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PRICE ELASTICITY AND DETERMINANTS OF RESIDENTIAL WATER CONSUMPTION IN AL AIN REGION

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This thesis is submitted in partial fulfillment of the requirements for the degree of Master of Science in Water Resources

Under the supervision of Dr. Mohamed Hamouda

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Declaration of Original Work

I, Bara Mohamad Alrefai, the undersigned, a graduate student at the United Arab Emirates University (UAEU), and the author of this thesis entitled "*Price Elasticity and Determinants of Residential Water Demand in Al Ain Region*", hereby, solemnly declare that this thesis is my own original research work that has been done and prepared by me under the supervision of Dr. Mohamed Hamouda, in the College of Engineering at UAEU. This work has not previously been presented or published, or formed the basis for the award of any academic degree, diploma, or a similar title at this or any other university. Any materials borrowed from other sources (whether published or unpublished) and relied upon or included in my thesis have been properly cited and acknowledged in accordance with appropriate academic conventions. I further declare that there is no potential conflict of interest with respect to the research, data collection, authorship, presentation, and/or publication of this thesis.

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Abstract

This thesis is concerned with the effect of water price on residential water consumption in Al Ain region. Water demand worldwide significantly increased due to high population growth, climate change, and changes in lifestyle. Fulfilling the growing water demand by constantly increasing supply has several environmental and economic implications. Water management strategies assist in driving the water industry to develop better solutions to address the increase in water demand. The UAE recently shifted its water management strategies towards demand management to reduce the growing demand in the country. Water pricing is considered one of the important tools to reduce residential water consumption in Abu Dhabi and Al Ain region. However, the impact of pricing on consumption rates should be investigated. This study includes a detailed review of the Abu Dhabi and Al Ain’s policies with respect to water demand management. Besides, it includes an intensive review of research studies concern with the price elasticity of demand in the residential sector. The review showed that price, income, and weather characteristics have been considered significant in most of the previous research.

An investigation into the determinants of water consumption in Al Ain, UAE was conducted. 400 households in Al Ain region were selected. Water consumption data and other household characteristics were collected for a two-year period (2016-2017) to evaluate the effectiveness of the new pricing tariff (implemented at the start of 2017). Data for the pricing structure, consumer characteristics, property characteristics, and weather characteristics have been collected from governmental authorities. Data gaps were identified, and a questionnaire was designed to collect missing data for the different determinants. Results of the questionnaire show that there are 2 to 3 males and females per household in the majority number of the sample. Further, 68.1% of the household sample have an income range from 11 to 30 thousand AED.

Data collected was transformed and used to construct a representative balanced panel data. Using econometric techniques, a semi-log model was developed to identify the effect of different significant determinants on residential water consumption. The study results show that the significant determinants include water price, income level, average temperature, number of adults, children, and elderly, and the existence of swimming pool, garden, and water-saving device. The coefficients of time-invariant variables were estimated using OLS and RE estimation techniques. The price elasticity of demand was found to be inelastic at values ranging between 0.231 to 0.364 using different estimation techniques.

This study is envisioned to help in evaluating the effects of a price change on water consumption. The results of this study could help in incorporating the impact of pricing strategies on existing water demand forecasting models. The outcomes of this study can be of benefit to decision-makers and stakeholders in the UAE and other similar nations.

Keywords: Water consumption, PED, Panel data, OLS, RE, FE, GMM.

Title and Abstract (in Arabic)

المرونة السعرية للطلب ومحددات استهلاك المياه السكنية في منطقة العين

الملخص

تُعنى هذه الرسالة بتأثير سعر المياه على استهلاكه السكني في منطقة العين؛ ذلك أن الطلب قد زاد عليه في جميع أنحاء العالم بشكل كبير بسبب النمو السكاني المرتفع وتغير المناخ والتغيرات في نمط الحياة، فضلاً عن تلبية الطلب المتزايد على المياه من خلال زيادة العرض باستمرار إذ كان له آثار بيئية واقتصادية عديدة. إلا أن هناك استراتيجيات تساعد إدارة المياه في دفع صناعة المياه إلى تطوير حلول أفضل لمواجهة الزيادة في الطلب عليه، حيث قامت الإمارات العربية المتحدة مؤخرًا بتحويل استراتيجيات إدارة المياه الخاصة بها نحو إدارة الطلب؛ لتقليل الطلب المتزايد في الدولة، كما يعد تسعير المياه من الأدوات المهمة التي تسهم في تقليل استهلاك المياه السكني في أبوظبي ومنطقة العين. ورغم ذلك، لا ينبغي التحقيق في تأثير التسعير على معدلات الاستهلاك دون النظر في محددات الطلب على المياه الأخرى .

وتتضمن هذه الدراسة مراجعة مفصلة لسياسات أبو ظبي والعين فيما يتعلق بإدارة الطلب على المياه، كما أنه يتضمن مراجعة مكثفة للدراسات البحثية المتعلقة بالمرونة السعرية للطلب في القطاع السكني، حيث أظهرت هذه المراجعة أن خصائص السعر والدخل والطقس مهمة في معظم الأبحاث السابقة.

وقد تم إجراء تحقيق في محددات استهلاك المياه في مدينة العين الإماراتية، فاختيرت 400 أسرة في منطقة العين، تم جمع بيانات استهلاكها للمياه والتعرف على خصائصها الأخرى لمدة عامين (2016-2017) لتقييم فعالية تعرفة التسعير الجديدة (التي تم تنفيذها في بداية عام 2017). وقد تم جمع بيانات هيكل التسعير وخصائص المستهلك وخصائص الممتلكات وخصائص الطقس من السلطات الحكومية. كما تم تحديد فجوات البيانات ، وتصميم استبيان لجمع البيانات المفقودة لمحددات مختلفة. وقد أظهرت نتائج الاستبيان أن هناك من 2 إلى 3 ذكور وإناث لكل أسرة في العدد الأكبر من العينة. علاوة على ذلك ، فإن 68.1٪ من أفراد عينة الأسرة يتراوح دخلهم من 11 إلى 30 ألف درهم.

وقد تم تحويل البيانات التي تم جمعها واستخدامها لبناء لوحة بيانات متوازنة تمثيلية. وقد تم تطوير نموذج شبه لوغاريتمي اعتمادا على تقنيات الاقتصاد القياسي لتحديد تأثير المحددات المهمة المختلفة على استهلاك المياه السكنية، إذ بينت نتائج الدراسة أن المحددات المهمة تشمل

سعر المياه ، ومستوى الدخل ، ومتوسط درجة الحرارة ، وعدد البالغين ، والأطفال ، وكبار السن ، ووجود حمامات السباحة ، والحديقة ، وجهاز توفير المياه. كما تم تقدير معاملات المتغيرات الزمنية الثابتة باستخدام تقنيات تقدير OLS و RE حيث وجد أن مرونة الطلب السعرية غير مرنة عند قيم تتراوح بين 0.231 إلى 0.364 باستخدام تقنيات تقدير مختلفة.

وقد هدفت هذه الدراسة إلى المساعدة في تقييم آثار تغير السعر على استهلاك المياه. ويمكن أن تساعد نتائج هذه الدراسة في دمج تأثير استراتيجيات التسعير على نماذج التنبؤ الحالية بالطلب على المياه. كما يمكن أن تكون النتائج مفيدة لصناع القرار وأصحاب المصلحة في دولة الإمارات العربية المتحدة وغيرها من الدول المماثلة.

مفاهيم البحث الرئيسية: استهلاك المياه ، المرونة السعرية للطلب ، قاعدة البيانات المدمجة ، طريقة المربعات الدنيا العادية ، طريقة التأثير العشوائي ، طريقة التأثير الثابت ، طريقة العزوم المعممة.

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Special thanks go to my parents, wife, brothers, and sisters who helped me along the way. I am sure they suspected it was endless.

Dedication

To my beloved parents, wife and family

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List of Abbreviations

AADC	Al Ain Distribution Company
AI	Artificial Intelligence
ANNs	Artificial Neural Network
DEWA	Dubai Electricity and Water Authority
FE	Fixed Effect
GMM	General Method of Moment
HCB	High Consumption Block
IWEM	Integrated Water Resources Management
KPI	Key Performance Indicators
LM	Lagrange Multiplier
LCB	Low Consumption Block
LSDV	Least Square Dummy Variable
MCM	Million Cubic Meters
OLS	Ordinary Least Square
PED	Price Elasticity of Demand
RE	Random Effect
SCAD	Statistical Center-Abu Dhabi
SSE	Sum of Square Error
SWM	Smart Water Meter
UAE	United Arab Emirates
UN	United Nations
USA	United State of America

WDM	Water Demand Management
WDMS	Water Demand Management Strategies
WSI	Water Sacristy Index
WSM	Water Supply Management

Chapter 1: Introduction

1.1 Background

The scarcity of water has become one of the significant issues that face the water sector around the world. In the UAE, conventional water resources (surface and groundwater) are limited. The water availability in the UAE is less than 30 m^3/capita/year from conventional resources in the country (Ahmed, 2010). On the other hand, the consumption per capita in Abu Dhabi is twice as large as global water consumption (Peck, 2010). Besides, the country is located in an arid zone where temperatures can reach 52°C in the summer and with only 100 mm of annual rainfall (*Climate*, 2017). The rare rainfall and high evaporation rate in addition to other factors will increase water scarcity in the country (Murad et al., 2007).

Despite being a country that suffers from water scarcity, the water consumption per capita in the UAE reached 550 L/Day (FEWA, 2015). This consumption rate is one of the highest if compared with the average world consumption at 170 to 300 L/capita/day (FEWA, 2015). The high use of water affects not just the quantity but also the quality of groundwater resources. The annual abstraction (643.9 m^3/capita) is 13 times more than the yearly recharge (48.3 13 m^3/capita) which led to saline water intrusion mainly in a coastal area (Wada et al., 2010). Depending on non-conventional resources (wastewater reuse and desalination), helped in filling the gap between water availability and water consumption. From 2007 to 2017 the annual desalination production increased from 5.1 million m^3 to 7.5 million m^3 (*Desalinated Water*, 2017).

The desalination water consumption between 2005 and 2017 increased from 161.2 million m^3 to 291.5 million m^3 in the Al Ain city, and the water demand is predicted to exceed 600.0 million m^3 in 2030 if the consumption behavior continues in the same manner (*Statistical Yearbook of Abu Dhabi*, 2017; Younis, 2016). The notion of unlimited water supply was built in the minds of UAE consumers because of subsidized utilities, the country's high living standards, and the government's continuous investment in desalination and infrastructure (Allan & Allan, 2002; Günel, 2016). The government has had a full subsidy for water services supplied to UAE nationals and around 70% subsidy for expats until 2014. A change in water pricing has been implemented to change water consumption behavior.

The pressures on the water sector resulting from increasing demand impose interest in studying the role of water pricing in managing domestic water demand. Some studies favored using scarcity pricing to managing drought and enforcing a restriction on water use (Barker et al., 2010). Other studies show that pricing policy changes could not have a significant effect on water demand which demonstrates that the effect of these policies on the public should be studied before it can be taken in action (Hewitt & Hanemann, 1995).

1.2 Statement of the problem

Understanding the influence of price changes on water consumption is very important to water management practices in the water sector. This is because it gives a clear insight into social and economic implications related to these pricing strategies. As an example, pricing strategies can impose a significant financial burden on certain families because of their incapability to tolerate the inflated household bills. Realizing the value of water in every person's life, this study will examine the water consumption fluctuation over different household categories in Al Ain region. Since the fluctuation can be a result of water price changes or other household characteristics.

1.3 Research objectives

This research aims to provide sufficient information on the impact of changes in pricing on water consumption for the stakeholders to arrive at a better understanding of the demand-price relationship. The detailed research objectives can be summarized in the following points:

1. Review of current regulations and policies in the Abu Dhabi region for water demand management and water pricing.
2. Reviewing previous research to identify the main parameters that would affect residential water price elasticity of demand and different water demand modeling approaches.
3. Developing demand-price relationships for households of different characteristics.

Besides, this thesis aims to answer the following question:

1. Is the water pricing as economical tool effective in reducing household water consumption?
2. What is the effect of the new tariff on different consumers characteristics?
3. What are the main characteristics that influence water consumption behavior?
4. Do the different characteristics need to be considered when new tariff implemented?

