative correlation between education and water conservation. Gilg and Barr [2006] identify the characteristics of the water saver using data on 1600 households from Denver. The results show a positive impact of education on water-saving behavior. Lam [2006] performs two studies to predict residents in Taiwan's intention to save water, finding a positive influence of income on the adoption of a dual-flush controller in one of the studies but not in the other.

Other socioeconomic variables such as age and gender are commonly considered in the literature. The literature shows no significant effect of these factors on pro-environmental behaviours [Lam, 2006; Millock and Nauges, 2010].

As mentioned above, the closest study to ours is Martínez-Espiñeira and García-Valiñas [2013], which analyzes the determinants of both the adoption of water-efficient technologies and the adaptation of water-conservation habits using data from a survey of Spanish households. In order to do so, they construct aggregated ordinal indexes for both decisions from a series of binary variables that indicate self-reported choices about conservation habits and decisions on the adoption of water-saving equipment. They then use a bivariate ordered probit model for the analysis, thereby accounting for possible correlation between the two decisions.

The relationship between the adoption of habits and technologies is at the core of the literature related to the efficiency losses in the use of residential devices. Indeed, there is a huge literature focused on the estimation and the causes of the so-called rebound effect. In particular, there are some fields which have devoted a lot of attention to this issue, such as energy [Freire-González, 2011; Ghosh and Blackhurst, 2014; Sorrell et al., 2009] or fuel consumption [Small and Dender, 2007; Smeets et al., 2014]. However, only a few studies have raised the possibility of a rebound effect in the residential water sector. Mayer et al. [1998] analyze the amount of water used by all possible appliances in single-family households from different municipalities in the U.S. and Canada, and the results show that households with low-flow showerheads increase shower time.

Campbell et al. [2004] estimated a reduction in water use of about 3.5% due to a regulation imposing the installation of low-flow fixtures and devices in Arizona. However, they found increases of about 3.8% to 4.6% in water use after the installation of free retrofit device kits. Another policy based on having similar devices installed during personal in-house visits with person-to-person communication led to water savings of between 2.4% and 6.4%. The authors suggest that the result of these policies may depend on whether the equipment is distributed for free or the resident actually makes investment to install it. Bennear et al. [2011], using data from North Carolina, showed that water savings attributable to the rebate program were less than one-half the expected savings associated with that installation. Davis [2008] uses data from a field trial in which randomly-selected households received high-efficiency washing machines free of charge. Households increased the use of washing machines by 5.6% on average after obtaining the high-efficiency appliance, that is, part of the efficiency gains are offset by increased usage.

These studies focused on the rebound effect in the residential water sector have shown that efficiency savings from the use of environmentally-efficient technology differ depending on the kind of device or appliance analyzed. Households may invest in a particular efficient appliance or demonstrate a specific conservation habit because of the resulting energy savings rather than the decrease in water use, due to the lower relative price of water. Thus, aggregate indexes such as those found in Martínez-Espiñeira and García-Valiñas [2013] may not fully capture the relationship between efficient technologies and habits, and their respective determinants. Our main contribution to the literature consists of using a disaggregated index for different technologies and habits, based on the classification explained in the next section.

4.3. Water-efficient technologies: public policies in Spain

Spain is the European country most severely affected by scarcity in the water sector. In particular, the Southeast region of the country exhibits the greatest levels of water stress in the European Union [EEA, 2009]. In this context, several public policies have been aimed at promoting the adoption of water-efficient technologies among Spanish households. These policies are implemented by both central, subcentral and supranational governments, who share environmental competences. As discussed in Chapter 2, European Union (EU) usually sets some general requirements regarding environmental regulation which is then adopted by each EU member. In Spain, the Spanish Ministry of Environment is responsible for the identification of the strategic objectives and the design of environmental protection plans. Then, the regional and local governments are in charge of implementing the plans.

In this research, a classification of water-efficient technologies into two different groups is proposed: electrical and non-electrical appliances. This classification is based on both the public policies related to those technologies and their specific features. A discussion of subsidies and public information programsin what follows shows a broad variety of policies applied in this field.

On the one hand, there are some efficient electrical appliances, such as washing machines and dishwashers, which could generate significant water saving at residential level. These appliances are identified by labelling schemes which specify different levels of efficiency ratings and enable buyers to compare the efficiency of different models. European Ecodesign Directive 2009/125/EC established some requirements for energy-using appliances such as washing machines and dishwashers. However, the European labelling framework is based on overlapping criteria (energy and water consumption, noise emissions, etc), with greater emphasis on certain dimensions. The European Commission has warned about the problems of this kind of labelling: "As these labels are more focused on aspects such as energy use and the environmental impacts associated with the overall life-cycle of the product, the product's water consumption could be seen as less important by consumers if a separate labelling scheme was not established" [EC, 2009, p. 244].

In this respect, the most relevant program applied in Spain is the household electrical appliance renewal program (*Plan Renove* of electrical appliances). This subsidy program was launched in Spain as part of the 2005-2007 Energy Saving and Efficiency Action Plan and it continues up to this day. Its main aim consists of providing financial incentives to households to replace electrical appliances (fridges, freezers, washing-machines and dishwashers, electric ovens, gas hobs and induction hobs) by others with a class A to A++ label. The subsidy was aimed at compensating for the price differential between the conventional appliance and the energy-efficient one. The amount of the subsidy, which was determined by each region (Autonomous Community, AC), varied from 85 to 125 euros depending on the appliance's efficiency rating [Martínez-Espiñeira et al., 2014].

On the other hand, the installation of some non-electrical devices are the aim of retrofit programs, such as efficient dual-flush toilets or low-flow showerheads and taps. In Europe, those devices are not obliged to include a label showing their water-consumption rating. However, there are a few private associations of those devices' manufacturers that have developed some water efficiency labelling schemes for the European fittings.[1]

In Spain, governments have introduced some regulations to promote the aforementioned water-saving technologies. The most generally applicable regulation is the Royal Decree 314/2006, which establishes some technical conditions to be complied with in the construction of new buildings. Those must be equipped with devices which lead to a sustainable water consumption and permit significant water savings. At the same time, there are some subsidy programs providing incentives to renew household appliances. Thus, the Royal-Decree 2066/2008 established a National Housing Program for the period 2009-2012, aimed at improving household energy and environmental efficiency. This National Program was implemented by the Autonomous Communities, with slight variations across the regions. Thus, the installation of mechanisms to obtain water savings and the adoption of greywater recycling systems are some of the investments granted. Subsidies range between 10% and 25% of the restoration total cost, with some limits. Additionally, beneficiaries should not have higher yearly income levels than 6.5 times the Public Index of Income for Multiple Purposes (IPREM; in 2011, the limit was set at 41,535.85 euros). Moreover, Personal Income Tax included a tax credit of 10% of households' investments in water system renewal carried out between April 2010 and December 2012, with some limits. As with the Plan Renove, beneficiaries should have lower yearly income levels than 53,007.20 euros. There also exist specific programs oriented towards the adoption of these efficient technologies, and basically promoted by water utilities and/or local governments.

4.4. Methodology

The probability of investing in an efficient appliance and that of manifesting water-conservation habits are analyzed conjointly using recursive semi-ordered bivariate probit models. A semi-ordered bivariate probit is used when one of the dependent variables is a binary variable and the other variable is an ordered categorical variable [Greene and Hensher, 2010, p.225]. Moreover, in a recursive bivariate probit model, one of the dependent variables appears on the right-hand

[1] Some examples of water labelling can be found at the following webpages: www.europeanwaterlabel.eu or www.well-online.eu.

side of the other equation [Greene and Hensher, 2010, p.77].

As with univariate ordered probability models, semi-ordered bivariate probit models are drawn from a latent variable model. Let us assume that the two latent variables are determined by:

$$\begin{aligned} &y_{1i}^* = \beta_1' x_{1i} + \varepsilon_{1i} \\ &y_{2i}^* = \beta_2' x_{2i} + \theta y_{1i} + \varepsilon_{2i} \\ &\begin{pmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right] \end{aligned} \tag{4.1}$$

where x_{1i} and x_{2i} are vectors of the k_1 and k_2 explanatory variables, β_1 and β_2 are parameter vectors, and ε_{1i} and ε_{2i} are the error terms that are joint normal with means zero, variances one, and correlation ρ. Then, the semi-ordered bivariate probit model specifies the observed outcomes using threshold values:

$$y_{1i} = \begin{cases} 0 & \text{if} \quad y_{1i}^* < 0 \\ 1 & \text{if} \quad y_{1i}^* > 0 \end{cases} \tag{4.2}$$

$$y_{2i} = j \quad \text{if} \quad \delta_{j-1} < y_{2i}^* < \delta_j, \quad j = 0, ..., J_2 \tag{4.3}$$

The likelihood ratio and Wald test are commonly used for testing the hypothesis that ρ equals 0 [Greene and Hensher, 2010, pp. 74-75]. The model would collapse to a probit model and an ordered probit model estimated separately if the error correlation ρ is equal to 0, but if the the hypothesis is rejected, then the joint probability for $y_{1i} = k$ and $y_{2i} = j$ is:

$$\begin{aligned} &Prob(y_{1i} = k, y_{2i} = j | x_{1i}, x_{2i}) = \Phi[\alpha_{1k} - \beta_1' x_{1i}, \alpha_{2j} - \beta_2' x_{2i} - \theta y_{1i}, \rho] \\ &- \Phi[\alpha_{1k-1} - \beta_1' x_{1i}, \alpha_{2j} - \beta_2' x_{2i} - \theta y_{1i}, \rho] \\ &- \Phi[\alpha_{1k} - \beta_1' x_{1i}, \alpha_{2j-1} - \beta_2' x_{2i} - \theta y_{1i}, \rho] \\ &+ \Phi[\alpha_{1k-1} - \beta_1' x_{1i}, \alpha_{2j-1} - \beta_2' x_{2i} - \theta y_{1i}, \rho] \end{aligned} \tag{4.4}$$

where Φ is the bivariate standard normal cumulative distribution function. The above probabilities enter the log-likelihood for a maximum likelihood estimation.

For reasons related to the identification of the model, at least one variable needs to be included in x_2 that does not enter in x_1. We define this set of variables as x_{-1}. In order to test that our model specification is correct, that is, x_{-1} should indeed not be included in x_1, we regress the generalized residuals, as defined by Gourieroux et al. [1987], from the second equation against x_2 and x_{-1}, and we perform a J-test. The test is used to determine whether these variables are correlated with the error term in the second equation and could therefore be omitted (for a more detailed explanation see Appendix C).

4.5. **Data**

This chapter uses data from the 2011 survey of households in the city of Granada (Spain). In what follows we investigate the determinants of the adoption of electrical and non-electrical water-saving appliances and the choice of the corresponding water-conservation habits. To do so, a series of binary indicators of self-reported water-conservation habits and water-saving appliances are used to construct the following indexes for each household:

- Electeff: an ordinal index that accounts for the number of efficient water-using electrical appliances in the household (possible efficient appliances are dishwashers and washing machines).
- Elect-habits: a dummy variable that takes value 1 if households operate automatic dishwashers and washing machines only when they are fully loaded, and 0 otherwise.
- Noelecteff: a binary indicator that takes value 1 if there are non-electrical water-saving devices in the household (such as low-flow taps and showerheads and dual-flush toilets), and 0 otherwise.
- Noelect-habits: a habits index is built by summing the individual scores of three self-described water-saving habits (household avoids letting water run while brushing teeth; household takes shorter showers; household has a paper bin in the bathroom to avoid using the toilet as a paper bin; household fills the sink with water when washing dishes by hand).

The decision to adopt efficient water-using electrical appliances (ordered variable) and the choice of the corresponding water-saving habit (binary variable) is formalized in Model 1:

$$\begin{aligned} &\textit{Electeff} = f_1(x_1) \\ &\textit{Elect-habits} = f_2(x_2, \textit{Electeff}) \end{aligned} \tag{4.5}$$

where x_1 and x_2 are the set of explanatory variables that are defined below.

Model 2 specifies the decision of adopting non-electrical water-saving devices (binary variable) and the water-saving habits (ordered) related to those devices:

$$\begin{aligned} &\textit{Noelecteff} = f_1(x_1) \\ &\textit{Noelect-habits} = f_2(x_2, \textit{Noelecteff}) \end{aligned} \tag{4.6}$$

with x_1 and x_2 being a set of explanatory variables that are defined below. In both models, subscripts 1 and 2 refer to the first and second equations, that is, the equations explaining efficient technologies and habits respectively.

As determinants of the above decisions and based on previous literature, we consider a set of explanatory variables that can be categorized into three groups: socioeconomic characteristics, attitudinal and behavioral factors, and policy variables. Among the first group, we include the number of members living in the house (*Members*), the age of the head of the household (*Age*), a binary indicator that takes value 1 if the head of the household is a male, and 0 otherwise (*Gender*), a dummy variable equal to 1 if the head of the household has higher education (*Education*), and a binary variable that takes value 1 for the richer households and 0 otherwise.[2] Additionally, we include an indicator of home ownership (*Owner*) since homeowners are expected to have more incentives than

[2] Household income was recorded as an ordered categorical variable, with households belonging to one of the following intervals (in Euros/month): [0-1100]; [1101-1800]; [1801-2700]; [2701-3500]; [3501- $+\infty$]. It would not be appropriate to use the interval categories as if they were values of a continuous variable. Usually, one would construct a set of five binary indicators of income level and introduce four in the model. However, because we did not seem to have enough sample variability to estimate all four corresponding parameters, we simplify our original income variable into a binary indicator of relatively higher income. In particular, we create a binary variable that identifies the richer households (those falling in the two highest income categories)

tenants to make investments in water-saving devices in the property, a categorical variable that accounts for the age of the house (*Home-age*) [3], and a binary indicator that accounts for renovation works in the house in the previous five years (*Remodel*). These variables are only included as determinants of efficient technologies, since they are expected to be correlated with the efficient water-using electrical appliances and water saving devices, but not to the water-saving habits.

As attitudinal variables we consider an environmental concern index (*Enviro*) that ranges from 0 (the respondent is not concerned about the environment at all) to 2 (the respondent is very much concerned about the environment), and a dummy variable that accounts for the knowledge of the existence of an environmental campaign (*Campaign*). Finally, as a policy variable we include the average price in 2010 since an increase in water price may motive households to engage in water-saving habits and invest in efficient technologies.

[3] The indicator *Home-age* was recorded in 10-year intervals ranging from 0 to more than 50 years old. In this case, the variable is treated as a continuous variable assuming that the ordering is linear.