1.4 Research scope

The research focuses on the residential sector in the Al Ain region which is located in the eastern region of Abu Dhabi emirates in the United Arab Emirates. It consists of 42 areas that extended over 15,100 km^2 and has an approximate population of 760,000 people that live in more than 61,000 households. The study aims to collect 400 households' data on water consumption, property, weather, and household characteristics in the period from January 2016 to December 2017. The study's final goal is to identify the significant determinants the influence water consumption behavior.

1.5 Method overview

The data for this study has been collected from Al Ain Distribution Company (AADC), Statistical Center-Abu Dhabi (SCAD), and a questionnaire. The AADC has provided the data related to the monthly water consumption, bill quantity and pricing structure whereas SCAD has provided bulk water consumption and weather characteristics data. Besides, a designed questionnaire that consists of 18 qualitative and quantitative inquiries has been used to collect data related to properties and household characteristics. Also, a study area investigation followed by identifying significant determinants using Ordinary Least Square (OLS), Fixed Effect (FE), Random Effect (RE) and General Method of Moment (GMM) estimation techniques have been done to achieve the analysis goal. Finally, an assessment for the Price Elasticity of Demand (PED) with the comparison of estimation techniques used in this study has been made to determine the demand-price relationship in the Al Ain region.

1.6 Chapters overview

There are five (5) chapters in this thesis. Chapter 2 illustrate the literature review related to the field of this study. The chapter is divided into five main sections based on the introduction, water demand management, water pricing as a tool for demand management, water consumption modeling and forecasting, and water consumption situation in UAE.

In Chapter 3, the method used in this study is illustrated in detail. The chapter cover 8 main sections. the sections in chapter cover the study area characteristics, water consumption and pricing data used in the study, exhaustively obtaining data from government authorities and identifying gaps in the data, the selection criteria used for the households used in the study, the use of a questionnaire to collect other required determinants, the scale and range of data included in the study and the water consumption model.

Chapter 4 demonstrates the result and analysis in 6 main sections. This section includes the introduction, result of study area investigation, identifying signification determinants of water consumption model in Al Ain, comparisons of estimation techniques, price elasticity of demand for water in Al Ain, and discussion.

Finally, Chapter 5 discusses the conclusion and implications related to this study. The chapter consists of 2 main sections, the research implication and challenges and policy implications.

Chapter 2: Literature Review

2.1 Introduction

This chapter presents the literature review of the topics related to this research. It starts with a brief review of water demand management (WDM) strategies and policies. It then focuses on water pricing as a major tool for WDM and outlines the principles of effective water pricing. Moreover, it defines the concept of Price Elasticity of Demand (PED) and its relevance in evaluating the impact of changes in pricing on the demand for a product. It then follows with a detailed review of water consumption modeling approaches used in evaluating the role of different determinants of water consumption. The last section provides a brief history of the WDM strategies developed and implemented by the government of the UAE to combat its water management challenges. A focus is given on water pricing and the recent changes in the past few decades. This is intended to set the scene for outlining the implemented methodology used to assess the impact of the recently implemented water tariff on water consumption in the city of Al Ain, in Abu Dhabi.

2.2 Water demand management

An effective water demand management strategy (WDMS) depends on a proper understanding of the factors that induce people to adopt excessive water consumption or water-saving behavior. Evaluating the uncontrolled factors (such as weather conditions) and demand management actions (such as pricing schemes, awareness campaigns, and education) are the bases to study the consumers' response to WDMS that serve new policies design and strategic planning. Several tools can be used to achieve better WDMS in the residential sector as Figure 1 shows. Evidence from household water conservation studies suggests that price interventions and regulation can be successful. However, other interventions that rely on engineering solutions are not as effective as pricing tools. However, others have suggested that adding a human touch can greatly improve the effectiveness of engineering solutions. Other educational and awareness efforts can also be effective but under particular conditions (Campbell et al., 2004; Syme et al., 2004).

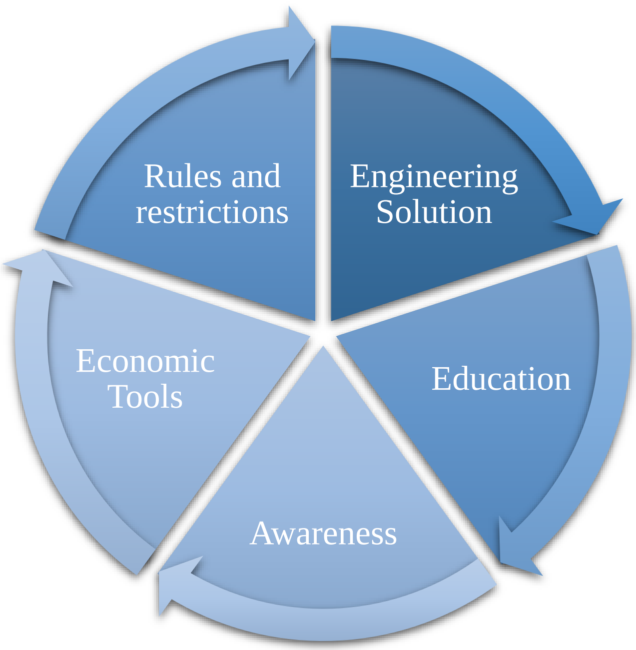


Figure 1: The water demand management tools in the residential sector.

Engineering solutions, such as smart meters, low-flow showerheads, and water-conserving washing machines, have been tried in different household settings (Campbell et al., 2004; Syme et al., 2004). Offsetting behavior, however, was observed by previous studies, where behavioral responses to engineering devices resulted in the latter not saving as much water as what was indicated by laboratory data (Campbell et al., 2004; Syme et al., 2004). Offsetting behavior can be in the form of taking longer showers while using low-flow showerheads than when using regular flow showerheads. Evaluating the possibility of such offsetting behavior is important in predicting the outcomes of water conservation interventions. Caution is thus advised before advising engineering solutions in areas where behavioral offsetting can reduce their effectiveness.

In the late 1990s, the smarts meters provide high accuracy data where the water consumption can be measured for different facilities in the household and for the range extended from days to few seconds. The data provided by the smart meters can help in constructing a model for different consumer behaviors which help in assessing consumer acceptance to a new WDMS (Cominola et al., 2015). There are two main approaches for the data gathering using smart meters. End-use meters and single water flow meters. The end-use meters measure the water consumption in the end-use location (such as toilet flush and washing machine). On the other hand, the single water flow meters measure the water consumption at the total water flow location for a single household. Although it has lower accuracy, the single flow meter is considered more acceptable to be used for households.

Awareness and communication are other tools that play an important role in water conservation. Numerous literature suggests that communication increases consumer cooperation in conservation, particularly in the case of common goods (such as water) (Campbell et al., 2004). This also suggests direct human communication of policies before implementing them may assist in the achievement of their outcomes.

Water pricing is classified as an economic tool, however, there are other monetary incentives such as tax relief and subsidies that affect consumer behavior. There is evidence that suggests that the PED for water is very inelastic (Espey et al., 1997). The consensus is that pricing can only influence water consumption if it influences the behavior of the consumer (Campbell et al., 2004). A balance is required such that the price is not too low that the consumer does not favor water conservation, and not too high that it negatively impacts the hygiene and livelihood of the consumer.

2.3 Water pricing as a tool for demand management

Efficient water consumption has a direct relationship with water pricing. Water pricing is considered by many as one of the most important tools that can be used in water demand management (Manouseli, 2017). The effectiveness of water pricing depends mainly on the accuracy of previous investigations determining the Price Elasticity of Demand (PED) (Arbués et al., 2010). Generally, there is a negative relationship between domestic water demand and price. This relationship can gain higher value during water efficiency campaigns that combine higher water pricing rates with awareness communication (Grafton et al., 2011). Nevertheless, previous research suggests that a high price increase is needed to achieve a demand reduction higher than 15% (Manouseli, 2017). In general, it has been reported that it is more effective to use price as a tool to decrease consumption compared with a non-price tool in the short run. However, it is more efficient to use a non-price tool in parallel with the price tool (Manouseli, 2017). Nevertheless, increasing water prices may be considered complicated and inapplicable in many cases due to local taxes or limited financial resources for many consumers. Alternative solutions such as water-saving devices, loans for the water sectors, and educational campaigns should then be taken into consideration (Manouseli, 2017).

The following sections will introduce the principles of devising an effective water price strategy. In addition, it sheds the light on the various tariff structures and the theory behind the determination of the price elasticity of demand.

2.3.1 Principles for an efficient price

There is a clear difference between water pricing for the industrial, agricultural, and residential sectors. Water in commercial and agriculture sectors is considered as a production input, whereas residential water consumption is for sustaining a healthy livelihood for the residents. Despite the positive relationship between residential water demand, marginal benefits, and consumer ability to pay for water (Russo et al., 2014), it unacceptable to deal with residential water pricing as a source of income. Household water should not be treated as a regular product because it is necessary for life which creates a need paradox between water needs and water prices. Ultimately, the billing price of water should follow the regulation of the water sector and governmental policies which ensure fair water prices for all social categories.

Generally, reasonable water prices should account for the full cost recovery of managing and supplying residential water. Assigning low price rates for water will lead to overuse and wasteful consumption. This can be exacerbated by the lack of consumer awareness, particularly with regards to the full cost of water production and supply. Moreover, water as a product will not be appreciated to its benefit on general social welfare under meager price, and that what can be called undervalued water (OhIsson, 2000). In contrast, a very high water price will impact the consumer negatively. This is because the benefit received by the consumer would be less than the full value paid. There is always a conflict between water needs and water prices especially in areas that suffer from water scarcity (OhIsson, 2000).

Effective water supply and demand management can assist in putting fair prices for different consumers. Water supply management (WSM) deals with water production efficiency and the variability of the water cycle. WSM would include storage, extraction, distribution, and treatment-disposal activity. The terminology of technological efficiency repeatedly appears in supply management. It referred to the extraction of more water with the same resources input. A clear example of technical efficiency would be the process of producing desalinated water at a lower cost available.

On the other hand, water demand management includes tariff water prices, awareness campaigns, environmental taxes, and the right to clean water access. The water demand management should take into consideration institutional efficiency and economic principal when the new price for water planes to be implemented. By doing so, demand management can achieve fair water prices and more efficient water management in general (Billi & Cannitano, 2004; Ohlsson & Turton, 1999).

Devising a suitable water price structure is essential to achieve efficiency, transparency, public acceptability, simplicity, public health, financial stability, and social equity (Arbués et al., 2003). Overall, the water pricing procedure should take several elements into consideration, these include the economic value of the water, water quality required by consumer, delivery cost, social and environmental cost, wastewater costs, and opportunity costs (Allan & Allan, 2002).

2.3.2 Determining an efficient water price

Economic efficiency which is also known as allocative efficiency can be defined as the welfare of the community that comes from public policy through the market (Markovits, 1998). Others describe it as the efficient management of resources in a way that meets society's welfare and economic goals (Allan, 1999). In the water sector, it can be defined as the methods and policies that increase public welfare from water resources (Allan & Allan, 2002). Water pricing is the primary tool to achieve allocative efficiency in the water sector (Ohlsson & Turton, 1999).

Broadly, better allocative efficiency can be achieved through higher water prices. Higher water prices will lead to a better distribution of water resources among the community, and a decline in demand usually occurs. As a result, it is necessary to increase water prices, particularly in water-scarce areas. According to Allan & Allan, 2002, it is not possible to achieve the same result by increasing the water supply. Despite that, it is important to notice when new water prices are implemented, the adaptive capacity of the society is profoundly affected by the new prices level (Allan & Allan, 2002)

In a good economy, society should use resources at the most optimum level possible to achieve allocative efficiency principles. The optimal level can be achieved when the marginal benefit (extra unit of water consumed) meets marginal cost because it will ensure adequate resource distribution within the economy (Markovits, 2008). A graphical analysis between water production cost (supply cost) and water consumption benefit (demand curve) is needed to locate the point of equity. Achieving equity gives them the incentive to use water resources efficiently because it provides a direct proportion of the full social cost and marginal water benefit (Billi & Cannitano, 2004). The maximum net profit can then achieved at the point of interaction between marginal benefit and marginal cost, as it is shown in Figure 2 below (Altmann, 2007).

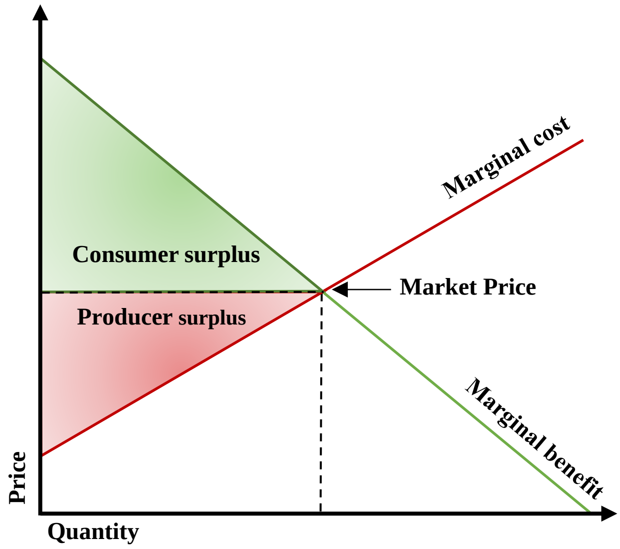


Figure 2: Maximization of the total Net Benefit (Altmann, 2007)

2.3.3 Tariff structure

The water pricing structure can be divided into three main types: (1) fixed price, (2) constant rate, and (3) block rate. Under the fixed price structure, consumers pay a constant amount of money regardless of their consumption quantity. Whereas under a constant rate, consumers are charged a constant amount of money per unit of consumption (Abu Qdais & Al Nassay, 2001).

Finally, The block rate has a dynamic structure by having a constant rate for different consumption brackets (Abu Qdais & Al Nassay, 2001). For example, the consumer under a low consumption block (LCB) will pay less if the consumed amount does not exceed the block limit. The LCB should be designed to include the water quantity needed for essential uses (i.e., cooking, bathing, cleaning, and others) at an affordable cost for all social categories. In contrast, consumers with a high consumption rate will be charged with a higher marginal price and that will motivate them to keep their consumption rate within the LCB limit. Figure 3 below gives a clearer picture of the difference between the three pricing structures under five levels of consumption.

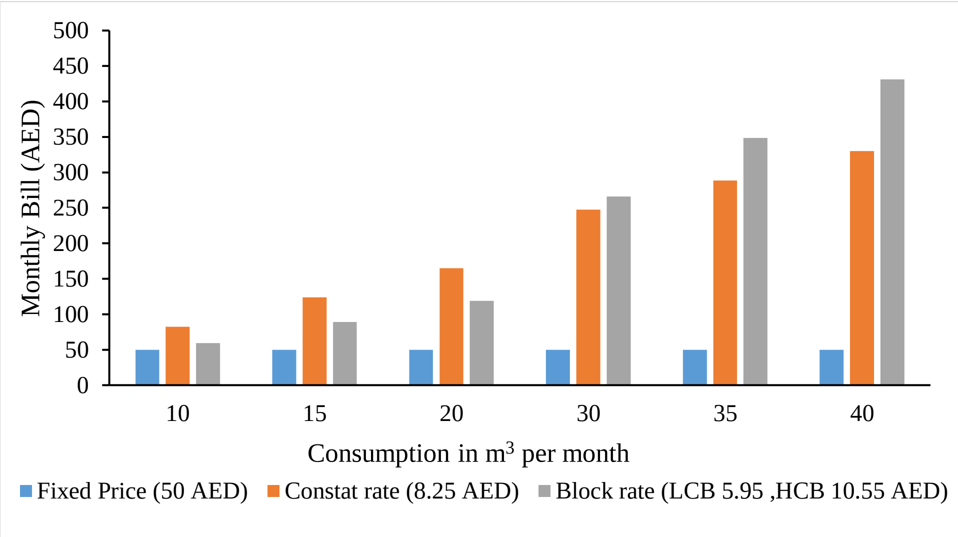


Figure 3: An illustration of the three types of pricing structure under different consumption rates (values assumed).

Some concerns were voiced that the increase in price between different price blocks will reduce social welfare, however previous empirical analyses suggest that block rate structure could aid consumer welfare by reducing total demand and providing sufficient revenue to the operator (Baerenklau et al., 2014; Gong et al., 2016). In some cases, though, high water demand is not necessarily due to wasteful behavior. Large families with low income may be forced to pay a higher price for water used for basic needs which could negatively impact their welfare (Borenstein, 2008).

2.3.4 Price Elasticity of Demand (PED)

The relationship between the change in water consumption and the variation in water price can be defined as PED. The PED can be simply calculated by dividing the change in quantity consumed over a change in price as appears in Equation 1 (Srouji, 2017).

$$PED = \frac{\left(\frac{Q_2 - Q_1}{Q_1}\right)}{\left(\frac{P_2 - P_1}{P_1}\right)} \tag{1}$$

Where:

Q_1 represent the quantity at old price P_1.

Q_2 represent the quantity after new price P_2 implemented.

This ratio measures the consumer's willingness to use an extra unit of water when the price varies. Previous studies have indicated that PED has an inelastic trend in developed countries such as the USA and Europe, whereas it could exhibit an elastic behavior in developing countries under different cases (Dhungel & Fiedler, 2014).

Usually, PED has a negative sign for most goods because the increase in price will often decrease the demand. In other words, a percentage change in price will reduce demand. Price elasticity can be described as elastic or inelastic depending on its value. A PED value of less than one is classified as inelastic. This indicates an insignificant effect of the price change on demand. In contrast, when the PED has an absolute value higher than one, the price change has an elastic change, which indicates a significant effect on price change on demand (Arnold, 2008). The primary goal of effective water price design is to have elastic PED. As a rule, the higher the PED value, the better the design of water prices because when the price increases, a higher decrease in consumption occurs. Studying price elasticity in the long and short-run will indicate the direct and dynamic price change effect. A survey of previous studies showed that price elasticity for a long and short run could range from -0.01 To -1.63 (Cader et al., 2004). The high absolute value of (1.63) indicates elastic price change and a low absolute value of (0.01) indicates inelastic price change.

A couple of studies were conducted in the Arabian Gulf region to find the water price elasticity of demand (Table 1). One study conducted in Saudi Arabia covered the cities of Jeddah, Makkah, Madina, and Taif. The study found that PED values were -0.40,-0.78, and -0.22 for houses supplied by tankers, homes provided by the public network, and for combined houses type respectively (Abu Rizaiza, 1991), Another study, conducted in UAE, shows that the PED value was -0.1 in Abu Dhabi in 2001. This study was conducted after a change in water pricing where an expatriate was charged a constant rate of 2.2 AED per meter cube consumed instead of charging 50 AED as a fixed price per month for any amount of water consumed. It is noticeable that the PED was inelastic because the water price (2.2 AED per meter cube) accounted for only 29% of the real total water cost with 71% subsidies by the government (Qdais & Al Nassay, 2001). Finally, The research conducted in Jordan found that price elasticity values at different cities were -0.47, -0.62, -0.004, -0.16, -0.33, and -1.18 for Amman-Zarka Basin, Amman city, Zarka city, low-income group, middle-income group, and high-income group respectively (Tabieh et al., 2012).

Table 1: Studies on the water price elasticity of demand.

Authors	**Study Area**	**Price variable**	**PED**
(Abu Rizaiza, 1991)	Saudia Arabia	Average price	-0.220
(Qdais & Al Nassay, 2001)	United Arab Emirates	Average price	-0.1
(Jansen & Schulz, 2006)	South Africa	Average price Marginal price	-0.32 to -0.97
(Wheeler et al., 2008)	Australia	Average price	-0.52 to -0.81
(Tabieh et al., 2012)	Jordan	Marginal price	-0.004 to -0.62
(Kotagama et al., 2017)	Oman	Average price	-2.10

The proper calculation of Price Elasticity of Demand (PED) requires the consideration of other determinants of water consumption that may have contributed to observed changes in consumption. This attribution of changes in consumption has been commonly addressed using regression methods. A regression Equation can be formulated to include price as well as other independent variables, such as household income, household price, number of members, temperature, precipitation, and others. Water consumption would then be the dependent variable and the regression Equation can be used to calculate PED. The independent variables can be measured directly or by using indirect methods. As an example, household size can be estimated depending on the number of dwellings and population (Dhungel & Fiedler, 2014). For example, a study, conducted in Cape Town, analyzed the block rate structure in the city and used the instrumented marginal price and rate structure premium (the difference between marginal price and average price) as the price variables in a regression equation. The PED in the study for instrumented marginal price and rate structured premium equal to -0.324 and 0.005 respectively.

2.4 Water consumption modeling and forecasting

To maximize the effectiveness of water demand policy instruments, it is essential to develop robust models for estimating and forecasting water consumption. Water consumption forecasting approaches can be classified into six different approaches (Figure 4). However, of these approaches, only two approaches will allow the proper attribution of water consumption changes to the changes in its various determinants. One approach, regression forecasting, entails statistically estimating historical relationships between the different determinants (independent variables) and, water consumption, if those relationships will continue. Another approach, Artificial Neural

Networks (ANNs), includes developing a set of mathematical models that work similarly to the processes of the brain. ANNs models consist of user inputs of determinants (e.g. rainfall, temperature, etc.) and the desired output (e.g. prediction of water consumption). These inputs and outputs are connected by a set of highly interconnected nodes arranged in a series of layers (Bougadis et al., 2005). Regardless of the approach used, there are several considerations that need to be addressed before a reliable model can be developed, these are explained in the following sections.

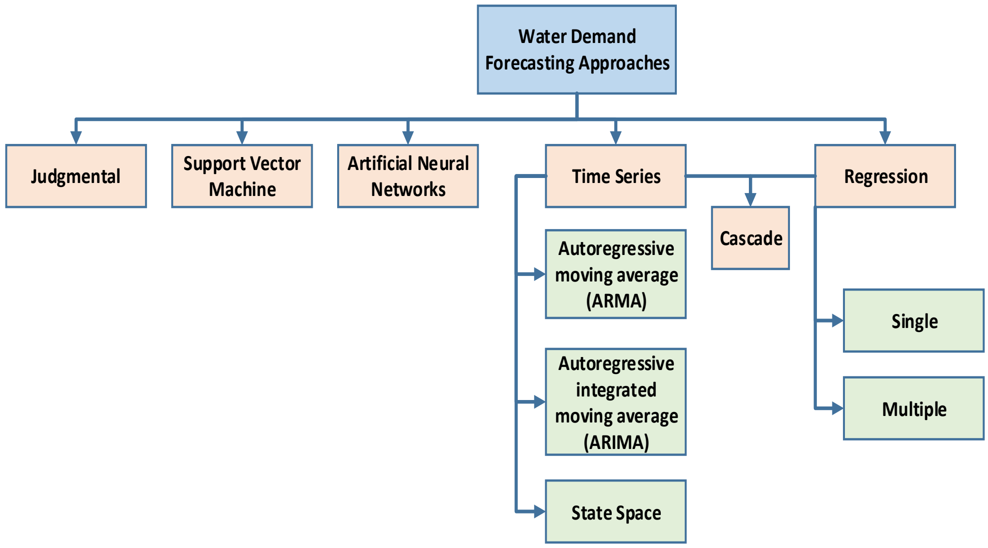


Figure 4: Main approaches in water demand forecasting (Mohamed and Al-Mualla, 2010).

2.4.1 Water consumption data

Previous research used two main types of water consumption data, bulk water consumption, and metered water consumption. Bulk water consumption data can be obtained from water utilities per period and divided over the population to come up with water consumption per period per capita. Mohamed and Al-Mualla (2010) used yearly per capita bulk water consumption data because, during the period of study, the consumer paid a fixed price regardless of the consumption value, and meters were not yet introduced (Mohamed & Al-Mualla, 2010). In another study, Ruijs et al. (2008) used the value of aggregate water data per capita per month, which represents the total water supplied to the consumer on monthly basis divided by the number of consumers (Ruijs et al., 2008). Although bulk data is much easier to obtain and can be used to detect water demand variability due to weather conditions, it cannot capture the real nature of variability due to other factors, particularly pricing. One of the reasons is that it is not possible to capture different groups of users under bulk water data. Another reason is that water consumption values could contain commercial, governmental, industrial, agricultural, in addition to residential users. Although some utilities could provide the bulk water supplied to the residential sector only, the variability within the residential group that are obscured in bulk data. For example, whether the resident lives in a flat or a villa, and whether the household contains a garden or not. On the other hand, the monthly metered data is considered more reliable in representing consumer behavior towards price change and different variables that could affect consumption.