Table 4.1: Definition of variables

Type	Variable	Description	Model	Equation
Dependent variables				
Investments	*Electeff*	number of efficient electrical appliances	1	1
	Noelecteff	=1 if the household is equipped with water saving devices, 0 otherwise	2	2
Habits	*Elect-habits*	=1 if the household runs fully loaded dishwasher and washing machine, 0 otherwise	1	1
	Noelect-habits	the sum of scores of water saving habits	2	2
Explanatory variables				
Socioeconomic characteristics	*Highincome*	=1 if the household income is over 2700€, 0 otherwise	1 & 2	1 & 2
	Members	number of people in the household	1 & 2	1 & 2
	Education	=1 if the head of the household has higher education	1 & 2	1 & 2
	Age	age of the head of the household	1 & 2	1 & 2
	Gender	=1 if the head of the household is male	1 & 2	1 & 2
	Owner	=1 if the house is owned by one of the household members, 0 otherwise	1 & 2	1
	Home-age	Age of the house	1 & 2	1
	Remodel	=1 if there renovation works in the house in the five years prior the survey, 0 otherwise	1 & 2	1
Attitudinal factors	*Enviro*	Index of environmental concern	1 & 2	1 & 2
	Campaign	=1 if the person has knowledge of any water conservation campaign, 0 otherwise	1 & 2	1 & 2

Table 4.2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Electeff	0.795	0.830	0	2
Noelecteff	0.484	0.5	0	1
Elect-habits	0.931	0.254	0	1
Elect-habits	2.575	0.841	0	4
Highincome	0.198	0.398	0	1
Members	2.751	1.197	1	9
Education	0.34	0.474	0	1
Age	52.693	19.37	18	94
Gender	0.555	0.497	0	1
Enviro	1.808	0.428	0	2
Campaign	0.564	0.496	0	1
Lagged AvP	1.695	0.461	1.011	8.281
Remodel	0.392	0.489	0	1
Home-age	3.893	0.85	1	6
Owner	0.747	0.435	0	1

As it is possible to observe in the Table 4.2, there are some differences in the adoption of the two groups of technologies. Although the comparison is difficult, in the sense that the scale of the dependent variable for each model is different, it seems that non-electrical devices are slightly more spread out. Thus, almost 50% of the households are equipped with non-electrical devices on taps, showers and toilets, while the average number of electrical appliances installed is lower than 1. Additionally, note that a high percentage of households declares having relatively good water conservation habits, especially in the case of the use of electrical appliances. Around 93% of surveyed households use electrical appliances only when they are fully loaded, which implies that they are taking advantage of all the efficiency gains generated by these kinds of appliances. The index related to the use of non-electrical appliances also registers high values.

The representative household considered in the sample has an average size of 2.75 members, where the head of the household is a 53-year old male. Approximately 19% of the households in our sample are in the highest income bracket, and 34% have higher education. Some 55% of the surveyed households are aware of some educational campaign and, on average, the respondents are seriously concerned and worried about environmental problems.

The housing stock in the sample is relatively old, as shown by the mean value of the indicator of housing age (see footnote 4). However, only a small percentage of them have carried out some remodelling. The sample is in line with the property tenancy regime structure in Spain. In 2011, the 82% of Spanish households were homeowners[4]. Our sample has an average ownership rate of 75%, a little bit lower than the national average. This could be explained by the fact that the rental market in this city is more developed and dynamic than in other Spanish cities[5].

4.6. **Results**

The results are presented in Table 4.3 for Model 1 and Table 4.4 for Model 2[6]. The correlation between the two disturbances (ρ) in Model 1 is negative and statistically significant, indicating that there are unobservable factors that are negatively related to the adoption of efficient water-using electrical appliances and positively related to the choice of the corresponding habit. The correlation coefficient for the two error terms in Model 2 is positive and significant, that is, unobservable factors influence both decisions in the same way. We performed the likelihood ratio test of the null hypothesis that ρ equals zero, and the null hypothesis was rejected for both models[7].

Regarding the variables that have not been included in equation 2, we can see that they are determinants of the decision of adopting efficient electrical and non-electrical water-using appliances, and they are not correlated with the generalized residual in the habits equations (see more details in Appendix C).

As shown in Table 4.1, we have considered the same set of explanatory variables in both models. However, the significance of the effects varies across them.

Beginning with the number of electrical appliances, there are several factors

[4]This and other data linked to the tenancy regime of Spanish households can be found at the website of the Spanish National Statistic Office: www.ine.es.

[5]Among other key drivers of this dynamism, the city registers high levels of temporary and seasonal visitors. For example, Granada receives more students through the Erasmus Programme than any other European University.

[6]Results for the marginal effects are shown in Appendix D

[7]The likelihood ratio test of independence of equations is equal to 3.40 and 7.22 with p-values 0.0653 and 0.0072 for Model 1 and Model 2 respectively, so the null hypothesis is rejected for both models

Table 4.3: Estimation results (efficient electrical appliances and habits)

Dependent variable	*Electeff*	*Elect-habits*
Electeff		0.607***
		(3.12)
Remodel	0.448***	
	(5.84)	
Home-age	-0.133***	
	(-3.07)	
Owner	0.567***	
	(5.54)	
Highincome	0.370***	-0.0405
	(3.88)	(-0.21)
Members	0.104***	0.0535
	(3.05)	(0.83)
Education	0.174**	0.146
	(2.19)	(1.03)
Age	-0.00686***	0.00211
	(-2.68)	(0.67)
Gender	0.156**	–0.0711
	(2.09)	(-0.61)
Lagged AvP	-0.0155	0.0657
	(-0.19)	(0.52)
Enviro	0.191**	-0.0425
	(2.18)	(-0.32)
Campaign	0.303***	0.239*
	(4.08)	(1.82)
Constant		0.546
		(1.27)
cut1	0.609*	
	(1.76)	
cut2	1.438***	
	(4.14)	
ρ	-0.455**	
	(-1.99)	
N	1126	
ll	-1305.9	
aic	2659.8	
bic	2780.5	

t statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

which influence the technology adoption decision. In this case, larger families where the head of the household is a younger male with higher income and higher education tend to invest in this kind of technology more intensively. Moreover, houses owned by one of the household members, which are newer and which have recently undergone renovation works, have a higher probability of adopting these efficient electrical appliances. The variables capturing environmental attitudes, *Enviro* and *Campaign*, have a strong impact on the adoption of this kind of technology. However, water price is not significant, probably because water expenditure is a small proportion of household income[8].

Regarding water-conservation habits, we observe a positive and significant relationship between habits and technologies. Thus, those households with a higher number of efficient electrical appliances exhibit better habits related to the use of those technologies. Additionally, educational campaigns have a significant role in the formation of pro-conservation habits.

In the case of non-electrical appliances, there are several socio-economic factors that significantly explain the installation of those devices. Richer households have a higher probability of installing these water-efficient technologies and owners of the houses with renovated dwellings are more likely to adopt non-electrical water efficient devices. In terms of attitudinal factors, the only variable that significantly affects the adoption of non-electrical appliances is the awareness of educational campaigns.

Concerning the factors affecting the performance of habits related to non-electrical appliances, larger families are more careful with the use of those devices, showing better habits. As in the case of electrical efficient technologies, those households aware of educational campaigns and that report themselves as concerned about the environment exhibit better water conservation habits. However, we observe that there is a negative relationship between efficient non-electrical technologies and their habits. Thus, it seems that households with efficient non-electrical equipment exhibit worse pro-conservation habits. This finding lappears to indicate that there are some efficiency losses in the use of those technologies.

[8]Energy prices would probably have a greater impact on the adoption of this kind of technology. Unfortunately, we do not have information on the price that households are paying for electricity.

Table 4.4: Estimation results (water saving devices and habits)

Dependent variable		
	Noelecteff	*Noelect-habits*
Noelecteff		-0.423*
		(-1.95)
Remodel	0.418***	
	(4.94)	
Home-age	-0.0261	
	(-0.56)	
Owner	0.470***	
	(4.19)	
Highincome	0.508***	0.00854
	(4.62)	(0.09)
Member	0.0484	0.0913***
	(1.26)	(2.92)
Education	0.140	-0.0002
	(1.57)	(-0.00)
Age	0.00005	-0.00002
	(0.02)	(-0.01)
Gender	0.0424	-0.0959
	(0.51)	(-1.43)
Lagged AvP	-0.151	-0.0707
	(-1.47)	(-0.99)
Enviro	0.0443	0.143*
	(0.46)	(1.89)
Campaign	0.473***	0.228***
	(5.68)	(3.03)
Constant	-0.859**	
	(-2.17)	
cut1		-1.599***
		(-6.17)
cut2		-1.060***
		(-4.18)
cut3		0.000358
		(0.00)
cut4	1.604***	
	(6.05)	
ρ		0.404***
		(2.58)
N	1124	
ll	-1967.2	
aic	3986.3	
bic	4117.0	

t statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Water savings could be higher if it went hand-in-hand with the right conservation behavior.

There are different reasons which could explain these results. First of all, in our model households need to control not only one behavior, but the combination of different behaviours linked to those devices, which is a more complex task. That makes it more difficult to take advantage of all potential efficiency gains generated by low-flow technologies. Second, the labelling policy in this field emerges as another significant issue. As we mentioned before, labels for low-flow technologies are not as widespread as for electrical appliances. As a consequence, the quality of information related to efficiency gains is lower, and households may find it more difficult to identify these technologies as an important source of savings. Additionally, the low levels of water pressure that is associated with this kind of technology could lead to increase the intensity in their use. Finally, and compared with electrical appliances, there is a higher probability that these kinds of devices were installed by the builder and households did not participate in the decision to adopt them. Moreover, the low price of water together with the adoption of efficient technologies creates a perverse incentive not to perform pro-conservation habits in the case non-electrical devices. However, water conservation habits related to electrical appliances may be also affected by the price of energy, which is much higher than the price of water, and therefore, encourages households to perform water conservation habits.

4.7. **Conclusions**

Water efficient technologies have emerged as a significant source of water savings at residential level [Kenney et al., 2008; Renwick and Archibald, 1998; Renwick and Green, 2000]. However, an inappropriate use of these technologies could lead to significant efficiency losses and lower savings levels. This research was aimed at identifying problematic areas where these efficiency losses are more likely to appear. Our main contribution consist of making a disaggregated analysis: two main groups of technologies have been distinguished, namely efficient electrical and non-electrical appliances. We have shown that public policies applied to the two groups are different. The different character of each group of technologies was also highlighted.

Our findings prove that there are significant differences in terms of the relationship between habits and technologies depending on the group of appliances/devices considered. Thus, when it comes to electrical appliances, households which tend to invest in this kind of technology also exhibit better habits. However, in the case on non-electrical appliances, the result is just the opposite.These findings call for a reconsideration of public policies applied to this area. Thus, the current policies should be reinforced by using information tools and educational campaigns strongly oriented towards the adoption of pro-conservation habits linked to these technologies. Additionally, pricing policies could also be used to improve the efficiency in the use of low-flow devices devices. In this respect, it may be that low water price levels make households less prone to react and save water. Definitively, the results of this research can help to reorient current public polices in order to reduce a potential rebound effect in the residential water sector.

Chapter 5

The impact of environmental behavior on the efficiency in residential water consumption

5.1. Introduction

About 52% of the world's projected inhabitants are expected to live in "water-stressed areas" by 2050, due to a combination of climate changes, an increase in the world population and economic growth [Schlosser et al., 2014]. This change is not only going to affect the developing economies, and has already highlighted the need for an appropriate policy response in many developed regions in the world.

In particular, Europe and the United States are facing more frequent and severe droughts. In Europe, the number of people and areas affected by water scarcity between 1976 and 2006 increased by almost 20%, generating a cost of €100 billion for this period [EC, 2012]. In the US, 36 states suffered water shortages and availability issues in 2013.[1]

In this context, the European Commission has launched a flagship initiative under the so-called Europe 2020 strategy – the 10-year strategy proposed by the European Commission for a "smart, sustainable, inclusive growth' – to create a resource-efficient Europe. In the US, the Energy Independence and Security Act

[1]Source: Environmental Protection Agency (EPA).

of 2007 was enacted to tackle the efficiency of water use in Federal facilities, and also residential consumption through improved and more efficient appliances.

Behavioral aspects may play an important role in more efficient water consumption. Russell and Fielding [2010] link the concept of water demand management to water-conservation behavior indicating that the latter encompasses actions to consume water more efficiently and also take into account that water demand management itself entails behavioral aspects. In this sense, we can distinguish two types of behaviors that may affect efficiency in water consumption: efficiency behaviors and curtailment behaviors [Stern and Gardner, 981a,b]. Efficiency behaviors refer to one-time behaviors, such as buying an efficient electrical appliance, and curtailment behaviors refer to individuals' actions that reduce water consumption involving inconvenient and sacrificial actions such as taking shorter showers. Therefore, any study of the scope for more efficient household water use should take such behavioral aspects into account.

The aim of this chapter is to measure the level of efficiency in residential water demand in order to determine potential water savings. Moreover, the effect of several efficiency and curtailment behaviors on water consumption is analyzed with the aim of identifying behaviors that could be promoted in order to enhance water savings. To compute potential water savings at the household level, we adopt a household production theory approach where households may differ in their ability to produce services in order to satisfy their preferences. Water is therefore considered as an input in the production function for household services and the demand for water is modelled as an input demand function. In order to estimate an input demand frontier function which takes into account both the efficiency and curtailment behaviors in a flexible manner, we use a semiparametric Smooth-Coefficient stochastic frontier model, following Sun and Kumbhakar [2013].

The analysis is carried out using the database of the city of Granada that has been described in Chapter 2. These data are of special interest for two main reasons. On the one hand, as discussed before, Spain is the most semi-arid country in the European Union [Lopez-Gunn et al., 2012], and is the European country most severely affected by water shortages. Moreover, droughts will worsen with future climate change [Collins et al., 2009]. The city of Granada is located in the

South of Spain, which is regularly affected by droughts and availability issues. On the other hand, the average water consumption in the sample analyzed in this chapter is around 95 liters per day per person. However, Gleick [2000] claims that the basic water human need per day is 55 liters per person in moderate climate conditions, including drinking water, water for sanitation services, water for human hygiene and for preparing food in a modest household. This indicates that there is still considerable room for water savings in this city.

As we will see, the results from our empirical application show that the majority of households in the sample were found to be highly efficient in water use. However, a substantial proportion were relatively inefficient and there is considerable potential for water savings. Moreover, efficiency behaviors are found to have a significant impact on water efficiency, whereas curtailments behaviors are not found to have a significant impact on the level of efficiency in water consumption. These results should prove useful for policymakers when it comes to designing policies aimed at promoting water efficiency.