2.4.2 Determinants of water demand

It is important to take into consideration the different factors that affect water consumption to build a better idea of consumer behavior towards water consumption in the study area. For instance, the variation in household characteristics affects their sensitivity to the price increase policies. For example, houses with gardens tend to have higher sensitivity for water-price changes compared with houses without gardens. In the same manner, houses that include swimming pools respond more to water-price changes compared with other houses. Moreover, different consumer groups respond differently to the price increasing policies. For instance, the increase in water prices has a higher effect on low-income consumers. In a study conducted in 2011, low-income consumers exhibited higher sensitivity in summer compared to winter which shows the common influence of temperature and income on water reduction (Mieno & Braden, 2011). Studies have considered several determinants of water consumption as independent variables in a consumption model. A literature review was conducted to identify the most common variables used to predict water demand, these can be clustered into 4 groups as follow:

- Price variables
- Consumer characteristics
- Weather characteristics
- Property characteristics

These factors will be explained in detail in the following sections.

2.4.3 Price variable

In the literature review, researchers have used different types of price variable to estimate PED, these include mainly: the average price, marginal price, and price difference. From Table 2, the marginal price is defined as the tariff price paid by the consumer for each additional quantity of water used, whereas average price can define the overall amount paid by the consumer over the total amount of water consumed in a billing period. The average price could include any service cost that is not included in the marginal price. The price difference variable was introduced by many researchers to compensate for the difference between the average price and marginal price in an elasticity study. One type of price difference variable is calculated as the ratio between average price and marginal price (Nauges & Thomas, 2000; Srouji, 2017). Other researchers prefer to use the difference variable suggested by Nordin (Nordin, 1976) which can be calculated as the difference between the household total bill paid by the consumer and the whole bill a consumer would pay if he is charged at marginal cost (Abrams et al., 2012; Martínez-Espiñeira, 2002). Studies such as Chicoine et al. (Chicoine et al., 1986) argued that Nordin's (Nordin, 1976) price difference variable is not necessary while Barakatullah (Barkatullah, 1996) supported the method implemented by Nordin (Nordin, 1976).

Moreover, Researchers used different types of instrumental variables to overcome the correlation relationship between the explanatory variable and error term (endogeneity problem) that appears with the price variables. For example, one group of researchers developed the 'Natural log of real instrumented marginal price' and 'Instrumented real rate structure premium' price variables, while others developed the 'real marginal price of water per gallon' and 'real average revenue' that solve the endogeneity problem by using different instruments (Kumaradevan, 2013). Other researchers use the price Tiers as instruments for endogeneity exist in average price variable (Abrams et al., 2012). However, the instruments used with price variables in different studies have been summarized in Table 2.

Table 2: Summary of pricing variables included in various studies.

Independent variable	Instruments	Price elasticity*	Reference
Average price: price per unit paid by the consumer. (bill quantity divided by water consumption volume)	Current marginal price	0.029 to 0.058	(Arbúes et al., 2004)
	–	0.080	(Arbues & Villanua, 2006)
	–	0.270 to 0.490	(Schleich & Hillenbrand, 2009)
	Lagged difference of independent variables	0.260 short run 0.400 long run	(Nauges & Thomas, 2003)
	Lagged difference of dependent variables	0.270 short run 0.470 long run	(Musolesi & Nosvelli, 2007)
	Tier 1 and Tier 2	0.082 short run 0.139 long run	(Abrams et al., 2012)
	–	0.260 short run 0.158 long run	(Schleich & Hillenbrand, 2019)
	Instrumented price	0.390 to 0.238	(Ščasný & Smutná, 2019)
	–	0.785to 0.594	(Maas et al., 2020)
	–	0.100	(Abbott & Tran, 2020)
Marginal Price: price per additional unite of water	Instrumental marginal price. Instrumental difference (actual bill minus bill at marginal)	0.120 to 0.170	(Martínez-Espiñeira, 2002)
	–	0.370 to 0.670	(Martinez-Espineira, 2003)
	–	0.070 to 0.130	(Martínez-Espiñeira*& Nauges, 2004)
	Natural log of real instrumented marginal price. Instrumented real rate structure premium	0.324 to 0.967	(Jansen & Schulz, 2006)
	Instruments of (Hausman & Taylor, 1981)	0.250	(Garcia & Reynaud, 2004)

*All price elasticity values are in negative and significant at P-value <=0.05 , otherwise mentioned in parenthesis

Table 2: Summary of pricing variables included in various studies (Continued).

Independent variable	Instruments	Price elasticity*	Reference
Marginal Price: price per additional unite of water	Instrumental marginal price Instrumental difference	0.560	(Martins & Fortunato, 2007)
	–	0.065 to 0.042 short run 0.061 to 0.051 Long run	(Schleich & Hillenbrand, 2019)
	Fixed Charged, marginal price in first block, different between each successive block and days of service	1.13	(Puri & Maas, 2020)
Average price (AP) Marginal price (MP) AP-MP	Exogenous-time-varying variables (exogeneity of the price variable)	0.220 to 0.240	(Nauges & Thomas, 2000)
Lag (AP) over (MP)	Fixed Charged, marginal price in first block, different between each successive block and days of service	0.47 (not significant at P<=0.05)	(Puri & Maas, 2020)
Central block tariff: cover the average cost of production and represent the basis of tariff policy	–	0.990 to 1.330	(Mazzanti & Montini, 2006)

*All price elasticity values are in negative and significant at P-value <=0.05 , otherwise mentioned in parenthesis

2.4.4 Consumer characteristics

Consumers' variables such as household size, income, shares of the population over 60, the share of population under 19, population density, and social status, could explain the nature of water consumption behavior depending on multiple variables as Table 3 shows. For example, Martinez-Espineira (Martinez-Espineira, 2003) noticed that households that contained youngsters and high income tend to consume a higher amount of water. Furthermore, Parker and Wilby (Parker & Wilby, 2013) in review for multiple studies observed that households containing retired people had consumed 70% more water compared to working households and this was attributed to the fact that elders tend to spend more time at home. Conversely, Martins and Fortunato (Martins & Fortunato, 2007) found that a higher number of elderly people can reduce the average water use per household.

Family income is considered an important factor in evaluating water consumption. There are different techniques to assess the family income as Table 4 shows. Some researchers used an index of wealth to identify family income (Arbués et al., 2004). Others prefer using previous survey data to calculate gross annual household income (Mansur & Olmstead, 2012). Another method gets indirect information on family income where people were asked about their level of monthly income rather than the exact number they earn in a survey question (Agthe & Billings, 2002).

Table 3: Summary of consumer characteristics included in multiple research.

Independent variable	**Description**	**Parameters**	**References**
Household size	Number of individuals per household	0.0982* (0.4794)	(Arbues & Villanua, 2006)
	Number of dependents per household	0.060*	(Garcia & Reynaud, 2004)
	Number of people per household	21.727*	(García-Valiñas, 2005)
	The estimated average number of members per household based on population and number of dwellings	-1.889* to 0.130	(Martínez-Espiñeira, 2002)
	Number of residents per households	1.481*	(Martins & Fortunato, 2007)

*significant, values between parentheses represent elasticity.

Table 3: Summary of consumer characteristics included in multiple research (Continued).

Independent variable	Description	Parameters	References
	Number of residents per households	0.012	(Mazzanti & Montini, 2006)
	Number of members per household	-1.890* to 0.130	(Martínez-Espiñeira, 2002)
	Number of residents per household	0.194*	(Mansur & Olmstead, 2012)
Household size	Average number of household members	-0.063* to 0.074	(Schleich & Hillenbrand, 2019)
	Number of family member	0.181*	(Ščasný & Smutná, 2019)
	Dummy=1 if single person live in household	-0.352*	
	Number of consumers receiving water supply services	-3.232	(Abbott & Tran, 2020)
Female	Dummy =1 if female present in the household	0.061*	(Ščasný & Smutná, 2019)
Shares of the population over 60	Percentage of population over 64 at 1,5 and 96 percent.	-29.671* to -4.639*	(Martínez-Espiñeira, 2002)
	Percentage of population over 64 at 1,5 and 96 percent.	-19.142* to 25.360*	(Martinez-Espineira, 2003)
	Percentage of people over 65	-34.856*	(Martins & Fortunato, 2007)
	Share of population ≥ 65 across municipalities and overtime	-0.089	(Mazzanti & Montini, 2006)
	Share of population aged more than 65 years	-0.090*	(Musolesi & Nosvelli, 2007)
	The proportion of the population ≥ 60	-0.171* to -0.102*	(Nauges & Thomas, 2000)
	Number of retired persons	-0.031*	(Ščasný & Smutná, 2019)
Shares of the population under 19	Percentage of population under 19 at 1,5 and 96 percent.	-8.686* to 8.189*	(Martinez-Espineira, 2003)
	Percentage of population under 19 at 1,5 and 96 percent.	–	(Martínez-Espiñeira, 2002)
	Share of population ≤ 19 across municipalities and overtime	0.519	(Mazzanti & Montini, 2006) (Nauges & Thomas, 2000)
	Number of children younger than 5 years	-0.59*	(Ščasný & Smutná, 2019)

*significant, values between parentheses represent elasticity.

Table 3: Summary of consumer characteristics included in multiple research (Continued).

Independent variable	**Description**	**Parameters**	**References**
Age	Average age of population in years	-0.001 to 0.005*	(Schleich & Hillenbrand, 2019)
Education	Dummy = 1 if highest education in the family less than graduate school	-0.013*	(Ščasný & Smutná, 2019)
	Dummy = 1 if highest education in the family more than graduate school	-0.018*	(Ščasný & Smutná, 2019)
Self-employed	Dummy =1 of head of the family are self-employed	0.071*	(Ščasný & Smutná, 2019)
Population density	Population over surface across municipalities and overtime	0.861	(Mazzanti & Montini, 2006)
	Inhabitants per square KM	–	(Martínez-Espiñeira, 2002)
	Inhabitants per square KM	0.000	(Nauges & Thomas, 2000)
	Number of citizen per square KM	0.036* to 0.091*	(Schleich & Hillenbrand, 2019)
Hours of supply	Number of daily hours supply restriction (hours/day)	-0.066*	(Martínez-Espiñeira, 2007)
	Number of daily hours supply restriction (hours/day)	-0.050*	(Martínez-Espiñeira* & Nauges, 2004)
	Number of supplied hours per period (hours/quarter)	0.029*	(García-Valiñas, 2005)
Social status	Households segmented based on Social status (ex. pensioners)	–	(Kumaradevan, 2013)

*significant, values between parentheses represent elasticity.

Table 4: Summary of income characteristics considered in a variety of research.

Independent variable	**Description**	**Income elasticity**	**References**
Income	Obtaining income by Index of wealth	0.074 to 0.208	(Arbués et al., 2004)
	Obtaining a proxy of the income based on of the survey of the wage structure. (Average income for a worker with a certain age and educational level)	0.790	(Arbues & Villanua, 2006)
	–	0.300 to 0.310	(Schleich & Hillenbrand, 2009)
	The average taxable income per household	Positive but not significant	(Garcia & Reynaud, 2004)
Income	Obtaining a proxy of the income	0.058	(García-Valiñas, 2005)
	Obtaining a proxy of the income	–	(Martínez-Espiñeira, 2002)
	Obtaining a proxy of the income	–	(Martinez-Espineira, 2003)
	Obtaining a proxy of the income	0.100	(Martínez-Espiñeira* & Nauges, 2004)
	Obtaining a proxy of the income (purchasing power indexes)	–	(Martins and Fortunato, 2007)
	Income per capita (municipal taxable income bases)	0.400 to 0.710	(Mazzanti & Montini, 2006)
	Average per capita income (municipal taxable income bases)	0.180	(Musolesi & Nosvelli, 2007)
	proxy for average income household income based on income tax	0.090 to 0.490	(Nauges & Thomas, 2000)
	Annual income per household	0.510	(Nauges & Thomas, 2003)
	Obtaining a proxy of the income	Positive but not significant	(Ayadi et al., 2002)
	Low, medium, and high-income levels in $/year	–	(Agthe & Billings, 2002)
	Average net income per capita per year in €	-0.056 to 0.195*	(Schleich & Hillenbrand, 2019)
	Net household income	0.155*	(Ščasný & Smutná, 2019)

*significant.