The chapter is organized as follows. The next section provides a literature review on the measurement of water efficiency. Section 5.3 discusses the rationale for the input demand function. Section 5.4 describes the empirical methodology. The data and the specification of the demand function are presented in Section 5.5, which is followed by Section 5.6 where estimation results are discussed and Section 5.7 concludes.

5.2. Literature review

In the context of water scarcity, emphasis has been increasingly placed on water demand management, that is, on any method that reduces the amount of water used or enables it to be used more efficiently [Brooks, 2006]. However, a crucial aspect is the awareness of the actual level of efficiency in water consumption and the potential for water savings. The European Environment Agency uses a resource intensity index as a proxy for the efficient use of a resource, such as energy or water. This index is defined as the quantity of resources required per unit of economic output [CEPS, 2012] and has been used in several studies concerning water use efficiency. For instance, Gleick [2003] compares the trends in the ratio of

GDP to water use for several countries, stressing the importance of and difficulties involved in appropriately measuring water use. Alcamo et al. [2003] compute a water intensity index for the domestic, industrial and agricultural sector in several countries. Di Cosmo et al. [2014] calculate the water intensity of the 27 countries in the EU for the year 2005 to analyze the patterns explaining water consumption. However, this resource intensity index has been criticized since it may not reflect all the behavioral and structural factors that would be necessary to measure resource efficiency adequately [EIA, 1995; Filippini and Hunt, 2012].

With this in mind, Filippini and Hunt [2012] construct a more appropriate measure of the level of efficiency for the US residential sector across 48 states in the period 1995 to 2007 using a parametric stochastic frontier analysis (SFA). At the European level, Filippini and Hunt [2013] estimate energy efficiency scores for the EU-27 country-members for the period 1996 to 2009 using the SFA methodology, finding a high level of inefficiency. Also using data at European level, Filippini et al. [2014] analyze the effect of the energy policy instruments promoted in the EU member states on efficiency using SFA. The results show that financial incentives and energy performance standards contribute to reduce energy inefficiency. However, information campaign measures were not found to have a significant effect on the inefficiency level. Stern [2012] measures energy efficiency in 85 countries using an energy distance function approach, in which the global production frontier is defined by the country using the least energy per unit output, given its mix of outputs and inputs. Thus, the level of efficiency is computed from the distance to the frontier. The results show that energy efficiency is higher in countries with smaller fossil fuel reserves, undervalued currencies, and higher total factor productivity. The aforementoned studies use aggregate data from the energy sector. Efficiency in water demand has been measured before using both parametric and nonparametric methodologies, but studies have been limited to water use in the agricultural sector. SFA is used in Kaneko et al. [2004] to analyze water efficiency in agricultural production in China and in Dhehibi et al. [2007] to compute a measure of irrigation water efficiency based on the concept of input-specific technical efficiency using data from 144 citrus farms in Tunisia. Regarding nonparametric techniques, several studies use Data Envelopment Analysis (DEA) to compute water use efficiency. Giannoccaro and Martin-Ortega [2010] and Veettil et al. [2013] analyze the effect of pricing policies on the efficiency of irrigation water use using DEA for a sample of farms in Southern Italy and in the agricultural production system in the Krishna river basin (India) respectively. Chemak [2011] also uses DEA to compute water use efficiency and the dynamic productivity of irrigated areas in Tunisian farms. However, as far as we are aware there has been no analysis carried out of efficiency in residential water consumption. This is therefore the first attempt to estimate the level of efficiency in household water consumption and the factors which determines it.

Regarding the inclusion of determining factors or 'environmental variables', the effect of these variables can be modelled empirically in several ways. The simplest approach would be to introduce these environmental factors into the production function as conventional inputs. However, this modeling strategy does not seem appropriate because these factors alone cannot produce any water services. Hence, a more subtle empirical strategy is to introduce them into the production function as facilitating inputs which affect conventional inputs' productivity [McCloud and Kumbhakar, 2008]. An alternative approach that has received considerable attention is to model the environmental variables as determinants of inefficiency [Alvarez et al., 2006]. A more recent and flexible approach is a combination of the last two which considers the effect of the environmental variables on the inefficiency while also including them as facilitating inputs, thereby allowing the frontier to shift in a flexible manner [Sun and Kumbhakar, 2013].

5.3. Utility maximization and input demand function

In order to model household behavior, we follow the household production function approach proposed by Becker [1965] which integrates consumer theory with production theory. Households obtain utility from underlying goods that are non-marketed goods, which Becker called commodities, and are produced in the household using the 'means' that households have at their disposal which are inputs of market goods, abilities, knowledge, technology and time. In this context, water can be considered as an input in the household production function. Water demand is an input demand, that is, households purchase water for the services it provides, not for the utility it provides by itself (except for drinking water, which represents a small percentage).

One of the main advantages of the household production literature is that it explicitly considers as restrictions part of what traditional consumer theory considers as preferences. Michael and Becker [1973] argue that “they [consumers] all derive that utility from the same ‘basic pleasures’ or preference function, and differ only in their ability to produce these ‘pleasures’ .” Stigler and Becker [1977] also indicate that preferences may be considered identical across individuals and constant over time and that differences in behavior can be caused by price and other constraints. However, this idea has been questioned in several studies. For instance, Hirschman [1984] criticizes the ‘parsimonious postulate’ in Economics that consumers choose rationally and freely among different options after analyzing the possible costs and benefits. Cowen [1989] highlights several issues with the Stigler-Becker approach such as problems of addiction, weakness of will and taste changes.

In this chapter, we attempt to account for the possible weaknesses of the household production model by controlling for preferences using several determining factors or ‘environmental variables’. These variables are considered to be potentially important in the production of water services, and may be thought of as proxies of the ability to produce water services as well as reflecting household preferences. As stated in the introduction, two types of environmental behaviors are considered as environmental factors. Self-reported water-conservation habits are included as an indicator of curtailment behavior, and the characteristics of the technology represent the efficiency behaviors.

The household’s decision can be thought as an optimisation problem in which the household minimizes the costs of producing the commodities, which in this case are water services. In this context, the frontier analysis approach can be used to estimate the level of cost efficiency. As explained by Schmidt and Lovell [1979], it is possible to estimate the cost function by using a set of input demand equations. However, for the estimation of a system of cost-minimizing input demand functions, information on input prices is required. In this case, there is a lack of data on prices of other inputs involved in the household production process, so only a water demand function is estimated. This follows Filippini and Hunt [2013] who argue that despite the fact that this approach does not allow some restrictions imposed by the household production theory to be taken into account, it does permit us to identify the difference between the actual input demand and the frontier input demand.

The production of water services can be also represented by a utility maximization problem in which the household's objective is to maximize the utility obtained from producing water services y and other commodity x. Water services are produced by combining water w and other inputs k, given some environmental factors Z. The additional inputs k can be thought of as appliances, which are capital inputs. The production function of the household is assumed to take a Cobb-Douglas form, where both the unobservable factor productivity and the input coefficient are function of Z. Income generated by household members is spent on both commodities. The utility maximization problem can therefore be expressed as:

$$\begin{aligned} &\underset{w}{max}\; U = U(y, x) \\ &s.t. \quad y = A(Z)w^{a(z)}k^{b(Z)} \\ &\qquad\quad I = p_w w + p_k k + p_x x \end{aligned} \tag{5.1}$$

where p_w, p_k and p_x represent the prices of water, capital inputs and commodity x respectively. In the spirit of Aigner et al. [1977], the expression $A(Z)$ in the production function can be written as:

$$A(z) = c(z)e^{-u(z)} \tag{5.2}$$

where $c(Z)$ is a parameter that is constant for each possible combination of Z and $u(Z)$ is the level of technical inefficiency and which also depends on the environmental factors. Those households for which $u(Z) = 0$ are the most efficient. The difference between the utility-maximizing input and the observed input demands represents technical inefficiency. Consequently, a household is said to be technically inefficient if water consumption is higher than the minimum possible level of consumption defined by its frontier.

Deriving the first-order condition for the utility maximization problem in equation (9), one can obtain the input demand for water. After taking logs, the input demand equation can be written as follows:[2]

$$lnw = \alpha(Z) + \beta_1(Z)ln\left(\frac{p_w}{p_k}\right) + \beta_2(Z)lnk + u(Z), \tag{5.3}$$

where u is a one-sided non-negative random disturbance representing inefficiency in water demand and which may depend on environmental factors, Z. The input frontier represents the minimum level of water consumption necessary to produce a given amount of water services, controlling for the level of capital equipment and the environmental factors.

5.4. Methodology

From equation (5.3), the log of water consumption can be written as a linear function of the log of water price and capital inputs, where the coefficients are functions of the environmental factors. Therefore, it seems appropriate to estimate this model using the semiparametric Smooth-Coefficient Stochastic Frontier model proposed by Sun and Kumbhakar [2013]. The reduced-form model can be expressed as:

$$lnw_i = \alpha(Z_i) + x_i\beta(Z_i) + u_i(Z_i) + v_i, \tag{5.4}$$

where lnw_i is the log of water consumption, x_i is a vector of explanatory variables (including the log price and the capital inputs), Z_i is a vector of discrete environmental factors (z is defined as a particular realization of the Z_i variable), $\beta(\cdot)$ is a vector of unspecified smooth functions of Z_i and $\alpha(\cdot)$ is the intercept, also an unspecified function of Z_i. Finally, $u_i(Z_i)$ is the positive inefficiency term, and v_i is a noise term, which is assumed to follow a centered normal distribution with variance $\sigma_v^2 > 0$. Following Simar et al. [1994], the efficiency term is assumed to be $u_i = \sigma_u(Z_i)\eta_i$, where $\eta_i \sim iidN^+(0,1)$, N^+ represents the half-normal distribution, and $\sigma_u(Z_i) = exp(\delta_0 + {\delta_1}'Z_i) > 0$. This assumption implies that

[2]Detailed derivations can be found in Appendix E.

$E[(u_i(Z_i)|z] = \sqrt{2/\pi}\sigma_u(Z_i) = \sqrt{2/\pi}exp(\delta_0 + {\delta_1}'Z_i)$. Thus, equation (5.4) can be rewritten as:

$$\begin{aligned} lnw_i &= \alpha(Z_i) + x_i\beta(Z_i) + v_i + (u_i(Z_i) - E[u_i(Z_i)|z] + E[u_i(Z_i)|z]) \\ &= \theta(Z_i) + x_i\beta(Z_i) + \epsilon_i, \end{aligned} \tag{5.5}$$

where $\theta(Z_i) = \alpha(Z_i) + E[u_i(Z_i)|z]$ and $\epsilon_i = v_i + u_i(Z_i) - E[u_i(Z_i)|z]$.

To estimate equation (5.5), and since the environmental factors considered in this analysis are going to be discrete, the semiparametric Smooth-Coefficient model with categorical covariates studied by Li et al. [2013] is used. Let $lnw_i = X_i\rho(Z_i) + \epsilon_i$, where $\rho(Z_i) = [\theta(Z_i), \beta(Z_i)]$ and $X_i = [1, x_i]$. A semiparametric estimator of $\hat{\rho}(Z_i)$ can then be constructed as follows:

$$\hat{\rho}(z) = \left[\frac{1}{n}\sum_{i=1}^{n} X_i' X_i L\left(Z_i, z, \lambda\right)\right]^{-1} \frac{1}{n}\sum_{i=1}^{n} X_i' y_i L(Z_i, z, \lambda), \tag{5.6}$$

where n is the sample size and $L(.)$ is a categorical nonparametric kernel function defined in Aitchison and Aitken [1976] as:

$$L\left(Z_i, z, \lambda\right) = \prod_{s=1}^{r} l(Z_{is}, z_s, \lambda_s) = \prod_{s=1}^{r} \lambda_s^{1(Z_{is} \neq z_s)}, \tag{5.7}$$

where z_s denotes the s^{th} component of the vector z and λ_s is a smoothing parameter, which is bounded in the interval $[0, 1]$ for all $s = 1, ..., r$. The closer the λ_s to 0, the greater the difference in the marginal effects of X on lnw for distinct categories of Z_s. By contrast, when $\lambda_s = 1$ for some s, this implies that the corresponding Z_s does not have any impact on the marginal effects. Indeed, it can be seen from equation (5.7) that when the smoothing parameter is equal to 1, the *weight* assigned to each possible category of Z_s is the same. In this case, we use the terminology in Li et al. [2013] and define Z_s as an *irrelevant covariate*.

In order to select the smoothing parameters, the following cross-validation

(CV) criterion function is employed:

$$CV(\lambda) = \frac{1}{n}\sum_{i=1}^{n}\left[lnw_i - X_i\hat{\rho}_{-i}(Z_i)\right]^2, \tag{5.8}$$

where $\hat{\rho}_{-i}(Z_i) = \left[\frac{1}{n}\sum_{j\neq i}^{n} X_j' X_j L(Z_j, Z_i, \lambda)\right]^{-1}\left[\frac{1}{n}\sum_{j\neq i}^{n} X_j' y_j L(Z_j, Z_i, \lambda)\right]$ is the leave-one-out kernel estimator of ρ_i.

Among others, the advantage of cross-validation in this context is that it can automatically identify and *smooth out* from the regression model irrelevant covariates by selecting a bandwidth equal to 1 [see Hall et al., 2004].

However, in our case it is not possible to directly estimate equation (5.5) because of a simultaneity issue arising from the structure of the tariff used to price the quantity of water consumed. As the latter increases jointly with the average price paid per cubic meter, a direct estimation would lead to a biased coefficient for the log price.

Therefore, in order to account for this simultaneity issue the smooth coefficient instrumental variable (IV) model proposed by Cai et al. [2006] is implemented here. This model takes the following form:

$$lnw_i = X_i\rho(Z_i) + \epsilon_i, \tag{5.9}$$

$$X_{1i} = g(X_{-1i}, \tau_i) + \zeta_i, \tag{5.10}$$

$$E(\epsilon|X_{-1i}, \tau) = 0, \tag{5.11}$$

where X_i now includes a constant term, an endogenous regressor X_1 and a vector X_{-1} of exogenous covariates. The variable τ comprises a vector Z of exogenous environmental variables and a vector D of instruments, and ζ is the error term.

The estimation of this model is conducted in two steps, as in the classical linear IV model. First, one estimates the conditional expectation $E(X_1|\tau)$ from equation (5.10), and obtains the predicted values, $\hat{X}_{1i}$. These predicted values are then used to replace the endogenous regressor X_{1i} in equation (5.9). Finally, one proceeds to the estimation of the semiparametric smooth coefficient model as in equation (5.5).

Cai et al. [2006] derive the properties of this estimator using local linear fitting techniques. However they state that other methods such as kernel regression or polynomial series are also applicable. We therefore implement nonparametric regression splines in the presence of continuous and categorical predictors as described in Ma and Racine [2012] and Ma et al. [2012], since this methodology fits the data best.[3] A more detailed discussion of this methodology can be found in Appendix F.

Before proceeding to the analysis of efficiency determinants, it is necessary to test whether equation (5.4) can be estimated as a standard stochastic frontier model in which the coefficients and the technical inefficiency term do not vary with Z_i. As discussed by Sun and Kumbhakar [2013], in order to test for the correct Smooth-Coefficient functional specification the test statistic proposed by Li et al. [2013] is constructed:

$$I_n = \frac{1}{n}\sum_{i=1}^{n}(\hat{\rho}(Z_i) - \hat{\rho})'\hat{\Sigma}_{\hat{\rho}}^{-1}(\hat{\rho}(Z_i) - \hat{\rho}), \tag{5.12}$$

where $\hat{\rho}(Z_i)$ is the Smooth-Coefficient estimator, $\hat{\rho}$ is the parametric estimator of ρ, that is, a vector of constant parameters, and $\hat{\Sigma}_{\hat{\rho}}$ is the estimated covariance matrix from the null model. A residual-based wild bootstrap method is used to approximate the null distribution of $\hat{I}_n$ (simulating B = 99 bootstrap samples for $\hat{I}_n$) and the nonparametric p-values are computed.

The null hypothesis of this test is $H_0 : \rho(Z_i) = \rho$. If the latter is rejected, we conclude that the semiparametric estimator ought be preferred over a simpler parametric frontier estimation. Moreover, it also implies that the environmental factors are relevant components in the consumption decision of the household.

We now turn to the efficiency determinants. Recalling the assumption on the efficiency term, obtain the residuals from equation (5.6) as $\hat{\epsilon}_i = lnw_i - X_i\hat{\rho}(Z_i)$. Defining $R_i = \hat{\epsilon}_i$, we can write:

$$\begin{aligned} R_i =& \sqrt{2/\pi}\sigma_u(Z_i) + v_i - \sigma_u(Z_i)\eta_i \\ =& \sqrt{2/\pi}exp(\delta_0 + \delta_1' Z_i) + v_i - exp(\delta_0 + \delta_1' Z_i)\eta_i \\ =& \sqrt{2/\pi}exp(\delta_0 + \delta_1' Z_i) + \epsilon_i^*, \end{aligned} \tag{5.13}$$

[3] The R^2 is equal to 0.7212 using the nonparametric categorical regression splines, whereas it is equal to 0.3516 using a Kernel regression and 0.3257 using Ordinary Least Squares regression.

where $\epsilon_i^* = v_i - exp(\delta_0 + \delta_1' Z_i)$. Following Sun and Kumbhakar [2013], in this second stage a parametric stochastic frontier estimation technique is applied. The log-likelihood function is written as:

$$lnL = constant - \frac{1}{2}\sum_i ln(\sigma_i^2) + \sum_i ln\Phi\left(\frac{\epsilon_i^*}{\sigma_i}\sqrt{\frac{\gamma}{1-\gamma}}\right) - \frac{1}{2}\sum_i \frac{\epsilon_i^*}{\sigma_i^2} \tag{5.14}$$

where $\sigma_i^2 = \sigma_v^2 + \sigma_u^2(Z_i) = \sigma_v^2 + exp[2(\delta_0 + \delta_1' Z_i)]$ and $\gamma = \sigma_u^2(z_i)/\sigma_i^2$. Here the parameterization of Battese and Corra [1977] is used instead of the one by Aigner et al. [1977], where the log-likelihood function may be written in terms of σ^2 and $\lambda = \frac{\sigma_u}{\sigma_v}$. This parameterization has the advantage that $\gamma \in [0, 1]$, whereas $\lambda \in [0, \infty]$. Therefore, the parameterization by Battese and Corra [1977] is preferred since using λ simplifies the numerical maximization of the log-likelihood function [Simar and Wilson, 2010]. By maximizing the log-likelihood function in equation (5.14), δ_1 and γ are estimated and then the rest of the unknown parameters can be obtained by using the fact that $\sigma_v^2 = (1-\gamma)exp(\tilde{\delta_0})$ and $\delta_0 = \ln(\gamma) + \tilde{\delta_0}$.

Finally, in order to obtain the efficiency in water consumption scores (WE), the Battese and Coelli [1988] point estimator, which Sun and Kumbhakar [2013] used, is adapted following [Kumbhakar and Lovell, 2000, p.142].

$$WE_i = E(exp\{-u_i\}|\epsilon_i) = \left[\frac{1-\Phi(\sigma_* - \mu_{*i}/\sigma_*)}{1-\Phi(\mu_{*i}/\sigma_*)}\right] exp\left[-\mu_{*i} + \frac{1}{2}\sigma_*^2\right] \tag{5.15}$$

where $\mu_{*i} = \epsilon_i \sigma_u^2/\sigma^2$ and $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$.

5.5. Data

The data used in this chapter is the unbalanced panel consisting of household level data in the city of Granada covering the period 2009 to 2011.

As explained in Chapter 2, the pricing structure is based on IBP and therefore we must consider the price endogeneity generated by the simultaneous determination of the price level and the level of consumption that determines the price block, as in Chapter 3. When dealing with this issue, we face the problem that water consumption and water bills, which determine the average price that will be used as explanatory variable, are the only variables in the data set that change within a given year in the data set. Therefore, in order to address the endogeneity problem, it was necessary to aggregate water consumption by year, which made it possible to use the set of marginal prices per block, which are reviewed annually, as instruments. Furthermore, after the data aggregation, it was necessary to exclude from the sample those individuals who were not observed for the six billing periods each year because of the possible bias introduced by seasonality in their water consumption[4].

After this transformation, the dependent variable is the log of the average bimonthly household water consumption per year, in cubic meters, which was calculated by dividing total consumption per year by the number of two-month billing periods.

Regarding the price variable, there are two main issues when analyzing water demand under a nonlinear pricing scheme that are worth discussing. The first one is the choice between marginal and average price. In this sample, consumers indicated that they were not properly informed about the pricing scheme. Therefore, we use the log of the average price ($log\ AvP$) since households may be more sensitive to changes in average price than in marginal price. The second issue, as commented above, relates to the price endogeneity caused by the simultaneous determination of price and water demand under block pricing. In order to deal with this, an instrumental variable approach is used as explained in Section 5.4. Following Hewitt and Hanemann [1995] and Olmstead [2009], the full set of marginal prices (in logs) are considered as instruments, since they are correlated with the average price and orthogonal to the error term.[5]

Household income was recorded as an ordered categorical variable, with households belonging to one of the following intervals (in Euros per month) [0-1100]; [1101-1800]; [1801-2700]; [2701-3500]; [3501- $+\infty$]. It would not be appropriate to use the interval categories as if they were values of a continuous variable. Usually, one would construct a set of five dummy variables indicating each household

[4]Due to the impossibility of finding a common seasonal pattern, water consumption and price series were not detrended

[5]Since there is no available test for relevance and exogeneity of the instruments in the semi/nonparametric setting, these have been tested using a linear IV model. Weak instruments are tested using a F-statistic, which is equal to 255.01, indicating that all the instruments are relevant. The Sargan test is equal to 5.124 with a $\chi^2(4) = 0.2748$, so that the null hypothesis that all the instruments are exogenous cannot be rejected.

income level and introduce four into the model. However, there is not enough sample variability to estimate all four corresponding parameters, so we include a binary indicator of relatively higher income (*Highincome*), where high income corresponds to the two highest income categories, that is, higher than 2700 euros per month. As other inputs used to produce water services we include the number of water appliances (*Electappl*) in the household including dishwashers, washing machines and water heaters, and the number of bathrooms (*Bathrooms*) in the household. Moreover, in order to control for the size of the household we use the variable *Members*, defined as the number of members living in the household. To control for unobserved water use due to the consumption of bottled water, a dummy variable (*Bottled*) that takes value 1 if household members frequently drink bottled water, and 0 otherwise, is included.

Turning to the environmental factors, a set of variables that are proxies of efficiency and curtailment behaviors are considered. As curtailment behavior, a water habit index (*Habits*) was constructed following the approach in Beaumais et al. [2010] by calculating the mean score on the answers related to the values of water use/conservation habits that were asked about in the survey (possible answers were 1 = yes or 0 = no).[6] The variables considered proxies for efficiency behaviors are the number of efficient water-using electrical appliances (*Electeff*), a dummy variable that takes value 1 if there are non-electrical water-saving devices (*Noelecteff*) in the house (such as low-flow taps and shower heads and dual-flush toilets), and 0 otherwise, and a variable accounting for the state of water infrastructure in the house (*New pipes*). This dummy variable takes value 1 if there was a renovation of the building's water and sewer pipelines in the previous five years. However, we do not consider this variable as an environmental behavior, as we believe that renovation in the water infrastructure is performed when it is needed, that is, when there are leakeage problems.

The descriptive statistics in Table 5.1 show that the representative household considered in this chapter consumes an average of 15.74 m^3 and pays on average 1.69 €every two months. The average household size is 2.69 members and 18.4% of the households frequently drink bottled water. Additionally, note that only

[6]See Appendix B for details about the survey questions used to construct the habits conservation index.

21.8% of the households have a monthly income higher than 2700 €per month. In terms of household equipment, the average number of bathrooms in the representative house is almost two, the average number of electrical appliances is around two, with the washing machine being the most common one.

Regarding the efficiency behaviors, more than 68% of the households have at least one efficient appliance in the house, and around 48% of them have at least one non-electrical water- saving device on taps, showers or toilets. Moreover, 19% of the sample had renovation works in the building's water and sewer pipelines in the previous five years. Concerning the curtailment behavior, the average score in the water habits index is relatively high, with almost 44% of the households declaring that they have more than six good water conservation habits.

Table 5.1: Descriptive Statistics - Efficiency in water consumption

Variable	Definition	Mean	Std. Dev.	Min.	Max.
ln w	the log of the average bimonthly water consumption per year (m^3)	2.625	0.526	0.154	4.174
Regressors					
ln AvP	the log of the average price (€/m^3)	0.498	0.234	-0.411	2.089
Members	number of people in the household	2.693	1.222	1	9
Bottled	=1 if members drink bottled water, 0 otherwise	0.184	0.387	0	1
Highincome	= 1 if the household income is over 2700€, 0 otherwise	0.218	0.413	0	1
Electappl	number of electrical appliances in the house	1.999	0.605	1	4
Bathrooms	number of bathrooms in the house	1.725	0.486	1	5
Environmental factors					
Habits	index of water conservation habits	0.616	0.160	0	1
Electeff	number of efficient water-using electrical appliances in the house	0.818	0.838	0	2
Noelecteff	= 1 if there are efficient water-using non-electrical appliances in the house, 0 otherwise	0.480	0.500	0	1
New pipes	=1 if 1 if there were renovation works in the water infrastructure in the five years prior the survey, 0 otherwise	0.190	0.392	0	1

5.6. Results

Table 5.2 reveals the bandwidths chosen for each covariate using the CV criterion function defined in equation (5.8). None of the environmental factors considered in the analysis are smoothed out since the smoothing parameters selected by the CV do not hit their upper bound. Therefore, it can be concluded that all the Z's are relevant covariates in the Smooth Coefficient Model. However, the smoothing parameters reveal that their impacts on water consumption differ. For instance, the water consumption difference between those households that had or did not have renovation works in the water pipes is bigger than that between households with and without non-electrical water-saving devices as reflected in the fact that the bandwidth associated with *Noelecteff* is much larger than the bandwidth associated with *New pipes*.

Table 5.2: Smooth coefficient model bandwidth summary

Variable	Bandwidth
Habits	0.0287
Electeff	0.0033
Noelecteff	0.1074
New pipes	0.0075
Multiple R-squared:	0.3915

Figure 5.1 plots the kernel density functions of the estimated regression coefficient in the semiparametric model and its standard parametric counterpart[7]. It can be seen that the marginal effects estimated using the semiparametric model are very heterogeneous, whereas the parametric model yields estimates that approximate the means of the regressors obtained from the Smooth-Coefficient model, as would be expected (a similar result was found by Sun and Kumbhakar [2013]). Therefore, the semiparametric model is more informative when analyzing water consumption at household level since it provides different marginal effects for each household depending on its environmental behaviors.

Moreover, in order to test for the relevance of the environmental factors, that is, whether the semiparametric model is preferred over the standard parametric

[7] Estimated results obtained using a standard Stochastic Frontier model are presented in Appendix G.