2.4.5 Property characteristics

Few studies have included determinants related to the characteristics of the different properties in modeling water consumption. This is primarily due to the lack of data availability related to property characteristics in most cities. Moreover, the collection of this data directly from consumers requires a lot of effort and a considerably long time. Also, many people consider this kind of information as private and its collection could result in a violation of some local laws. Property characteristics as appear in Table 5 could include (1) property located within the city; (2) type of property (villa, duplex, apartment, etc.); (3) type of metering method (smart or otherwise); (4) size of the property; (5) Number of bathrooms; (6) Number of kitchens; (7) property age; (8) type of resident (tenant or owner); (9) type and size of luxury water consuming fixtures such as gardens (or lawns), swimming pools, hot tubs, or jacuzzies; and (10) type and the number of water-saving devices that may be installed in the house.

Normally, household size should have a positive correlation with water consumption as Table 5 below shows. Yet, according to Arbués et al. (Arbués et al., 2003), a household size would have to increase significantly before a growth in household consumption is observed, they attributed this to the economies of scale. This implies that a wider range of household sizes should be observed to detect the effect of size on water consumption. In addition, some researchers use property size instead of house size to include the garden in the size calculation (Abrams et al., 2012). asking people about their property sizes may not be answered in an accurate manner. Instead, consumers can be asked about the dwelling’s types or the number of bedrooms in their house as a proxy indicator to the house size.

Surveys of property characteristics have used proxy questions to attempt to quantify as many descriptors as possible. Survey questions include inquiries on whether the property includes a swimming pool and garden, it could then attempt to ask about the size of the garden or swimming pool. The existence of a swimming pool and garden has resulted in a positive significant effect on water demand as Table 5 below shows. The surveys can include other factors that may have different impacts in the winter and summer months (Agthe & Billings, 2002).

Finally, few studies have included the Water-saving device and geographical location as part of the residential water consumption study that focuses on price elasticity. However, houses that use indoor and outdoor water-saving devices exhibit a negative significant effect on water use as Table 5 shows whereas geographical location appears to be not significant on it is own if the cultural aspect did not change as appear in Table 5.

Table 5: Summary of property characteristics considered in different research studies.

Independent variable	Description	Parameters	References
Property age	Age of complex in years	0.130* to 0.161*	(Agthe & Billings, 2002)
	Percentage of old and new homes	–	(Kenney et al., 2008)
	Home age (year/10)	0.097*	(Mansur & Olmstead, 2012)
Property size	Lots size in square meter	–	(Balling Jr. et al., 2008)
	Include different floor areas in a high-rise apartment in the study where correlations between water use and housing size appear.	significantly differ	(Bradley, 2004)
	Clustering households data by property size in square meter	Positive	(Abrams et al., 2012)
	Home size in square foot Lot size in square foot	0.125* 0.008*	(Mansur & Olmstead, 2012)
Property type	Include different housing types and sizes in the study where correlations between water use and housing type appear.	significantly differ	(Bradley, 2004)

*significant value.

Table 5: Summary of property characteristics considered in different research studies (Continued).

Independent variable	**Description**	**Parameters**	**References**
Property type	The house type for 500 properties was tested against the consumption profile	–	(Kowalski & Marshallsay, 2005)
	The study examines water use patterns for a verity of domestic dwellings	Not significantly differ	(Troy & Holloway, 2004)
	Examine the effect of housing units (single, duplex, multi, group, and mobile homes) in water demand forecasting	–	(Dhungel & Fiedler, 2014)
Property type	Dummy variable =1 if family lives in a cooperative flat	0.147*	(Ščasný & Smutná, 2019)
	Dummy variable =1 if family lives in detached house	0.067*	(Ščasný & Smutná, 2019)
	Dummy variable =1 if family lives in terraced house	0.115*	(Ščasný & Smutná, 2019)
Property ownership	Data grouped to the owner and tenanted to include the variable in an indirect method	–	(Abrams et al., 2012)
	Dummy =1 if family owns their flat or house	0.120*	(Ščasný & Smutná, 2019)
Number of bedrooms	Number of bedrooms	9.740* to 10.700*	(Agthe & Billings, 2002)
	Properties with a different number of bedrooms correlated with water demand	Positive significant	(Fox et al., 2009)
	The median number of bedrooms	–	(Kenney et al., 2008)
Bathrooms	Number of bathrooms in household	0.056*	(Mansur & Olmstead, 2012)
Water-saving devices	complex uses drip + timer irrigation for non-grass landscaping=1, otherwise=0.	-1.210* to -0.442*	(Agthe & Billings, 2002)
	The study examined the effect of indoor Water-saving devices on household water use	-0.058	(Fielding et al., 2012)

*significant value.

Table 5: Summary of property characteristics considered in different research studies (Continued).

Independent variable	Description	Parameters	References
Washing - machines	Number of automatic washing-machines	-0.027*	(Ščasný & Smutná, 2019)
Dishwashers	Number of dishwashers	0.025*	(Ščasný & Smutná, 2019)
Garden	Presence of garden (ex. Garden or no garden)	Positive significant	(Fox et al., 2009)
	Type of irrigation for different garden types vs. low and high-income residents.	Positive	(Domene et al., 2005)
	Effect of owning garden on peak water demand	Positive	(DayD, 2003)
Swimming pool	Existence of swimming pool (swimming pool=1,othwise=0)	1.74 to 3.09*	(Agthe & Billings, 2002)
	Presence of Swimming poo1	–	(Balling Jr. et al., 2008)
Geographical location	Households segmented based on geographical location (ex. coastal areas vs. inland areas)	–	(Kumaradevan, 2013)
	Household in 6 regions in the US and Canada	–	(Mansur & Olmstead, 2012)

*significant value.

2.4.6 Weather characteristics

Weather variables such as rainfall, evaporation, and temperature are considered critical factors in explaining water consumption. Many studies have directly included temperature and rainfall data in the model as it appears in Table 6. Other studies suggested weather data deviation from average in order to use them in a model (Abrams et al., 2012). It was found that temperatures ranging between 4 and 21°C have a relatively small effect on water consumption (Maidment et al., 1985). Several studies observed better model results when the deviation of weather variables from their average value was used instead of the absolute values (Abrams et al., 2012). Other studies used the maximum values of weather variables or the values observed on rainy days (Martínez-Espiñeira, 2002, 2007).

Table 6: Summary of the weather characteristics included in a group of research studies.

Independent variable	Description	Parameters	References
Temperature	Dummy variable where is equal to 1 if the maximum monthly temperature >18 ºC and zero otherwise	-0.0057*	(Arbues & Villanua, 2006)
	Average monthly temperature (ºC)	-0.041 to 0.121*	(Martínez-Espiñeira, 2002)
	Average monthly temperature (ºC)	-0.001 to 0.314	(Martinez-Espineira, 2003)
	Maximum monthly temperature (ºC)	0.002*	(Martínez-Espiñeira, 2007)
	Average monthly temperature (ºC)	0.197*	(Martins & Fortunato, 2007)
	Average mean daily temperature over billing cycle	0.032*	(Maas et al., 2020)
	Maximum daily temperature over a billing period (ºC)	-0.010	(Puri & Maas, 2020)
	Minimum daily temperature over a billing period (ºC)	-0.070*	(Puri & Maas, 2020)
	Average daily temperature over billing period (ºC)	0.100	(Puri & Maas, 2020)
Temperature	Number of cooling degree days over a billing period (days)	0.010*	(Puri & Maas, 2020)
	Average maximum temperature in location	1.629*	(Abbott & Tran, 2020)
Rainfall	Rainfall in summer (mm)	-0.0003*	(Garcia & Reynaud, 2004)
	Number of rainy days per month	-0.959* to 0.559*	(Martínez-Espiñeira, 2002)
	Monthly precipitation (mm)	0.000	(Martínez-Espiñeira, 2007)
	Monthly precipitation (mm)	-0.000	(Martínez-Espiñeira* & Nauges, 2004)
	Monthly precipitation (mm)	0.004	(Martins & Fortunato, 2007)

*significant value.

Table6: Summary of the weather characteristics included in a group of research studies (Continued).

Independent variable	**Description**	**Parameters**	**References**
Rainfall	Rainfall in summer (mm)	-0.010 to 0.024	(Nauges & Thomas, 2000)
	The daily rainfall deviation from average daily rainfall	-0.010	(Abrams et al., 2012)
	Total precipitation(mm) over billing cycle	-0.003*	(Maas et al., 2020)
	Average precipitation over a billing period (mm)	-0.080	(Puri & Maas, 2020)
	Number of precipitation days over billing period (days)	-0.010*	(Puri & Maas, 2020)
	Total amount of precipitation over billing period (mm)	0.000	(Puri & Maas, 2020)
	Average rainfall in the location	-0.022*	(Abbott & Tran, 2020)
Evaporation	The evaporation deviation from average daily evaporation	0.080	(Abrams et al., 2012)
Evapotranspiration	Average evapotranspiration rate over billing period (mm)	0.150*	(Puri & Maas, 2020)
Humidity	Average relative humidity over billing period (Fraction)	2.000*	(Puri & Maas, 2020)

*significant value

2.4.7 Model functional forms

There is no specific water consumption function that can be used for all consumption studies. Different forms of functions appeared in the literature, each can be used to fit different data types, demand function, and PED characteristics as appear in Table 7. However, economic models require good functional form assumptions to estimate the parameters’ value accurately. There is no clear guidance to match a specific functional form to a certain demand function (Kumaradevan, 2013). This will leave the choice to the researcher to pick the appropriate functional forms which will satisfy the requirements of the problem under consideration.

Some studies, such as Nauges and Thomas, 2003, chose specific functional forms without justifying their choice. Others, like Agthe and Billings (1980), chose the one that comes up with the best statistical outcome. Moreover, researchers chose the double-logarithmic function because there was no theoretical consideration that can collectively fit a certain functional form (Kumaradevan, 2013). Other researchers justify their choice of the double-logarithmic function and the linear function because both can estimate a constant-elasticity (Dandy et al., 1997; Williams, 1985). However, the double-logarithm function faces a consistency problem with the utility theory which "maximization of utility has been used to drive the consumer demand function" (Calvo, 1983). Nevertheless, it has a curvilinearity nature that can fit the choke price principle (a price where demand equals zero).

The Stone-Geary specification was used by Gaudin et al. (2001) and Al-Qunaibet and Johnston (1985) because it solves the limitation where the amount of water consumed cannot equal zero even at a very high price. Furthermore, it also solves the limitation of other demand functions that assumes an infinite amount of water consumed at a price equal to zero. On the other hand, the Stone-Geary function faces several drawbacks, such as the complexity of implementing it in the model. Furthermore, the model results are difficult to interpret.

Finally, the semi-log function was used by many researchers due to its sensitivity to high price changes and its curvilinearity nature, which will accommodate the choke price principle (Arbués et al., 2010; Schleich & Hillenbrand, 2009). It is considered by Abrams et al. (2012) to be the most suitable choice for water consumption modeling.

Table 7: Summary of the functional forms included in a group of research studies.

Study location	**Functional forms**	**Estimation technique***	**References**
Spain	Linear	OLS	(Martínez-Espiñeira, 2007)
Spain	Stone-Geary	GLS	(Martínez-Espiñeira & Nauges, 2004)
Spain	Semi-log	GMM	(Arbúes et al., 2004)
Germany	Log-log	Pooled OLS, RE,FE	(Schleich & Hillenbrand, 2009)
Germany	Log-log, Semi-log	OLS, IV	(Schleich & Hillenbrand, 2009)
Germany	Log-log	Symmetric & asymmetric response model	(Schleich & Hillenbrand, 2019)
Czech Republic	Log-log	OLS,2SLS	(Ščasný & Smutná, 2019)
Australia	Semi-log	GMM	(Abrams et al., 2012)
Australia	Semi-log	Pooled OLS, RE, FE, GMM	(Kumaradevan, 2013)
Australia	Linear	GLM	(Abbott & Tran, 2020)
Canada and the USA	Semi-log	GLS RE, 2SLS GLS	(Mansur and Olmstead, 2012)
USA	Log-log	OLS	(Dhungel & Fiedler, 2014)
USA	Log-log	2SLS,IV,FE	(Puri & Maas, 2020)

*OLS: Ordinary Least Square; GLS Generalized Least Square; 2SLS: Two-Stage Least Square; FE: Fixed Effect Estimation; RE: Random Effect estimation; GLM: General Liner Model, GMM: General Method of Moment; IV: Instrument variable procedure.