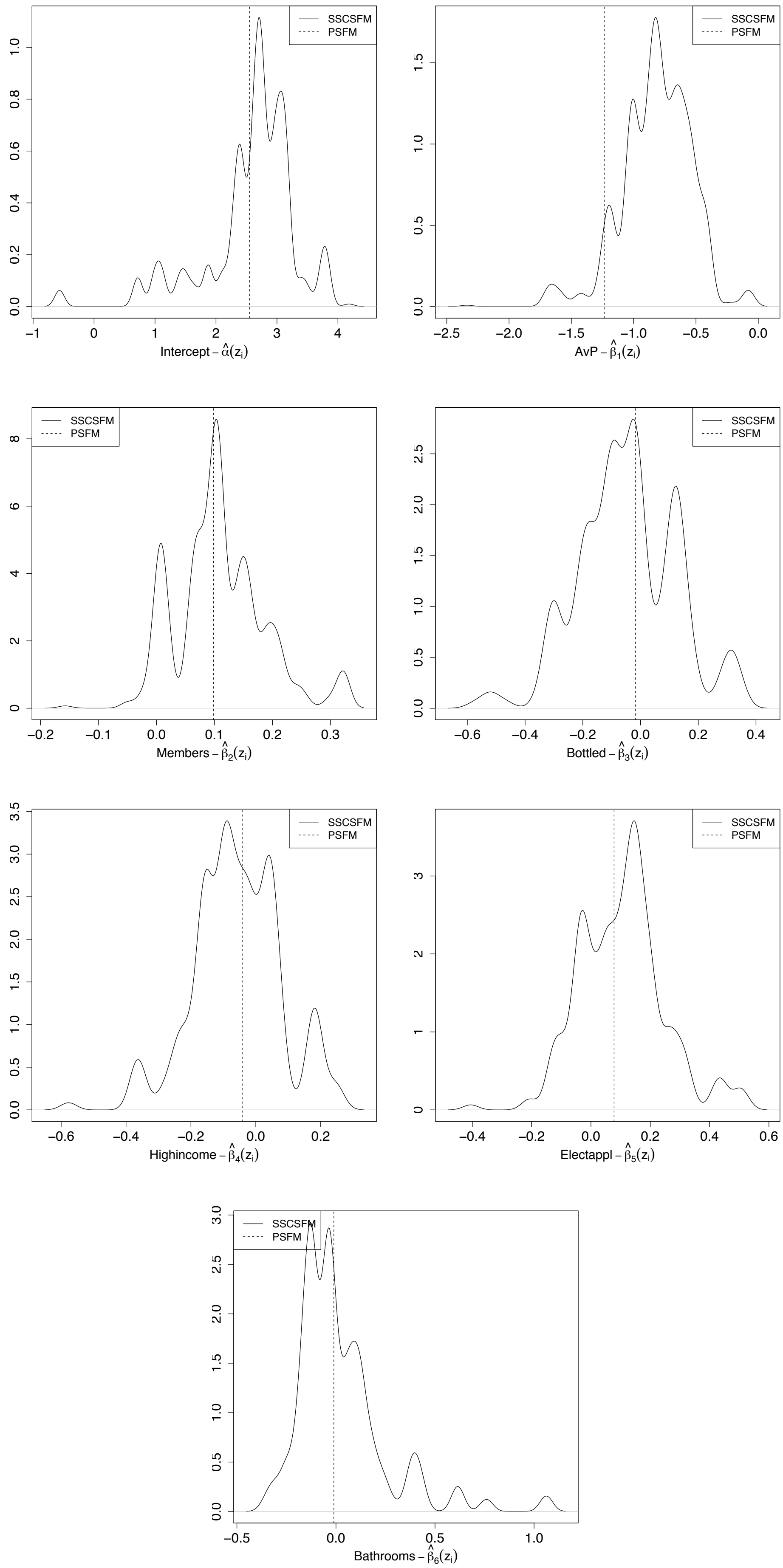


Figure 5.1: Kernel density plots of estimated coefficients

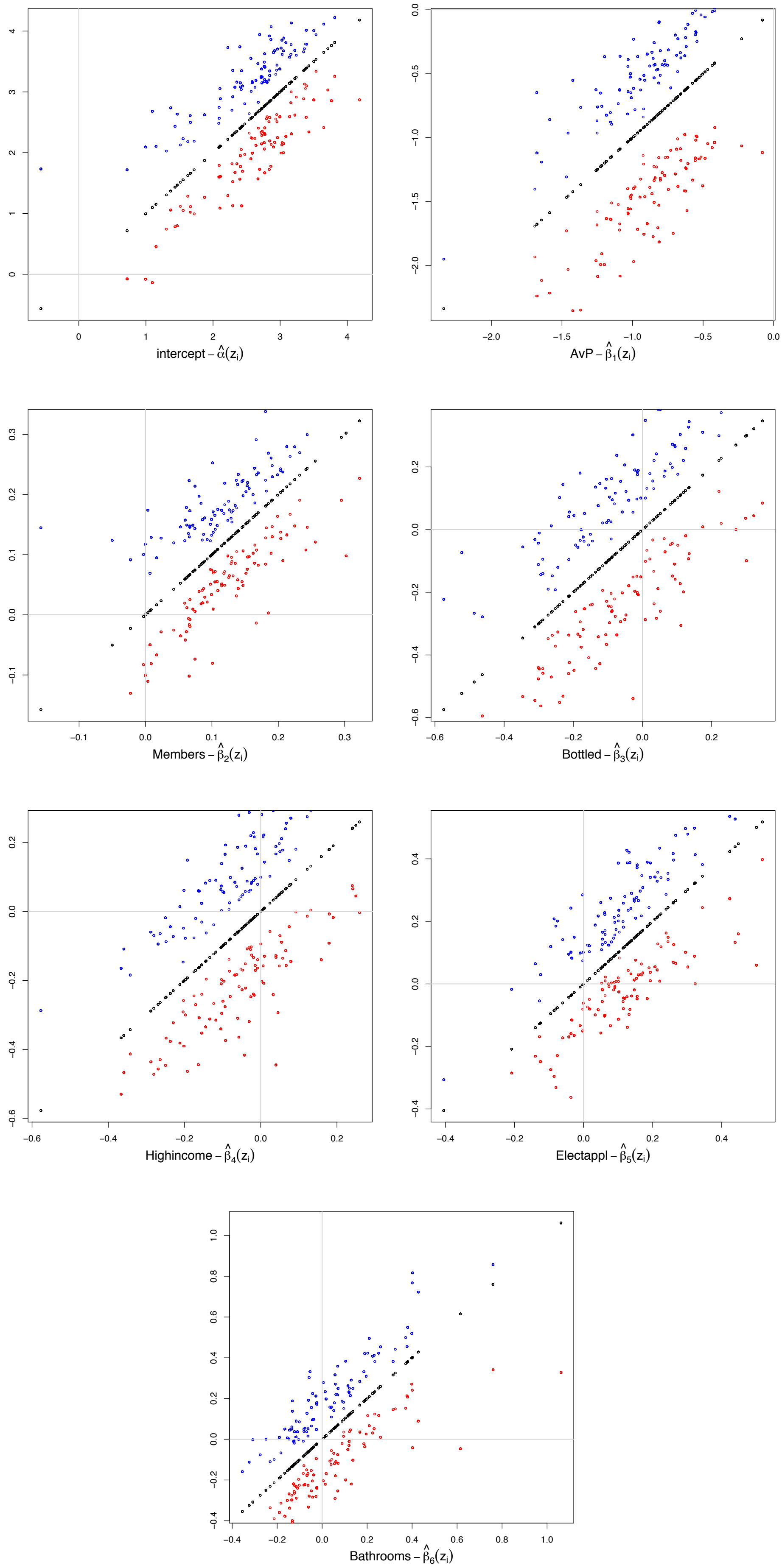


Figure 5.2: Plots of estimated coefficients

model, we perform a specification test of one model against the other. To do so, the test statistic proposed in equation (5.12) is used. The result from the model specification test rejects the null hypothesis that the model can be estimated as a standard stochastic frontier model with a p-value less than 0.000.

Estimated coefficients and their 95% confidence intervals, which have been computed using the wild bootstrap, are reported in Figure 5.2. For each coefficient, we plot the estimated coefficient against itself so that all the coefficients are represented on the 45 degree line. Then, the upper and lower bound of the confidence intervals are also plotted for each observation above and below the 45 degree line, respectively. The axis lines at the origin are used to illustrate the significance of the estimated coefficients. The two axis lines divide the plot into four quadrants, each of them defined by its position with respect to the origin (*North-East*, *North-West*, *South-East*, *South-West*). For each value of the coefficient, if both the upper and lower bound belong either to the *North-East* or *South-West* quadrant, then that particular coefficient is said to be significant at the 5% level. As can be seen in this figure, the coefficients that measure the effect of the price ($\hat{\beta}_1$) and the number of members in the house ($\hat{\beta}_2$) on water consumption are significant for the majority of the observations. However, the rest of the coefficients are not significant for some of the observations, indicating that there is a heterogeneous effect of these variables on residential water demand depending on the combination of environmental factors. This heterogeneity can be also seen in Table 5.3, which shows the percentage of observations with significant coefficients.

Table 5.3: Coefficients' significance

	% of significant coefficients
Intercept	92.3761
ln AvP	88.6496
Members	73.1966
Bottled	25.6410
Highincome	12.5128
Electappl	35.8632
Bathrooms	19.3162

In order to gain more insight into the effects of the environmental variables on the estimated smooth coefficients, some selective results are shown for different combinations of these variables. Given that all the environmental factors are relevant covariates, we construct a baseline household type and four other types of household, showing the variation in the marginal effects when specific environmental factors differ from the values set for the baseline household type. The different household types considered are the following:

- *Baseline*: This is the median household, in which all the environmental factors are set at their median values, that is, the household has one efficient appliance but does not have efficient devices, there have been no renovations in the water infrastructure and its water habits index is equal to 0.6,
- *Bad habits and no efficient technology*: The habits index is equal to 0.3, that is, to the first decile of the water habits index distribution, and there are no efficient technologies in the household.
- *Bad habits and efficient technology*: This household type differs from the previous in that the efficient electrical and non-electrical appliances are set at their maximum possible values.
- *Good habits, no efficient technology*: This household type has a good score on the water habits index (0.8), but the efficient electrical and non-electrical appliances are set at their minimum possible value.
- *Good habits and efficient technology*: The habits index is set at its ninth decile (index value of 0.8) and the efficient electrical and non-electrical appliances are set at their maximum possible values.

The regressors and the standard errors computed using wild bootstrap for these household types are reported in Table 5.4.

It is worth noting that, in general, water demand is quite inelastic to price, with the household type with bad habits and no efficient technology being the most elastic. This implies that households that are equipped with efficient technologies and/or whose family members exhibit good water conservation habits are less sensitive to changes in price, since these households cannot easily adjust their consumption. Regarding the other explanatory variables, the estimated coefficients have the expected signs for most of the household types, but

Table 5.4: Smooth-Coefficient stochastic frontier model for selected values of the environmental variables Z

	Baseline	Bad *Habits* & no eff technology	Bad *Habits* & eff technology	Good *Habits* & no eff technology	Good *Habits* & eff technology
Intercept	2.9597***	3.7641***	1.6630***	2.7631***	0.9952
ln AvP	-0.4190*	-0.8028***	-0.6236***	-0.6081***	-0.5032
Members	0.2128***	-0.0003	0.1513***	0.0743	0.1640
Bottled	-0.0957***	-0.3012***	-0.1868	-0.1042	-0.0224
Highincome	-0.2373	0.0328	0.2415	-0.0677***	-0.0606
Electappl	-0.0102	-0.0955	0.2607***	0.1467***	0.2665***
Bathrooms	-0.1549*	-0.1660*	0.1255***	-0.0237	0.4275***

as commented above, their effects on water consumption differ. Among these other marginal effects, it is worth commenting further on the differences in the marginal effects for *Electappl*. For households with a low level of efficient technology and bad habits, an extra electrical appliance decreases water consumption. However, as the level of efficient technology and habits increase, the decrease in water consumption becomes smaller, reaching a level after which the marginal effect becomes positive. A similar effect is also observed in the marginal effect of *Bathrooms*.

Besides estimating the level of efficiency in water consumption, another important goal of this analysis is to explain the possible sources of this (in)efficiency. As described in Section 5.4, the covariates included in the Smooth-Coefficient model may also affect the inefficiency levels. Therefore, the next stage involves the estimation of equation (5.13), where the dependent variable is the sum of the noise term and the actual inefficiency term so that a negative coefficient of a covariate implies that the corresponding variable would decrease inefficiency. The results from this estimation are shown in Table 5.5.

Starting with the proxy for curtailment behaviors, the estimated coefficient for the *Habits* indicator is negative as expected. Note, however, that it is not significant at conventional levels, which is probably due to the fact that there is not enough variability in the regressor.

Regarding the efficiency behaviors, the *Electeff* variable has a negative and significant coefficient, indicating that the greater the number of efficient electrical

Table 5.5: Determinants of efficiency

	Estimate	Std. Dev
Intercept	-1.7983***	(0.3126)
Habits	-0.1162	(0.0910)
Electeff	-0.0543***	(0.0191)
Noelecteff	0.0103	(0.0310)
New pipes	-0.3033***	(0.0390)
Sigma	0.3649	(0.0001)

*** Significance at the 1% level

water-using appliances, the higher the level of efficiency in water consumption. However, the coefficient for the indicator of efficient non-electrical water-saving devices is not significant. The negative coefficient for the variable *New pipes* indicates that those households that had a renovation of the building's water and sewer pipelines in the previous five years are more efficient. In other words, the more efficient households have a higher quality of water infrastructure.

Finally, the point estimates of the efficiency in water consumption are obtained using equation (5.15). Some summary statistics are presented in Table 5.6 and a histogram illustrating the distribution of efficiency scores for each household is presented in Figure 5.3. The average estimated efficiency in water consumption is 0.8932, that is, households in Granada could reduce their water consumption by an average of 10.68% while maintaining a constant level of water services. The majority of the households in the sample have a high level of efficiency, with the median being equal to 0.9054. Household efficiency does not vary widely, and only 25% of the households in the sample have water efficiency scores less than 0.87, implying that they could reduce their water consumption by over 13%.

Table 5.6: Descriptive statistics of computed efficiency scores

	Mean	Std. Dev	Min	1st Qt	Median	3rd Qt	Max
Water efficiency	0.8932	0.0583	0.5597	0.8691	0.9054	0.9328	1

In order to measure the potential effects on water consumption of policies to encourage the adoption of water saving habits or the investment in efficient water-using technologies, such as those described in Chapter 2, we compute the

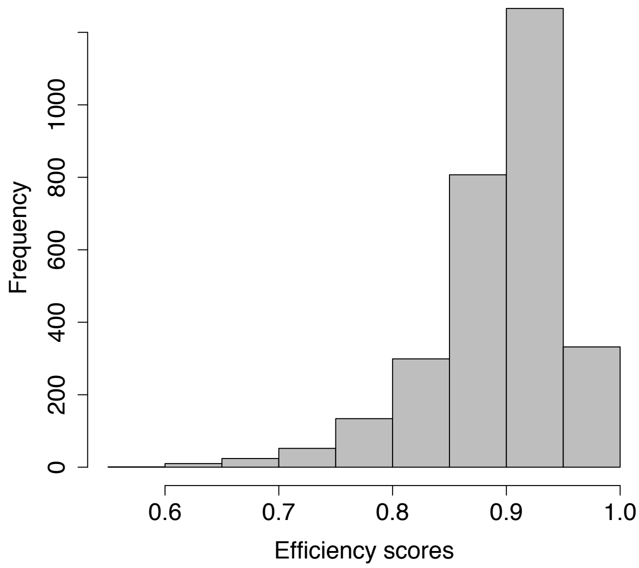


Figure 5.3: Efficiency in water consumption scores

expected changes in water consumption under a series of scenarios in line with those promoted by the Europe 2020 strategy to create a resource-efficient Europe. To do so, we use the estimated coefficients and efficiency scores from the empirical model.

Table 5.7 shows the potential per capita water savings generated by a shift in the frontier (in column 1) and improvements in efficiency (column 2). The former are computed by comparing the predicted water consumption when some of the environmental factors are varied with the predicted water consumption at current values of the Z variables. The latter are obtained by comparing the predicted efficiency scores under changes in the environmental factors and the predicted efficiency scores obtained in the estimation. We check what the expected water savings would be under the following scenarios:

- Scenario 1: All households (except for those that originally have a water habits index score greater than or equal to 0.8) improve their water conservation habits so that the *habits* index increases to the ninth decile (i.e., 0.8).

- Scenario 2: All households (except for households that currently have the maximum number of efficient electrical appliances) increase the number of efficient electrical appliances to its maximum level, that is, the variable *Electeff* is set equal to 2.

- Scenario 3: Households in the sample invest in efficient non-electrical appliances, so the dummy variable *Noelecteff* is set to 1.

- Scenario 4: In this scenario we simultaneously improve only those environmental factors that actually induce reductions in water consumption according to the scenarios above.

Water savings from improvements in efficiency are not computed in Scenarios 1 and 3, since neither habits nor efficient non-electrical devices have a significant effect on efficiency.

Table 5.7: Potential per capita water savings under a set of policy scenarios

	Water savings in the frontier (m^3)	Water savings in the efficiency (m^3)	Total water savings (m^3)
Scenario 1 (Δ in Habits)	1.14	-	1.14
Scenario 2 (Δ in Electeff)	2.17	0.0004	2.17
Scenario 3 (Δ in Noelecteff)	-0.58	-	-0.58
Scenario 4 (Δ Total)	2.11	0.0013	2.11

From Table 5.7 it can be seen that potential water savings are mainly generated by shifts in the demand frontier caused by a change in Z. By contrast, the gains due to improvements in efficiency are very small.

Under Scenario 3, there is actually an increase in per capita water consumption. This may reflect a possible *rebound effect* in the sense that the actual water savings are different from the expected savings from the installation of efficient non-electrical water-using devices. Improvements in efficient non-electrical devices therefore have a perverse effect on water consumption: households may perceive these technologies as very efficient and they may end up using them more often, leading to an increase in total water consumption. This is what is generally referred to in the literature as *backfire* [Saunders, 1992]. This result is consistent with evidence provided in the previous chapter.

Under Scenarios 1, 2 and 4, positive, though small, potential per capita water savings are generated. However, when considering the entire population of Granada, water savings can be substantial. We consider the population of the city (237,818 inhabitants) in the year 2013, and we compute the potential total water savings for this city under Scenario 4. This, of course, assumes that the sample observed is sufficiently representative of the population in Granada. The total savings amount to about 502,000 m^3 of water per year, which could cover the basic water needs of around 25,000 people in a year. Considering the scarcity problems that this city has had in previous years and the negative expectations for the future, these potential water savings are quite substantial.

5.7. Conclusion

This research is the first attempt in the literature to estimate the level of efficiency in household water consumption and analyze the effect of water conservation behaviors on this efficiency. In order to do so, we use data from the city of Granada (Spain) in the period 2009-2011.

A water (input) demand frontier is derived from the demand of household water services and it is estimated using a semiparametric Smooth-Coefficient Stochastic Frontier model. This recently-developed methodology allows us to analyze the effect of some environmental factors (in particular, efficiency and curtailment behaviours) on the inefficiency term and to include these variables in the frontier part so that the intercept and the slope coefficients are expressed as unknown functions of the environmental factors. Statistical analysis reveals that this methodology is more appropriate than a standard parametric stochastic frontier for our sample.

All the environmental factors considered in the analysis are found to be relevant covariates, that is, the marginal effects are functions of these variables which in turn allows the frontier to shift non-neutrally. The estimates for the efficiency in water consumption are relatively high for the majority of households. Unfortunately, the fact that there are no previous studies of efficiency in residential water consumption precludes a direct comparison of the results.

Regarding the efficiency determinants, the results indicate that households with a greater number of efficient appliances and that have undergone a renovation of the water and sewer pipelines in the previous five years have a higher level of efficiency in water consumption. However, the efficient non-electrical devices do not seem to have a significant effect on efficiency.

The results regarding the effects of water conservation habits on efficiency were mixed, as the sign of the estimated coefficient indicated that they reduce water consumption but this relationship was not found to be statistically significant at conventional levels.

Moreover, the potential water savings generated by a shift in the demand frontier and improvements in efficiency are calculated under different scenarios for these environmental factors to exemplify the usefulness of the model. This simulation of scenarios shows that there is a possible rebound effect related to the efficient non-electrical devices and the renewed water pipelines in the data analyzed in this paper. However, when improving the other environmental factors, that is, water habits and efficient electrical appliances, substantial water savings can be achieved.

In this sense, policies promoting investment in efficient electrical appliances may actually reduce water consumption and increase households' efficiency in water consumption. However, policies encouraging the adoption of efficient non-electrical devices may not be successful in decreasing water consumption. Therefore, information campaigns to raise awareness of the water scarcity problem should be reinforced to complement the adoption of efficient technologies so that these technologies can be used in a more competent manner.

Chapter 6

Conclusions and extensions

Although residential water demand has been extensively investigated in recent decades, there are still interesting topics to be analyzed from the point of view of consumers' preferences and behavior. On the one hand, in a context where water resources are becoming increasingly scarce, it is crucial to understand the effect of pricing and non-pricing policies on the behavior of residential consumers. On the other hand, heterogeneity in preferences may make these policies more or less effective depending on the composition of the targeted population.

The essays in this thesis shed some light on the heterogeneity of preferences for residential water and study household behavior in a way that allows us to better understand water conservation technologies and habits. The first essay clearly demonstrates the presence of unobserved heterogeneity that affects the estimation of water demand functions and the need for this to be taken into account in order to design water demand management policies. The second essay analyzes the relationship between the adoption and use of water-efficient technologies disaggregating them into electrical efficient appliances and non-electrical efficient devices. Having found some evidence of a negative relationship between water conservation habits and non-electrical efficient technologies, the level of efficiency in residential water consumption and its determinants are studied in the final essay, computing the potential water savings associated with the different efficient technologies and water conservation habits.

The first essay, in Chapter 3, analyzes household heterogeneity in water demand using a Latent Class Model, identifying four different residential water consumer profiles and therefore four different response patterns to changes in the drivers of water use, including different price elasticities. In this sense, two of the classes, which represent more than 33% of the sample, are found to be perfectly inelastic to prices since price has no significant effect on residential water demand. The effect of price on water demand is significant for the remaining classes but price elasticities differ across classes. When comparing these price elasticities with a single-class model and a random-effects model, we realized that the heterogeneity is being masked in these models. Regarding the effect of the change in the price structure in 2011, our results show that water demand became more inelastic for only one group of consumers (Class 3), indicating that the change in the price structure was perceived differently by different groups of consumers. The remaining coefficients have the expected signs, but, the magnitude of the coefficients vary across classes, underlining the high level of heterogeneity in the sample.

In order to provide a description of the type of consumer belonging to each class, class membership probabilities are parameterized including attitudinal factors, personal capabilities, habits and routines, and contextual factors as determinants of water demand behaviors [Russell and Fielding, 2010; Stern, 2000]. Some of the covariates are found to be useful for classifying consumers into different groups. For instance, Class 1, whose water demand is perfectly inelastic, has a higher proportion of children under 15, adults over 65 and a greater number of efficient electrical appliances, as well as the lowest level of water consumption and standard deviation of consumption within the year. In this case, school-based educational campaigns and information campaigns targetting older people could be useful to reduce water consumption within this group. On the contrary, Class 4 is the most responsive to price and exhibits a relatively high level of water consumption, so both pricing and non-pricing policies could be applied to this group of consumers. That is, pricing and non-pricing policies can be jointly used to encourage reductions in water consumption for those consumers that are more price-responsive in our sample. However, non-pricing policies should be reinforced in the case of consumers that are not price-responsive and have the lowest level of water consumption. In this sense, the results in this chapter suggests that the design of water demand management policy could be tailored to the specific demand function of a group of consumers identified using information that could be easily observed by water regulators such as the presence of children or household income.

This work is already being extended in a study that is currently in progress and that aims at designing a set of water tariffs using the price elasticities obtained in this chapter. Being able to distinguish between groups of consumers permits alternative block tariffs to be designed which can improve social welfare compared to those which could be designed with the more limited information from a single-class model. Another possible extension would be to replicate this analysis using household level data from different municipalities in Spain, accounting for differences in the geographical position and hydrological characteristics of the surroundings. This would allow us to identify specific demand functions for different groups of consumers and test if they are linked to greater environmental awareness in areas where water scarcity is more severe or water prices are higher.

The second essay studies the determinants of the adoption of different water-efficient technologies and the corresponding water-saving habits, taking into account the potential relationship between both decisions, as inappropriate habits related to those technologies could lead to significant efficiency losses and lower saving levels. Two groups of efficient technologies are distinguished, namely electrical efficient appliances and non-electrical efficient devices, since the public policies affecting each type of technology are different, as are their technical characteritics.

In order to control for unobserved household-specific effects that may influence the adoption of each type of efficient technology and the corresponding water-saving habit, and the possible effect of the tecnology on the habit, a recursive semi-ordered probit is estimated.

The results show that there are significant differences in terms of the determinants affecting each set of decisions, indicating that each decision may be driven by different factors. Moreover, one of the more interesting results is that households with a higher number of efficient electrical appliances exhibit better habits related to the use of those technologies. However, in the case of non-electrical efficient appliances, there is a negative relationship between efficient non-electrical technologies and their habits, indicating that these households have worse water-conservation habits, in a manner consistent with a potential rebound effect. These results indicate that public policies that aim to reduce residential water consumption should be reconsidered. In this sense, information and educational campaigns targeting the adoption of good habits linked to non-electrical efficient devices may be preferable in order to promote reductions in water consumption.

Among the avenues for future research, I would like to analyze the effect of actual subsidies on the adoption of each type of efficient technology in order to assess the extent to which the subsidy programs suffer from free-rider effects. Free ridership occurs when households would have invested in efficient technologies even in the absense of the subsidy. In this sense, the household's willingness-to-pay (WTP) for water savings that accrue through the investment in efficient electrical appliances and efficient non-electrical devices could be estimated. If the household's WTP exceeds the observed cost, a free-rider effect would exist, undermining the social benefits of that particular subsidy program.

Finally, the last chapter measures the level of efficiency in residential water consumption and analyzes the effect of different environmental behaviors on it. In order to do so, a water demand frontier consistent with household production theory is estimated using a semiparametric Smooth-Coefficient Stochastic Frontier model. This methodology allows us to investigate the effect of environmental behaviors, and in particular efficiency and curtailment behaviors, on the inefficiency term and to include these variables into the main regression function so that the intercept and the slope coefficients are expressed as unknown functions of them.

The environmental behaviors considered in the analysis are efficiency behaviors, defined as one-time behaviors such as obtaining efficient electrical appliances and efficient non-electrical appliances, and curtailment behaviors, defined as individuals' actions that reduce water consumption and which involve inconvenience and sacrifice. All the environmental factors included in the model are found to be relevant covariates, indicating that the marginal effects are unknown functions of these variables.

Regarding the efficiency in water consumption, it is relatively high for most of the households, with efficiency scores higher than 0.87 for 75% of the sample. The analysis of the efficiency determinants shows that those households with a higher number of efficient electrical appliances and that have performed a renovation of the water and sewer pipelines in the previous five years show a higher level of efficiency in water consumption. However, the efficient non-electrical appliances do not have a significant effect on the level of efficiency. The effect of water conservation habits on efficiency is not significant but the sign of the estimated coefficient indicates that they improve the level of efficiency.

Moreover, the expected changes in water consumption under a set of scenarios are calculated. These changes in water consumption are generated by a shift in the frontier and improvements in efficiency, and the scenarios represent changes in each of the environmental behaviors considered in the analysis. The results show that improvements in water conservation habits and a higher number of efficient electrical appliances would lead to reductions in water consumption. However, and as inferred in Chapter 4, there is a perverse effect of efficient non-electrical devices in the sense that an increase in their number would generate increases in water consumption. As discussed above, information campaigns to affect consumers' water demand behaviors should be reinforced.

This research could be extended by assessing the level of water consumption and efficiency before and after the adoption of efficient technologies. This would allow us to examine the presence of a rebound effect and quantify it, providing a better understanding of the households with efficient technologies.

In conclusion, this thesis allows us to better understand household water behavior and the extent to which water demand side policies are effective in reducing water consumption. In Chapter 3, water demand is found to be perfectly inelastic for two of the groups of consumers identified. Moreover, water price is not a significant determinant of the adoption of water-saving technologies and pro-environmental habits analyzed in Chapter 4. Therefore, pricing policies should be complemented with non-pricing policies to effectively affect household water behavior. Efficient water-using technologies do not always lead to reductions in water consumption, as demonstrated in Chapter 5 for efficient non-electrical devices. Efficiency labels for non-electrical devices are not very common, so there is less information related to efficiency gains and as a consequence it is more difficult for households to properly use these efficient devices. Therefore, it is crucial to improve the knowledge about this technology through the use of standard labelling schemes. Moreover, since investment in efficient technologies has been heavily subsidized, ex-post monitoring could be applied to affect consumers' incentives with respect to water conservation. Finally, information campaigns should be reinforced, as they were a significant determinant of the four water-conservation behaviors analyzed in Chapter 4. Our results are in line with the current policy in the sense that international and national institutions are carrying out more and more information campaigns and educational programs to raise awareness of the issue of water scarcity.

Chapter 7

Conclusiones y futuras extensiones

A pesar de que la demanda residencial de agua ha sido ampliamente estudiada en los últimos años, todavía existen temas a analizar desde el punto de vista de las preferencias y comportamiento de los consumidores. Por un lado, en un contexto en el que el agua es un recurso cada vez más escaso, es de suma importancia comprender el efecto de polticas precio y no-precio en el comportamiento de los consumidores residenciales de agua. Por otro lado, la heterogeneidad en las preferencias puede afectar a la efectividad de estas políticas según la composición de la población objetivo de las mismas.

Los ensayos en esta tesis arrojan luz sobre la heterogeneidad de las preferencias en el consumo residencial de agua y en el estudio del comportamiento de los hogares de forma que permiten comprender mejor la adopción de hábitos y tecnologías de conservación de agua. En el primer ensayo se demuestra la presencia de heterogeneidad inobservable que afecta a la estimación de las funciones de demanda de agua y la necesidad de controlar por ello en el diseo de políticas de gestión de demanda de agua. En el segundo ensayo se analiza la relación entre la adopción y el uso de tecnologías de agua eficientes, diferenciando entre electrodomésticos eficientes y dispositivos eficientes no eléctricos. Habiendo encontrado evidencia de una relación negativa entre hábitos de conservación de agua y dispositivos eficientes no eléctricos, el nivel de eficiencia en el consumo residencial de agua y sus determinantes son estudiados en el ensayo final, calculando el ahorro potencial de agua asociado con las diferentes tecnologías y hábitos de conservación de agua.