2.4.8 Demand function form

The simplest method for water demands functions is in the linear form. The linear model does not require transformation and can be easily interpreted. The slope in the linear function represents the variation demand due to the variation in independents variables (ex. Price). The mathematical form for the linear model can be expressed as in Equation 2 and 3 (Kumaradevan, 2013).

$$D_h = \alpha_h + \sum \beta_h I_h + \varepsilon_h \tag{2}$$

$$E(\varepsilon_h) = 0 \tag{3}$$

Where,

D_h= Regressand variable or water demand for household h.

I_h=Regressor variables

The elasticity of demand for linear form expressed as in Equation 4 (Kumaradevan, 2013).

$$(\frac{\partial E(D)}{\partial E(I)}) = (\frac{\partial D}{\partial I}) \times (\frac{D}{I}) = \beta_h \times (\frac{E(D)}{E(I)}) \tag{4}$$

The elasticity of demand (β) represents the rate of change in demand per rate of change in independent variable measures. This indicates the higher the price the higher consumption sensitivity. However, the linear form cannot serve all types of demand curves. This is because there will be a price for water when the consumption reaches zero (choke price). Water cannot follow the typical demand curve because it is crucial to people's life. The linear can fit a part of the water demand curve to calculate elasticity at the curve section or point.

Many researchers select the double-log form to be used with water demand data. Because of the curvilinearity, the double-log fit better with the water demand curve and avoid the choke price problem. Although it gives constant elasticity and evades chock price, it cannot follow the utility theory (each extra unit in quantity lower consumer satisfaction). Thus, the semi-log function is selected in this study with general form as in Equation 5 and 6 (Kumaradevan, 2013).

$$\ln(D_h) = \beta_0 + \sum \beta_h I_h + \sum \beta_h LnI_h + \varepsilon_h \tag{5}$$

$$E(\varepsilon_h) = 0 \tag{6}$$

The model can explain the high consumer sensitivity when the price experiences a massive increase. Also, the model avoids choke price and has a higher advantage over the double-log model. Moreover, the natural log form increases linearity, and the natural log parameter can be explained as elasticities directly. Other variables required semi-log interpretation and it is a little bit complicated because it needs to be computed mathematically. Equations 7 to 11 (Dranove, 2009) below explains how this could be done.

$$\ln(D) = \beta_h I_h \tag{7}$$

$$\mathrm{D} = e^{\beta_h I_h} \tag{8}$$

$$\frac{\partial D}{\partial I} = \beta_h e^{I_h} \tag{9}$$

$$\varepsilon_{D,I} = \frac{\partial D}{\partial I} \times \frac{I}{D} \tag{10}$$

$$\varepsilon_{D,I} = \beta_h e^{I_h} \frac{I}{e^{\beta_h I_h}} \tag{11}$$

In conclusion, the semi-log model and GMM estimation method have been used in this research. Water consumption is the regressand and thus, it is converted to natural log form. The essential price variable is the average price. Block 1 and block 2 instruments for the average price used to break the endogeneity with water consumption. The weather, household, and consumer characteristics are included in the model as continuous and discrete values to assist their contribution to the consumption value.

2.4.9 Economics techniques

The econometrics techniques are the main methods used to panel analysis data related to water consumption. Generally, panel data consist of cross-sectional data with time series at the same time. The water consumption over 24 months (time series) and the 12 independent variables recorded in each month (cross-sectional) are clear examples of complex panel data. Using penal data provides a higher level of accuracy to the regressor coefficients as those associated with other data types. Moreover, econometric techniques control the omitted variable and their time-invariant effects (Allison, 2009). Section 4.4 explains three different types of estimation techniques and provide the reasons for choosing GMM for analyzing study data.

Panel Data or longitudinal data can be defined as a type of data where multiple individuals are measured over time. The panel data include a variety of observations for different phenomena that have been measured over time for the same individuals or units.

The statistical inferences in economics considered false if there are unobserved variable correlate with variable under study, including regressand and regressors. The unobserved heterogeneity exists if there is variation in different units of data set from variable out said the study scope. For instance, the water consumption data under study differ from one consumer to another because of dependent and independent factors (observed heterogeneity) and other unobserved variables. Under the presence of unobserved heterogeneity, a valid statistical inference can be achieved through the econometrics models that assessed the effect of unobserved variables (Arellano, 2003).

The ordinary least square (OLS) method has been used by many researchers to estimate the coefficient of the explanatory variable related to a water consumption model. The OLS follows a linear regression model that minimizes the sum of square error (SSE) between observed and predicted variables. However, it can be applied when we have a complete exogenous explanatory variable; The independent variables and error term are completely uncorrelated and it has the same value across all regressors variable (Arellano, 2003).

The model is chosen in this study follow natural logarithm, and there are hidden endogeneity and collinearity between different variables. This condition imposes the estimation bias and violates the OLS assumption. The pooled OLS model can be represented as in Equation 12 and 13 (Arellano, 2003).

$$Y_{it} = \beta_{it}X_{it} + \varepsilon_{it} \qquad i = 1 \ldots N \; t = 1 \ldots T \tag{12}$$

$$E(u_{it}|X_k) = 0 \tag{13}$$

Where Y_{it} is the dependent variable vector for observation unit I in time unite t.

X_{it} Dependent variable row vectors

β_{it} Parameter column vector

ε_{it} Error term

As can be seen from the above equation, the second term has been violated because of the correlation between the independent variable and the error term. These violations create bias OLS models and inconsistent with an auto-correlated variable. In the bias model, the omitted variable effect (part of his effect embraced in the error term) excluded and observed variable parameter exaggerated. In addition, the omitted variable will create inconsistency because if more data can be collected, then the result will mirage away from true population parameters. These issues can be handled by implementing other panel data estimation techniques (Wooldridge, 2012). The panel estimation techniques analyze the following:

1. Effect source (cross-sectional or time-series effect)
2. Effect type (fixed or random effect)

On one hand, the Random effect considers that effect source that can't be explained by the independent variable as a disturbance in the regression equation. On the other hand, the fixed effect hypothesis that the source of effect can cause intercept in the regression equation. Identifying the effect type will lead to the use of an efficient method in panel data analysis (Park, 2010). for instance, the general form for the fixed-effect model follow Equation 14 (Arellano, 2003).

$$Y_{it} = \beta_{it} X_{it} + \alpha_i + \varepsilon_{it} \tag{14}$$

Where α_i is a fixed effect parameter (time-invariant intercept) for the unobserved variable.

The unobserved variables assumed to have a constant effect α_i in the fixed-effect model. Estimating the fixed parameters α_i can be done by creating a dummy variable for each observation and applying the least square dummy variable (LSDV) method. Another approach estimates the model by subtracting mean value from individual observation (Cottrell & Lucchetti, 2017). The further step is to determine the fixed-effect parameter which can be achieved using Equation 15 (Arellano, 2003).

$$\widehat{\alpha_\iota} = \frac{1}{T_i}\sum_{t=1}^{T_i}(Y_{it} - X_{it}\hat{\beta}) \tag{15}$$

Where T_i is the number of cross-sectional units at independent variable i.

Generally, both methods are arithmetically equivalent, but LSDV can be more efficient with very large data (Cottrell & Lucchetti, 2017). However, fix effect estimate can be biased and suffer from inconsistency when t (the time set number) is large (Nickell, 1981). The inconsistency appears in the model not only if the auto-correlated variable exists but even with lagged dependent variables (Robertson & Symons, 1992).

On the other hand, the random effect model presumes that the effect of unobserved variables is random drawings that come from a certain probability distribution (Cottrell & Lucchetti, 2017). The random effect takes the form of Equation 16 (Arellano, 2003).

$$Y_{it} = \beta_{it}X_{it} + v_i + \varepsilon_{it} \tag{16}$$

Where v_i is the random parameter.

The random effect assumes the absence of correlation between the unobserved variable and independent effect while the fixed effect assumes the opposite. If the random effect assumption can hold, the model is more reliable than the fixed effect. In contrast, if the premise is invalid, then the unobserved effect will be inconsistent with the independent variable. Figure 5 illustrates a summary for tests that could be used to choose between pooled OLS, Fixed, and random effect (Park, 2010). In this study, it is more logical to assume the absence of a correlation relationship between observed and unobserved variables.

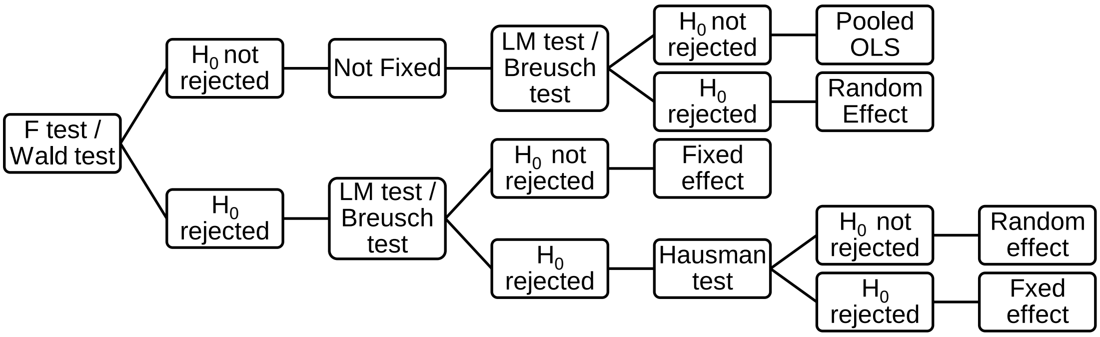


Figure 5: Test required to choose between pooled OLS, fixed and random effect (Park, 2010).

Finally, the general method of moment (GMM) is one of the most popular and efficient methods used to evaluate parameters in an econometric equation. The method was introduced in 1982 by Lars Peter Hansen (Cottrell & Lucchetti, 2017). The method joints both population moment conditions and instruments with economic data to estimate the equation parameter. The population moments condition is a function of the data and the model parameters. The expected moment condition value is zero when the model reaches the parameters' true value. The raw moment’s values ease implementing restrictions on distribution shape, scale, and location without the need to specify the full distribution. The population information is not sufficient to estimate population parameters. In further analysis step, the relationship between sample statistics and population statistics used to estimate population parameters. For example, the population unknown means μ with variance equal to one that needs to be estimated (Zsohar, 2012). The method of the moment will follow equations 17 to 19 to estimate the mean μ (Zsohar, 2012).

$$E[x_i] = \mu \qquad where\ \{x_i : i = 1,2 \ldots, n\} \tag{17}$$

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{18}$$

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i = \widehat{\mu_n} \tag{19}$$

Simply the method of moment follows the following step:

1. Identify the first moment
2. Obtain the sample analog
3. Use the sample analog to estimate the population parameter

This will imply certainly that the better the sample quantity the better estimation for population quantity is. In this study, a semi-log equation will be used to estimate water consumption. The general form of the semi-log equation is as appear in Equation 20 (Zsohar, 2012).

$$ln(y_i) = \beta_0 + \beta_i x_i + controls + u_i \tag{20}$$

Where $controls$ is the constant factor in the experiment which could include a dummy variable.

Estimating the parameters β_i with OLS will be bias and inconsistent if x_i correlated with unobserved factors that included in the error term u_i. To overcome this issue, an instrumental variable should be used with x_i so exogeneity assumption can behold with the population moment condition appears in Equation 20 (Zsohar, 2012).

$$E[z_i(\ln (w_i) - \beta_0 - \beta_i x_i - controls)] = 0 \tag{21}$$

Where z_i is the instrument vector that contains variables that will not be affected by other variables in the model.

Even though the moment condition is more than the parameter, the GMM will estimate the parameter's true value by approximate the sample moment to zero as much as possible (Zsohar, 2012).

The GMM model has been used by many researchers to estimate dynamic panel data related to water consumption in a different part of the world. For example, Nauges and Thomas, 2003, use GMM to analyze aggregate water consumption data in the residential sector in France. Moreover, Nauges & Thomas, 2003, use a modified GMM model to estimate long-run water consumption in the same country. In 2007, the GMM used in Italy to determine residential water demand function based on municipality water data (Musolesi & Nosvelli, 2007). Finally, a survey has made on Réunion island to estimate the effect of price perception on residential water demand using the GMM estimation technique (Binet et al., 2014).

The comparison process between different types of estimation methods turns out that GMM is the most suitable technique for the data set in this research. Block 1 and block 2 were used in this study as an instrumental variable for price. Using them as instrument variables will endogeneity problems and allowing the GMM to estimate the block pricing technique.

To summarize, this study covers Al Ain region in the period from January 2016 to December 2017. The data has been collected mainly from AADC, SCAD, and the survey conducted on 465 houses. A selection method that contains several restrictions has been created to eliminate miss leading data. Finally, different types of estimation methods have been introduced; however, GMM has been selected. This is due to the ability of the GMM technique to avoid the endogeneity problem that appears in the price variable.

2.5 Water consumption situation in UAE

Water management challenges in UAE comprise of two main categories: physical challenges and management/policy challenges. The main driver for physical challenges is the continuous increase in water demand which puts pressure on the available water resources. This is exacerbated by very scarce renewable water resources in the country. Management and policy challenges stemming from the need for continuous development in current and future policies and regulations to cope with the physical challenges. Other challenges include the need for cautious adaptation for climate change in water resources planning, achieving cost recovery for drinking water production, and supply to relieve the governmental burden, achieving an effective and fair water pricing structure.

For the past few decades, increasing pressure on the UAE's infrastructure developed because of the rising annual water demand. Up to the year 2006, the water infrastructure in the UAE included 36 desalination plants to cover the sharp increase in demand in the country (Murad et al., 2007) which cost billions of dollars that could have been directed to serve other critical public services if consumers had adopted water-saving behavior. The subsidized desalinated water becomes essential in facing water scarcity issues and a solution to follow the growing demand in the country as Figure 6 shows. The desalination process in UAE supports almost 98% of domestic supply in a country that has limited renewable water resources as Figure 6 shows

(Mohamed et al., 2005; Sommariva & Syambabu, 2001) which make it vital and irreplaceable. The domestic and industrial sectors depend entirely on desalinated water, whereas the agricultural sector relies on treated wastewater, groundwater, and some desalinated water (Al-Rashed & Sherif, 2000; Murad et al., 2007). The water demand between 2000 and 2010 increased by almost 25% at a highly subsidized rate, and it is predicted to increase by 59% in 2025 if the consumption behavior continues in the same manner.

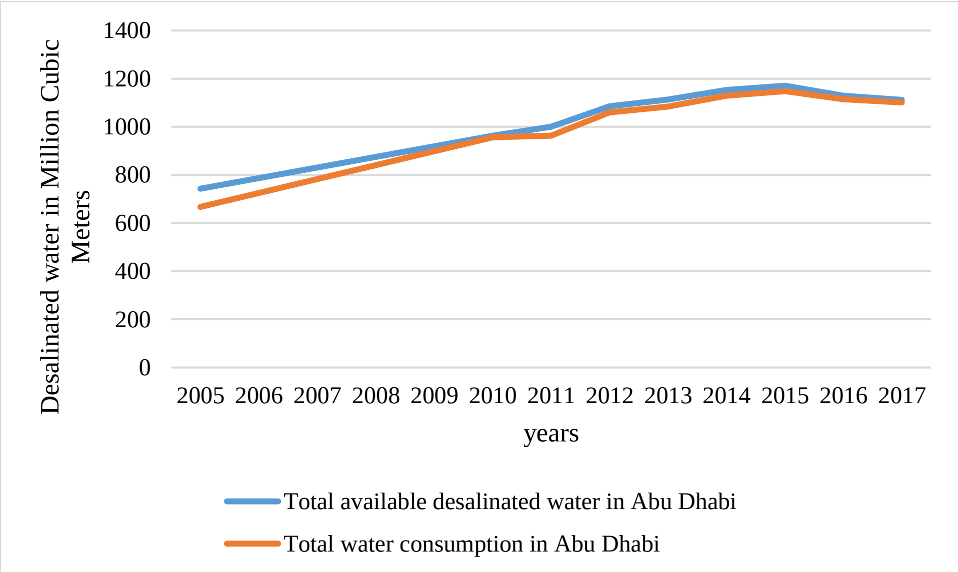


Figure 6: Desalinated water production and consumption in Abu Dhabi between 2005 and 2015 (*Statistical Yearbook of Abu Dhabi*, 2020).

Over the past years, the image of unlimited water supply was built in the minds of UAE consumers because of subsidized prices of utilities (water and energy), the country's oil resources, and the government's investment in desalination and infrastructure (Allan & Allan, 2002; Günel, 2016). Up to the year 2014, the government followed a differential pricing policy where the price was subsidized for UAE nationals by 100% whereas it was subsidized by 71% only for expatriates. This has led to extravagant consumption behavior as can be seen in Figure 6. Moreover, the UAE has one of the highest per capita water consumption rates compared with countries in the region. The desalinated water consumption in UAE has reached 602.2 l/c/d in 2016 where it reaches 168 l/c/d in Saudi Arabia and 173.5 l/c/d in Oman in the same period (GCC-STAT, 2018).

The investment in better water technology and infrastructure becomes mandatory to meet the demand and overcome any possible water supply shortage. Nevertheless, low oil prices affect water projects under construction and led to the need for more innovative and unusual solutions. In addition, research suggests that the UAE is in need of an advanced integrated water resources management (IWRM) plan to overcome the phenomenon of excessive water consumption (Murad et al., 2007).

2.5.1 Government strategies and visions

The government's goals have changed to meet these challenges and achieve better water demand management through improving policies and regulations, investing in education, researching and developing new water technologies, and more effective desalination methods. Their plan to handle this issue has shifted from meeting the growing water demand towards water consumption awareness, reducing the governmental subsidies gradually, putting new policies regarding consumption in general, and investing in a water desalination process that has a higher efficiency (*United Arab Emirates - Water*, 2019). The government started in January 2015 reducing power and water subsidy and raising the tariffs in 2016 and 2017 (Srouji, 2017; *Water & Electricity Tariffs*, 2017). Furthermore, the government agreed on $1.6 billion allocated for energy and water projects (Staff, 2019). In general, the water pricing policy is considered a substantial topic in environmental economics where the environmental issues are integrated with the social, political and economic problems. This is particularly true for the UAE since water scarcity complicates the situation.

The decision-makers in The UAE have put enormous effort to achieve better IWRM. These efforts can be seen clearly through implementing new tools, policies, regulations, strategies, and visions for the federal government and by different emirates. It is important to study the effect of the government efforts in reducing water demand to elucidate the more effective policies to adopt. The following a brief account of the main tools adopted by the UAE government in their effort in managing water demand.

2.5.2 Smart water metering

In 2018, Dubai Electricity and Water Authority (DEWA), revealed that 80.6% of all water meter in the emirates will be converted to the smart water meter (SWM) at the end of 2019 and the authority has already appointed 595,755 SWM across Dubai emirates. The new meters served a total of 343,000 clients in the first phase of the project is planned to enroll all residential consumers at the end of the SWM installation project. The advertisement was made in the WETEX 2018 Exhibition between 23-25 October 2018. DEWA plans to be Superior in digital service and artificial intelligence (AI) usages in the water sector around the world. This step was part of the Smart Dubai initiative which aim to make Dubai one of smartest city in the globe. The SWM will reduce water effusion and increase water Usage transformation and operational efficiency as the authority announce in the exhibit. Besides, SWM will help the consumer to monitor his consumption in a better way which will help in Achieving the sustainability of resources goal under the UAE 2030 strategy.

The new meter helped in discovering 20,000 leakage areas, 1,400 over-usage point, and 4,700 faults which have a total Money-saving value of AED 52.6 million as the authority announced. The SWM established by the authority assists the consumers through the “High Water Usage Alert” feature. This feature will keep the consumer aware of any possible water seepage inside the household. The consumer will be notified by the system if there is an unusual rise in consumption which will allow him to fix any leak and repair the internal connection. The system also will enable the customer to view his current consumption at any time and any place. Furthermore, the system will compare the customer consumption with other average home consumption, which will allow him to assist his usage over different months and encourage healthy competition among people. Overall, the new system will help in lowering costs of water usage and water wastage and achieve DEWA’s Green Dubai strategy (*DEWA Installs 595,755 Smart Water Meters*, 2018; *Smart Applications*, 2020).

2.5.3 Policy and Strategy tools for demand management

The instruments used to achieve efficient water consumption in urban water management can be divided into pricing and non-pricing tools. There was always controversy when an increase in price was implemented as a primary policy to control water consumption. Many claim it could affect the equality between different consumer segments. Therefore, it the least favored policy by any society segment. Policymakers should always maintain a balance between social welfare and resource sustainability when new pricing or non-pricing policy implemented. A higher water tariff is considered a direct method to increase the net revenue, efficiency, and sustainability of resources used taking into consideration water price affordability to different consumer segments. A new water price can have an effective effect on consumer behavior in specific cases only. Moreover, studies show that new water pricing can encourage conservation behavior in a similar way to the tariff block extending (Tortajada et al., 2019).

Non-Pricing tools such as water-saving technologies, regulation promoting water conservation, awareness, and educational campaigns can have a noticeable effect on altering consumer behavior from water overuse to conservation. A European study has made 13 water demand policies in four different cities in 2018 prove this fact. The study observes that the policies based on investment in network maintenance and renovation have the highest effect on water conservation. The regulations that promoting water conservation comes in second place in its effect on water conservation followed by public Campaigns publicizing new water-saving technologies and promoting adapting water-conservation practices. The study result consists of another German study made in 2009 on different 600 water supply areas in the country (Tortajada et al., 2019).

The UAE government has put these studies into consideration in the country's environmental vision 2021. The vision focuses on ensuring sustainable development and preserving the environment components in the country. The vision has Key performance indicators (KPI) as a method to measure the performance. One of the KPI is directly related to water consumption, which is the water scarcity index (WSI). The WSI is an indicator used to monitor freshwater consumption as a percentage of all renewable water existing in the UAE. The vision stipulates that one of the goals is to decrease the water scarcity index.

In addition, the vision will use the Blockchain system as a self-awareness tool that will help the consumer digitalize the transactions into the blockchain platform. The new system will have many advantages such as time, resources, and effort saving. The system will cover the water sector which will help the consumer to monitor his water consumption cost from his smartphone and it will lead to better management of the water resources for individual and save the water resources for the entire country (Emirates Blockchain Strategy 2021, 2018).

In alignment with United Nations (UN's) Agenda 2030, Abu Dhabi and the Dubai Emirates have put a several Visions for 2030. In Abu Dhabi, The Visions covers economics, environment, transportation mobility management, surfaced transportation master plan, and Plan Abu Dhabi 2030. The Environment Vision 2030 focuses on creating cooperative and sustainable environmental, economic, and social visions in the Abu Dhabi Emirates. Moreover, the vision seeks to achieve efficient resource use and better life quality with enriching natural heritage in the emirates. It also aims to improve and find a Suitable solution in five main areas. These areas include climate change where the goal is to reduce the effect of climate change and increase healthy and safe living situations by achieve clean air and reducing noise pollution. Also, adapting the best conservation and management strategy to achieve the highest level of efficiency in water resource consumption. Finally, focusing on improving the level of waste management, Biodiversity, cultural heritage, and habitats to accomplish the sustainability value throughout the emirates (Ahmad, 2010).

Finally, the government launched 'UAE Water Security Strategy 2036' which aim to maintain sustainable access to water during drought and normal situation. Also, the strategy will involve all supply chains in the country to achieve a reduction in water demand by 21% through IWRM. Moreover, the strategic goal is to cut the water scarcity index by 3 degrees and surge the water productivity index to $ 110 m^3. Finally; the strategy will raise the percentage of recycled sewage water to 95% and upsurge the storage capacity from water to 2 days (*The UAE Water Security Strategy 2036*, 2018).

2.5.4 Tariff structure in Abu Dhabi region

In 2008, the water consumption in Abu Dhabi reached 525 liters per capita per day while the global average consumption equal to 195 liters per capita per day. This makes the emirate has one of the highest per capita consumption in the world (Srouji, 2017). The high per capita water consumption encourages the government of UAE to forecast the demand and the supply curve starting from 2010 to notice a gap that will begin from 2017. Based on that, the UAE government set a target to reduce water use to 200 liters per capita per day to overcome this issue (Srouji, 2017).

The solution proposed was to create a conservation strategy by the ministry of environment and water in 2010. The plan consisted of 8 points that focus on reducing the water demand and wastewater resources. As an example, initiative number 6 focuses on increasing water tariff prices to reduce governmental support for desalination water and motivate the public to adopt a better water-saving attitude.

The marginal cost value of desalinated water in the UAE equal to 7.6 AED per meter cube in 2010 (Srouji, 2017; *Water and Electricity Sector Overview*, 2013). The desalinated water cost indicates a full government subsidy to the national resident whereas the expat was charged 2.2 AED per mater cube which covers 29% only of the water desalination process and service (Srouji, 2017; Qdais & Al Nassay, 2001).