El primer ensayo, en el Capítulo 3, analiza la heterogeneidad en la demanda de agua a nivel de hogar usando un Modelo de Clases Latentes, identificando cuatro perfiles distintos de consumidores residenciales de agua y, por lo tanto, cuatro respuestas distintas a cambios en los determinantes del uso de agua, incluyendo distintas elasticidades precio. En este sentido, dos de las clases, que representan más del 33% de la muestra, son perfectamente inelásticas respecto al precio ya que el precio no tiene un efecto significativo en la demanda residencial de agua. El efecto del precio en la demanda de agua es significativo para las clases restantes, pero las elasticidades son distintas a lo largo de las mismas. Respecto al efecto en el consumo de agua del cambio en la estructura de precios en 2011, nuestros resultados muestran que la demanda de agua únicamente se volvió más elástica para un grupo de consumidores (Clase 3), es decir, el cambio en la estructura de precios fue percibido de distinta manera para distintos grupos de consumidores. El resto de coeficientes tienen los signos esperados, pero la magnitud de los coeficientes varía entre las clases, resaltando el alto nivel de heterogeneidad en la muestra.

A fin de describir el tipo de consumidor que pertenece a cada clase, las probabilidades de pertenencia a cada clase son parametrizadas incluyendo factores de actitud, capacidades personales, hábitos y rutinas, y factores de contexto como determinantes de comportamientos de demanda de agua [Russell and Fielding, 2010; Stern, 2000]. Algunas de las covariables permiten clasificar consumidores en distintos grupos. Por ejemplo, la Clase 1, cuya demanda de agua es perfectamente inelástica, tiene una alta proporción de menores de 15 años, adultos de más de 65 años y un número mayor de electrodomésticos eficientes, así como los niveles más bajos de consumo de agua y desviación estándar del consumo a lo largo del año. En este caso, las campañas educativas escolares y campañas de información enfocadas a mayores de 65 años podrían ser útiles para reducir el consumo de agua en este grupo. Por el contrario, la Clase 4 es las más sensible al precio y muestra un consumo de agua relativamente elevado, por lo que políticas tanto precio como no-precio pueden ser aplicadas a este grupo de consumidores. Es decir, pueden combinarse políticas precio y no-precio para fomentar reducciones en el consumo de agua para aquellos consumidores que son más sensibles al precio en nuestra muestra. Sin embargo, las políticas no-precio deberían ser reforzadas en el caso de los consumidores que no son sensibles al precio y tienen el nivel más bajo de consumo de agua. En este sentido, los resultados de este capítulo sugieren que el diseño de políticas de gestión de demanda de agua podrían hacerse a la medida de una función de demanda específica de un grupo de consumidores identificados utilizando información que puede ser facilmente observable por los reguladores del sector del agua como la presencia de menores en el hogar o la renta familiar.

Este trabajo está siendo extendido en un estudio actualmente en curso y que tiene como objetivo el diseño de una serie de tarifas de agua usando las elasticidades precio obtenidas en este capítulo. La distinción entre grupos de consumidores permite diseñar tarifas por bloques alternativas que pueden mejorar el bienestar social en comparación con aquellas que se diseñan a partir de la información más limitada que proporciona un modelo con una única clase. Otra posible extensión sería replicar este análisis usando información a nivel hogar de distintos municipios españoles, controlando por las diferencias en posición geográfica y características hidrológicas del entorno. Esto permitiría identificar funciones de demanda específicas para distintos grupos de consumidores y comprobar si estas están relacionadas con una mayor preocupación por el Medio Ambiente en áreas donde la escasez de agua es más intensa o los precios del agua son más altos.

El segundo ensayo analiza los determinantes de la adopción de diferentes tecnologías eficientes y los correspondientes hábitos de ahorro de agua, teniendo en cuenta la relación potencial entre ambas decisiones, ya que la falta de hábitos de conservación relacionados a estas tecnologías podría causar pérdidas significativas de eficiencia y niveles de ahorro de agua inferiores a los esperados. Se distinguen dos grupos de tecnologías eficientes, que son electrodomésticos eficientes que usan agua y dispositivos de agua eficientes no eléctricos. Esta distinción se realiza debido a que las políticas públicas que afectan cada tipo de tecnología son distintas, así como sus propias características técnicas.

Para controlar por los efectos inobservables específicos de cada hogar que puedan influir en la adopción de cada tipo de tecnología eficiente y el hábito de ahorro de agua correspondiente, y el posible efecto de la tecnología en el hábito, se estima un probit recursivo semi-ordenado.

Los resultados muestran que hay diferencias significativas desde el punto de vista de los determinantes que afectan a cada set de decisiones, indicando que cada decisión puede estar motivada por distintos factores. Además, uno de los resultados más interesantes es que los hogares con un mayor número de electrodomésticos eficientes presentan mejores hábitos en relación al uso de estas tecnologías. Sin embargo, en el caso de los dispositivos eficientes no eléctricos, existe una relación negativa entre este tipo de tecnología y sus hábitos, es decir, estos hogares tienen peores hábitos de ahorro de agua. Estos resultados indican que las políticas públicas cuyo objetivo sea reducir el consumo residencial de agua deberían ser replanteadas. En este sentido, serían preferibles campañas educativas y de información enfocadas a la adopción de buenas hábitos asociados a dispositivos eficientes no-eléctricos para promover reducciones en el consumo de agua.

Entre las futuras vías de investigación destaca el análisis del efecto de subvenciones reales en la adopción de cada tipo de tecnolog'ia eficiente para poder evaluar en qué medida los programas de subvenciones experimentan comportamientos oportunistas. Este problema ocurre cuando los hogares habrían invertido en tecnologías eficientes incluso en ausencia de subvención. En este sentido, la disposición a pagar de los hogares por ahorros de agua correspondiente a la inversión en electrodomésticos eficientes y dispositivos eficientes no-eléctricos puede estimarse. Si esa disposición a pagar es mayor que el coste observado, existiría un comportamiento oportunista que reduciría los beneficios sociales del programa de subvenciones.

Por último, en el último capítulo se mide el nivel de eficiencia en el consumo residencial de agua y se analiza el efecto de distintos comportamientos ambientales sobre el mismo. Para ello, se estima una frontera demanda de agua según la teoría de la producción adaptada al consumidor, usando un modelo semiparamétrico denominado "Smooth-Coefficient Stochastic Frontier model". Esta metodología permite investigar el efecto de comportamientos ambientales, y concretamente comportamientos de eficiencia y de reducción, en el término de ineficiencia, y además incluir estas variables en la función principal de forma que el términos independiente y los coeficientes se expresan como funciones desconocidas de las mismas.

Los comportamientos medioambientales considerados en el análisis son comportamientos de eficiencia, definidos como comportamientos puntuales como adquirir electrodomésticos eficientes y dispositivos eficientes no-eléctricos, y comportamientos de reducción, definidos como acciones de los consumidores que reducen el consumo de agua y que implican sacrificios y molestias. Todos los factores medioambientales incluídos en el modelo resultaron covariables relevantes, indicando que los efectos marginales son funciones desconocidas de estas variables.

En cuanto a la eficiencia en el consumo de agua, es relativamente alta para la mayoría de los hogares, con índices de eficiencia superiores a 0.87 para el 75% de la muestra. El análisis de los determinantes de eficiencia muestra que aquellos hogares con mayor número de electrodomésticos eficientes y que hayan llevado a cabo obras de renovación en las tuberías en los últimos cinco años tienen un mayor nivel de eficiencia en el consumo de agua. Sin embargo, los dispositivos eficientes no-eléctricos no tienen un efecto significaticos en el nivel de eficiencia. El efecto de los hábitos de conservación de agua en la eficiencia no es significatico, pero el signo del coeficiente estimado indica que mejoran el nivel de eficiencia.

Adem'as, se han calculado los cambios esperados en el consumo de agua bajo una serie de escenarios. Estos cambios en el consumo de agua son generados por un desplazamiento de la frontera y mejoras de eficiencia, y los escenarios representan cambios en cada comportamiento medioambiental considerado en el análisis. Los resultados muestran que mejoras en los hábitos de conservación de agua y aumentos en el número de electrodomésticos eficientes conducirían a reducciones en el consumo de agua. Sin embargo, y como ya se pudo observar en el Capítulo 4, hay un efecto perverso de los dispositivos eficientes no-eléctricos en cuanto a que un aumento en su número generaría aumentos en el consumo de agua. Como ya se ha discutido anteriormente, se deberían reforzar las campañas informativas para incidir en el comportamiento de demanda de agua de los consumidores.

Esta investigación podría ser extendida al evaluar el nivel de consumo de agua y eficiencia antes y después de la adopción de tecnologías eficientes. Esto nos permitiría investigar la presencia de un efecto rebote y cuantificarlo para poder comprender mejor el comportamiento de los hogares con tecnologías eficientes.

En resumen, esta tesis permite comprender mejor el comportamiento de demanda de agua de los hogares y en qué medida las políticas de de demanda de agua son efectivas en reducir el consumo de agua. En el Capítulo 3, la demanda de agua es perfectamente inelástica para dos de los grupos de consumidores identificados. Además, el precio del agua no es un determinante significativo de la adopción de tecnologías y hábitos de ahorro de agua analizados en el Capítulo 4. Por lo tanto, las políticas precio deben ser complementadas con polt́icas no-precio para afectar de forma efectiva el comportamiento de demanda de agua de los consumidores. Las tecnologías eficientes de uso de agua no siempre conducen a reducciones en el consumo de agua, como se demostró en el Capítulo 5 para los dispositivos eficientes no-eléctricos. No existe un formato estándar de etiquetas informativas relativas a la eficiencia de este tipo de tecnologías, por lo que hay menos información en relación a las ganancias de eficiencia y como consecuencia es más difícil para los hogares usar este tipo de dispositivos eficientes de forma adecuada. Por lo tanto, es importante mejorar el conocimiento sobre esta tecnología a trav'es del uso de planes de etiquetado estándar. Además, como la inversión en tecnologías eficientes ha sido fuertemente subvencionada, se podrían realizar controles ex-post para incidir en los incentivos de los consumidores para la conservación del agua. Por último, las campañas informativas deberían reforzarse, ya que son un determinante significativo de los cuatro comportamiento de conservación de agua analizados en el Capítulo 4. Nuestros resultados están en consonancia con la política actual, ya que varias instituciones a nivel internacional y nacional están llevando a cabo cada vez más campañas informativas y programas educativos para aumentar la concienciación sobre la escasez de agua.

Appendix A

As explained in Section 3.5, the estimation using LCMs is nonlinear, therefore, two-stage least squares models are likely to be inconsistent [Howard and Roe, 2013]. Hence, we used a control function approach to correct for price endogeneity.

Consider the model:

$$W = \delta z_1 + \alpha AvP + u_1 \tag{1}$$

where W is residential water demand, AvP the average price (i.e., the endogenous explanatory variable) and z_1 a vector of exogenous explanatory variables.

This methodology uses the same first stage that would be used in 2SLS, that is, the endogenous explanatory variable is regressed on the exogenous explanatory variables and the set of instruments. Let z_2 denote a vector of instruments.

$$AvP = \pi_1 z_1 + \pi_2 z_2 + u_2 \tag{2}$$

$$E(z_1' u_2) = 0 \qquad E(z_2' u_2) = 0$$

The average price would be endogenous if and only if u_1 is correlated with u_2, where $\gamma = E(u_2 u_1)/E(u_2^2)$.

$$u_1 = \gamma u_2 + \epsilon \tag{3}$$

Since u_1 and u_2 are uncorrelated with z_1 and z_2, $E(u_2\epsilon) = 0$ and $E(z_2\epsilon) = 0$.

Substituting equation (3) into equation (1):

$$W = \delta z_1 + \alpha AvP + \gamma u_2 + \epsilon \tag{4}$$

In this equation u_2 is included as an explanatory variable. As explained above, ϵ is uncorrelated with u_2, z_1 and z_2. Moreover, AvP is defined as a linear function of the explanatory variables, the instruments and the residual u_2, so AvP is uncorrelated with ϵ. Therefore, δ and α can be consistently estimated with equation (4).

Results from the first stage estimation as defined in equation (2) are presented in Table 1. Following Hewitt and Hanemann [1995] and Olmstead [2009], we used the full set of marginal prices in each block as instruments. The Hansen test indicated that all the instruments are exogenous. The residuals were obtained from this estimation and the second stage estimation included the average price and the control function as defined in equation (3), that is, the residuals from the first stage and a standard normal random variable [Howard and Roe, 2013].

Table 1: Control Function Estimation

	AvP
Block1	-1.035
	(-0.60)
Block2	29.948***
	(4.47)
Block3	-26.959***
	(-4.06)
Block4	18.151***
	(4.12)
Block5	-12.443***
	(-4.07)
Highincome	0.038
	(1.22)
Members	-0.039***
	(-4.40)
Electappl	-0.078***
	(-3.76)
Habits	-0.028
	(-0.29)
Electeff	-0.014
	(-1.05)
Owner	0.049**
	(2.04)
Year2011	-34.596***
	(-4.16)
Priceinfo	-0.012
	(-0.53)
Constant	20.368***
	(3.99)
N	3012
Hansen test (overidentification	5.961
test of all instruments)	$\chi^2(4)$ p-value = 0.2021
Endogeneity test of endogenous regressors:	17.670
	$\chi^2(1)$ p-value = 0.0000

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix B

Selected questions from the survey used to construct a water habits index:

P.17. In general, do you have any of the following water conservation habits in the household?
a) Do you recycle water, for example, making use of the water while you wait for the shower to get hot?
b) Do you store drinking water in the refrigerator rather than letting the tap run every time you want a cool glass of water?
c) Do you defrost food in advance in order to avoid using running hot water to thaw meat or other frozen foods?
d) Do you fill the sink with water when washing dishes by hand?
e) Do you operate automatic dishwashers and washing machines only when they are fully loaded?
f) Do you slightly turn off the backflow valve to reduce the tap flow?
g) Do you use a rubbish bin in the toilet rather than flushing the toilet unnecessarily?
h) Do you avoid letting water run while brushing your teeth?
i) Do you take shorter showers?
j) Do you avoid washing the cars with drinking water?

Appendix C

As explained in Section 4.4, a J-test is used to assess the model specification. The test statistic used has a $\chi^2(m-k)$ distribution under the null hypothesis that the residuals and the excluded variables x_{-1} are orthogonal [Angrist and Pischke, 2009]. However, since bivariate probit models are nonlinear, we compute the generalized residuals, which have properties similar to those of the residuals in the linear model, following Gourieroux et al. [1987].

In our two semi-ordered probit models, we need to test the exclusion of x_{-1} in the first model in the equation explaining a binary dependent variable, and then in the second model in the equation that explains an ordered categorical dependent variable. For the first model, the estimation and inference of probit models is usually based on maximum likelihood estimation. The log likelihood function is written:

$$ln\mathcal{L}(\beta|X) = \sum_{i=1}^{n} (y_i ln\Phi(\beta' x_i) + (1-y_i)ln(1-\Phi(\beta' x_i))) \tag{5}$$

In order to calculate the generalized residuals, we need to take the first derivative of the log likelihood with respect to β:

$$\begin{aligned}
\frac{\delta ln\mathcal{L}(\beta|X)}{\delta\beta} &= \sum_{i=1}^{n}\left[y_i\frac{\phi(\beta' x_i)}{\Phi(\beta' x_i)}x_i + (1-y_i)[\frac{-\phi(\beta' x_i)}{1-\Phi(\beta' x_i)}x_i\right] \\
= \sum_{i=1}^{n}&\left[\frac{y_i\phi(\beta' x_i)x_i}{\Phi(\beta' x_i)(1-\Phi(\beta' x_i)} - \frac{\Phi(\beta' x_i)(1-y_i)\phi(\beta' x_i x_i x_i}{\Phi(\beta' x_i)(1-\Phi(\beta' x_i))}\right] \\
= \sum_{i}^{n}&\left[\frac{\phi(\beta' x_i)(y_i-\Phi(\beta' x_i))}{\Phi(\beta' x_i)(1-\Phi(\beta' x_i))}\right]x_i = 0
\end{aligned} \tag{6}$$

Regarding the second model, that is, the ordered probit model, the log likelihood function is:

$$ln\mathcal{L}(\beta|X) = \sum_{i=1}^{n}\sum_{j=0}^{J} m_{ij} ln[\Phi(\alpha_{j+1} - \beta' x_i) - \Phi(\alpha_j - \beta' x_i)] \tag{7}$$

where $m_{ij} = 1$ if $y_i = j$ and 0 otherwise.

Therefore, the first derivative of the log likelihood with respect to β is written:

$$\begin{aligned} \frac{\delta ln\mathcal{L}(\beta|X)}{\delta\beta} &= \sum_{i=1}^{n}\sum_{j=0}^{J} m_{ij}\left[\frac{1}{\Phi(\alpha_{j+1} - \beta' x_i) - \Phi(\alpha_j - \beta' x_i))}\right] \\ &[-(\phi(\alpha_{j+1} - \beta' x_i) - \phi(j - \beta' x_i))x_i] \\ &= \sum_{i=1}^{n}\sum_{j=1}^{J} m_{ij}\left[-\frac{(phi(\alpha_{j+1} - \beta' x_i) - \phi(\alpha_j - \beta' x_i))}{\Phi(\alpha_{j+1} - \beta' x_i) - \Phi(\alpha_j - \beta' x_i)}\right] x_i = 0 \end{aligned} \tag{8}$$

Table 2 shows the regressions of the generalized residuals against x_{-1} and x_2. The J-tests for each regression show that the null hypothesis cannot be rejected, that is, the variables that were not included in the second equation are not correlated with the generalized residuals.

Table 2: Regression for testing the exclusion

	Generalized residual Model 1	Generalized residual Model 2
Remodel	-0.0285	0.00540
	(-0.86)	(0.10)
Home age	0.0176	0.0560*
	(0.96)	(1.84)
Owner	0.0554	0.0564
	(1.25)	(0.77)
Highincome	0.0010	0.0126
	(0.02)	(0.18)
Members	0.0006	0.0017
	(0.04)	(0.07)
Enviro	-0.0141	-0.0910
	(-0.39)	(-1.50)
Campaign	-0.0039	0.0166
	(-0.12)	(0.32)
Age	-0.0008	-0.0028
	(-0.71)	(-1.56)
Gender	0.0014	0.0186
	(0.04)	(0.35)
Education	-0.0051	0.0005
	(-0.15)	(0.01)
Lagged AvP	-0.0061	-0.0002
	(-0.18)	(-0.00)
Constant	0.0337	-0.0126
	(0.23)	(-0.05)
N	1076	1076
J-test	2.6615	3.8469
p-value	0.2643	0.1461

t statistics in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Appendix D

Table 3: Marginal effects Model 1

	Electeff			Elect-habits
	Category 1	Category 2	Category 3	
Remodel	-0.155***	0.0277***	0.127***	
	(-6.08)	(4.95)	(6.00)	
Home age	0.0458**	-0.00819**	-0.0377**	
	(3.10)	(-2.92)	(-3.09)	
Owner	-0.196***	0.0350***	0.161***	
	(-5.73)	(4.96)	(5.60)	
Hinghincome	-0.128***	0.0229***	0.105***	-0.00644
	(-3.93)	(3.46)	(3.94)	(-0.21)
Members	-0.0361**	0.00645**	0.0296**	0.00852
	(-3.08)	(2.87)	(3.07)	(0.87)
Enviro	-0.0661*	0.0118*	0.0543*	-0.00676
	(-2.19)	(2.16)	(2.18)	(-0.31)
Campaign	-0.105***	0.0188***	0.0862***	0.0380*
	(-4.15)	(3.78)	(4.11)	(2.04)
Age	0.0024**	-0.0004**	-0.0019**	0.0003
	(2.71)	(-2.62)	(-2.69)	(0.69)
Gender	-0.0539*	0.0096*	0.0442*	-0.0113
	(-2.10)	(2.05)	(2.09)	(-0.60)
Education	-0.0603*	0.0108*	0.0495*	0.0233
	(-2.20)	(2.13)	(2.20)	(1.08)
Lagged AvP	0.0054	-0.0010	-0.0044	0.0105
	(0.19)	(-0.19)	(-0.19)	(0.52)
Electeff	0	0	0	0.0965*
				(2.17)

Table 4: Marginal effects Model 2

	Noelecteff	Noelect-habits				
		Category 1	Category 2	Category 3	Category 4	Category 5
Remodel	0.146***					
	(5.12)					
Home age	-0.00911					
	(-0.56)					
Owner	0.164***					
	(4.29)					
Highincome	0.178***	-0.0006	-0.0008	-0.0017	0.0018	0.0014
	(4.77)	(-0.08)	(-0.09)	(-0.09)	(0.09)	(0.08)
Members	0.0169	-0.0070*	-0.0086**	-0.0186**	0.0190**	0.0151**
	(1.26)	(-2.49)	(-2.81)	(-2.92)	(2.91)	(2.78)
Campaign	0.165***	-0.0175*	-0.0215**	-0.0465***	0.0476***	0.0379**
	(5.95)	(-2.34)	(-2.90)	(-3.30)	(3.30)	(2.71)
Education	0.0490	0.00001	0.00001	0.00003	-0.00003	-0.00003
	(1.57)	(0.00)	(0.00)	(0.00)	(-0.00)	(-0.00)
Enviro	0.0155	-0.0109	-0.0134	-0.0290	0.0297	0.0236
	(0.46)	(-1.76)	(-1.86)	(-1.89)	(1.89)	(1.85)
Age	0.00002	0.0000	0.0000	0.0000	-0.0000	-0.0000
	(0.02)	(0.01)	(0.01)	(0.01)	(-0.01)	(-0.01)
Gender	0.0148	0.00734	0.00903	0.0195	-0.0200	-0.0159
	(0.51)	(1.40)	(1.41)	(1.40)	(-1.40)	(-1.43)
Lagged AvP	-0.0529	0.00541	0.0067	0.0144	-0.0147	-0.0117
	(-1.47)	(0.96)	(0.98)	(1.00)	(-0.99)	(-0.98)
Noelecteff	0	0.0324	0.0399	0.0861*	-0.0883*	-0.0702
	(.)	(1.52)	(1.92)	(2.29)	(-2.28)	(-1.73)

Appendix E

We start with the utility maximization problem as defined in Section 5.3, in which a household seeks to maximize the utility obtained from a given level of water services with a technology summarized by the production function:

$$
\begin{aligned}
&\max_{w} U = U(y, x) \\
&s.t. \quad y = A(Z) w^{a(Z)} k^{b(Z)} \\
&\qquad\quad I = p_w w + p_k k + p_x x
\end{aligned} \tag{9}
$$

The first-order conditions are as follows:

$$
\begin{aligned}
\frac{\delta \mathcal{L}}{\delta w} &= \lambda \frac{\delta U}{\delta y} a(Z) w^{a(Z)-1} A(Z) k^{b(Z)} - p_w = 0 \\
\frac{\delta \mathcal{L}}{\delta x} &= \lambda \frac{\delta U}{\delta x} - p_x = 0
\end{aligned} \tag{10}
$$

From equation (10), the input demand equation is obtained:

$$
w = \left(\frac{p_x}{p_w}\right)^{\frac{1}{1-a(Z)}} k^{\frac{b(Z)}{1-a(Z)}} \left(\frac{u'(y)}{u'(x)} a(Z) A(Z)\right)^{\frac{1}{1-a(Z)}} \tag{11}
$$

And finally, taking logs we obtain:

$$\begin{aligned} ln\ w = &-\left(\frac{1}{1-a(Z)}\right) ln\left(\frac{p_w}{p_x}\right) + \frac{b(Z)}{1-a(Z)} ln\ k + \\ &\frac{1}{1-a(Z)} ln\ A(Z) + \frac{1}{1-a(Z)} ln\left(\frac{u'(y)}{u'(x)} a(Z)\right) \end{aligned} \tag{12}$$

In order to obtain the Stochastic Frontier model, $A(z)$ is replaced by $c(z)e^{-u(z)}$, as indicated in Section 5.4.

$$\begin{aligned} ln\ w = &\underbrace{\frac{1}{1-a(Z)} ln\ c(Z) + \frac{1}{1-a(Z)} ln\left(\frac{u'(y)}{u'(x)} a(Z)\right)}_{\alpha(\mathbf{z})} + \underbrace{\frac{1}{1-a(Z)} u(Z)}_{u(z)} \\ &-\underbrace{\left(\frac{1}{1-a(Z)}\right)}_{\beta_1(z)} ln\ \frac{p_w}{p_x} + \underbrace{\frac{b(Z)}{1-a(Z)}}_{\beta_2(z)} ln\ k \end{aligned} \tag{13}$$

The terms in braces represent parameters that are constant for a given set of environmental variables Z and ought to be estimated.

Appendix F

This appendix is largely based on the work by Racine [2014], Ma and Racine [2012] and Ma et al. [2012] and interested readers are referred to these articles for a detailed explanation and for the properties of B-splines and categorical regression splines.

In the present context, recall that we are interested in estimating the following auxiliary model:

$$X_{1i} = g(X_{-1i}, \tau_i) + \zeta_i, \text{ for } i = 1, \ldots, N$$

where ζ_i is a (possibly heteroskedastic) error term and $g(\cdot, \cdot)$ is a function of X_{-1i} and $\tau_i = \{Z_i, D_i\}$, with Z_i denoting a vector of environmental factors and D_i a vector of instruments. For simplicity, we assume that X_{-1i} and D_i are purely continuous variables; while Z_i are the categorical components. The estimator applies verbatim when X_{-1i} contains some discrete regressors.

For each component of the continuous regressors, X_{-1i} and D_i, we construct a matrix of B-spline basis functions, B, of order q, such that:

$$\mathcal{B}(x_{-1}, d) = B(x_{-1}) \otimes B(d),$$

where $\otimes$ denotes the tensor product (that is, the product column by column) of two matrices of basis functions $B(x_{-1})$ and $B(d)$, evaluated at the points x_{-1} and d. For the discrete regressors Z_i, we use the discrete kernel approach as described in section (5.4), where $L(Z_i, z, \lambda)$, denotes the kernel, evaluated at the point z, with bandwidth λ. Therefore, for $Z_i = z$, we can write:

$$g(X_{-1i}, D_i, Z_i = z) = \mathcal{B}(X_{-1i}, D_i)\gamma(z),$$

where $\gamma(z)$ is a vector of coefficients that depends on the value taken by the environmental factors, and it ought to be estimated using an appropriate method.

The coefficient $\gamma(z)$ is estimated by minimizing the following weighted least squares criterion, for a sample of size N:

$$WLS(\gamma) = \sum_{i=1}^{N} \left\{X_{1i} - \mathcal{B}(X_{-1i}, D_i)\gamma(Z_i)\right\}^2 L(Z_i, z, \lambda).$$

Let, $\mathcal{L}_z = diag\left\{L(Z_1, z, \lambda), \ldots, L(Z_N, z, \lambda)\right\}$, $\mathbf{B} = \left\{\mathcal{B}(X_{-11}, D_1), \ldots, \mathcal{B}(X_{-1N}, D_N)\right\}$, and $\mathbf{X}_1 = \left\{X_{11}, \ldots, X_{1N}\right\}$ then we have that:

$$\hat{\gamma}(z) = \left(\mathbf{B}'\mathcal{L}_z\mathbf{B}\right)^{-1}\mathbf{B}'\mathcal{L}_z\mathbf{X}_1.$$

There are several advantages of this approach. First of all, the use of categorical kernels allows one to improve the efficiency of the estimator. Other nonparametric techniques have to resort to sample splitting instead, which implies a loss of degrees of freedom. This is particularly relevant in cases such as ours where the dimension of the environmental factor Z is very large.

Moreover, the approach is easy to implement and completely adaptive. On the one hand, the estimation is carried by a simple minimization of a least square criterion, which is more similar to a linear model. On the other hand, the order of the B-spline basis for the continuous components is chosen using cross-validation, and it is thus fully nonparametric.

The above estimation is fully implemented in *R* [R Core Team, 2014], using the *crs* package [Racine and Nie, 2014].

Appendix G

Table 5: Standard Stochastic Frontier Model

Variable	Coefficient	Std. Error
Constant	2.568***	(0.0573)
ln AvP	-1.055***	(0.0483)
Members	0.1132***	(0.0073)
Highincome	-0.03627*	(0.0212)
Bottled	-0.04684**	(0.0219)
Electappl	0.09197***	(0.0142)
Bathrooms	-0.02178	(0.0186)
Constant	-12.43	(11.0702)
Habits	-14.58	(10.1953)
Electeff	-5.844	(4.6685)
New pipes	0.7768	(2.2752)
Noelecteff	5.686	(4.9989)
σ^2	3.466	(2.3373)
γ	0.9446***	(0.0379)

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