The situation has changed dramatically in 2015 where the water tariff and governmental subsidy differ according to citizenship, type of property, and the consumption amount. The new price for a non-national resident is higher by 350% if it compares with national residents. The government subsidies national with a range between 75% to 77.6% and expat by the value of 21.7% if the consumption level below the LCB limit. The water price for an expat has set to be less than the marginal cost that covers production and service charge. This is due to the high percentage of expat in the country. Furthermore, the new tariff will give a better picture of the real value of the desalinated water to most consumers which will eventually lead to decrease consumption to an acceptable limit. Table 8 below summarizes the price structure in Abu Dhabi city from 2000 until 2015.

Table 8: Abu Dhabi residential water tariff from 2000 to 2015 (*New slabs, rates for water, electricity for 2015*, 2014; Srouji, 2017).

Customer	**Property**	**Tariff AED/ m^3 In 2000**	**Subsidy AED/ m^3 In 2000**	**Tariff AED/ m^3 In 2015**	**Subsidy AED/ m^3 In 2015**	**Daily consume. limit in m^3/day**
National	Flat	0	7.6 (100%)	1.70	5.90 (77.6%)	Up to 0.7
				1.89	5.71 (75.0%)	Over 0.7
	Villa	0	7.6 (100%)	1.70	5.90 (77.6%)	Up to 7.0
				1.89	5.71 (75.0%)	Over 7.0
Expat	Flat	2.2	5.4 (71%)	5.95	1.65 (21.7%)	Up to 0.7
				9.90	0.00 (0.00%)	Over 0.7
	Villa	2.2	5.4 (71%)	5.95	1.65 (21.7%)	Up to 5.0
				9.90	0.00 (0.00%)	Over 5.0

The tariff for the expat under the high consumption block (HCB) category was the only change in 2016, whereas significant changes happened for the water prices in 2017. The expat price under the HCB increased from 9.90 AED to 10.55 AED between 2015 and 2016. The price for national in LCB and HCB increased by 22.9% and by 37.6%, respectively, from 2016 to 2017. For the expat, the prices increased by 31.8% for LCB and decreased by 1.3% for HCB. The governmental subsidy for national LCB and HCB decreased by 5.1% and by 9.2% respectively. For the expat, the government subsidy was eliminated in 2017. Table 9 below shows in detail the new tariff structure in 2016 and 2017 with the percentage of governmental subsidy for a different category.

Table 9: Abu Dhabi residential water tariff from 2016 to 2017 (*Residential Rates and Tariffs*, 2016; 2017).

Customer	**Property**	**Tariff AED/ m^3 In 2016**	**Subsidy AED/ m^3 In 2016**	**Tariff AED/ m^3 In 2017**	**Subsidy AED/ m^3 In 2017**	**Daily consume. limit in m^3/day**
National	Flat	1.70	5.9 (77.6%)	2.09	5.51 (72.5%)	Up to 0.7
		1.89	5.71 (75.0%)	2.60	5.00 (65.8%)	Over 0.7
	Villa	1.70	5.9 (77.6%)	2.09	5.51 (72.5%)	Up to 7.0
		1.89	5.71 (75.0%)	2.60	5.00 (65.8%)	Over 7.0
Expat	Flat	5.95	1.65 (21.7%)	7.84	0.0 (0.0%)	Up to 0.7
		10.55	0.0 (0.0%)	10.41	0.0 (0.0%)	Over 0.7
	Villa	5.95	1.65 (21.7%)	7.84	0.0 (0.0%)	Up to 5.0
		10.55	0.0 (0.0%)	10.41	0.0 (0.0%)	Over 5.0

In Al Ain region, the situation is identical taking in mind the town belongs to the Abu Dhabi region and follows the same regulation. Table 10 below shows the tariff structure for national and expat for 2016 and 2017. The Tariff has increased, as shown in Table 8 below for 2017. The tariff remains the same during 2018 but includes a 5% VAT tax (*Residential Rates and Tariffs*, 2018).

Table 10: Al Ain residential water tariff in 2016 and 2017 (*Water and Electricity Tariff*, 2016; 2017) .

Customer	**Property**	**Tariff AED/ m^3 In 2016**	**Subsidy AED/ m^3 In 2016**	**Tariff AED/ m^3 In 2017**	**Subsidy AED/ m^3 In 2017**	**Daily consume. limit in m^3/day**
National	Flat	1.70	5.9 (77.6%)	2.09	5.51 (72.5%)	Up to 0.7
		1.89	5.71 (75.0%)	2.60	5.00 (65.8%)	Over 0.7
	Villa	1.70	5.9 (77.6%)	2.09	5.51 (72.5%)	Up to 7.0
		1.89	5.71 (75.0%)	2.60	5.00 (65.8%)	Over 7.0
Expat	Flat	5.95	1.65 (21.7%)	7.84	0.0 (0.0%)	Up to 0.7
		10.55	0.0 (0.0%)	10.41	0.0 (0.0%)	Over 0.7
	Villa	5.95	1.65 (21.7%)	7.84	0.0 (0.0%)	Up to 5.0
		10.55	0.0 (0.0%)	10.41	0.0 (0.0%)	Over 5.0

Chapter 3: Methodology

3.1 Introduction

This chapter explains the methods applied in this study. Different data types have been included in the analysis. econometrics analysis techniques have been used to analyze the data.   Figure 7 outlines the steps taken in this research. Details of these steps will appear in the following sections.

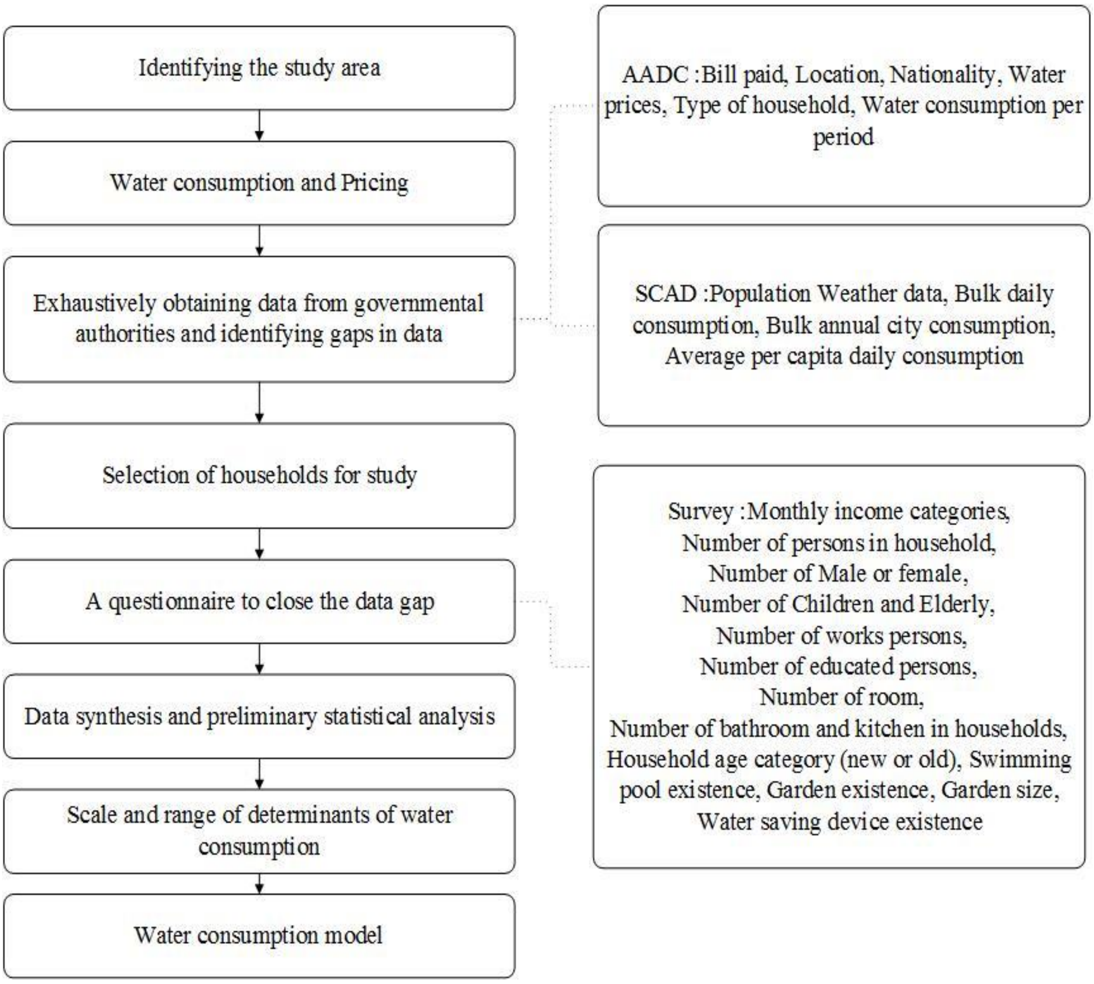


Figure 7: Flowchart for the steps to build the water consumption model.

3.2 Study Area

The study was conducted in the Al Ain region which extends over an area of 15,100 km^2 where approximately 770,000 people live in more than 61,000 households (*Statistical Yearbook of Abu Dhabi*, 2020). There is a high local percentage living in the Al Ain region compared with other areas in the Abu Dhabi Emirates. Cites in the western region have many similarities with the Al Ain region which makes the study representative. The region is located on the border of the Sultanate of Oman and 160 km away from Abu Dhabi city. Figure 8 shows the Al Ain region that extends between 24.207500 latitudes and 55.744720 longitudes.

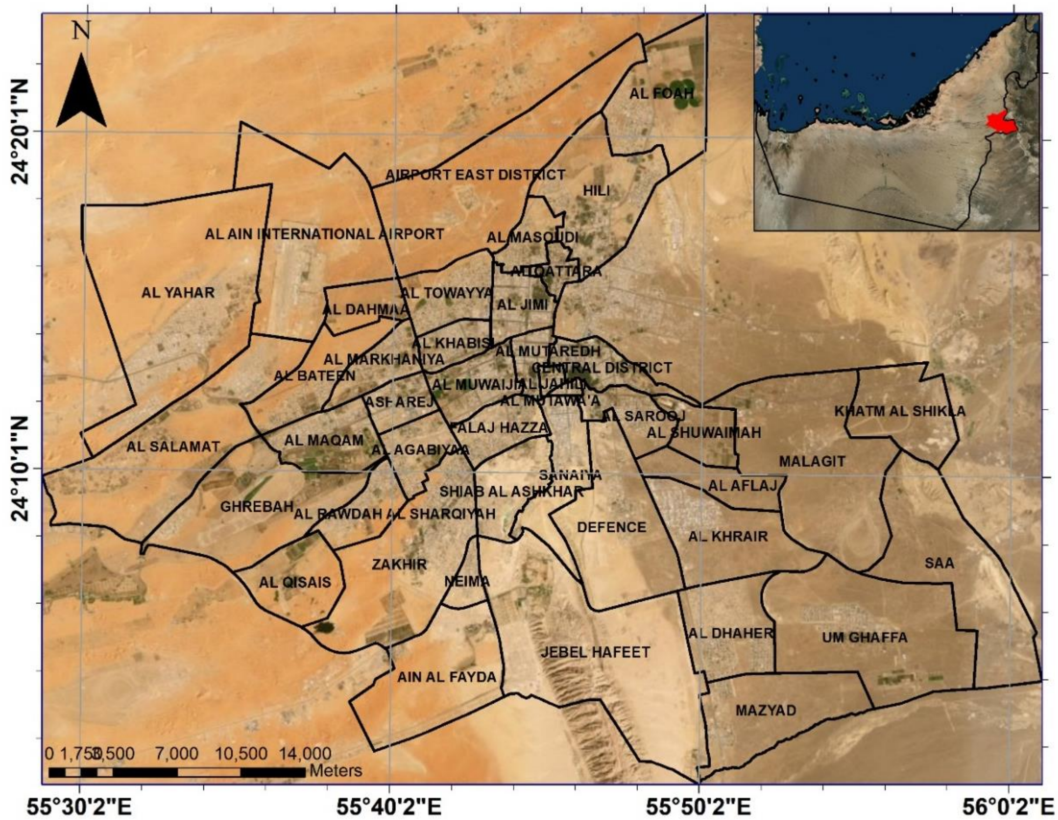


Figure 8: Al Ain region map.

Al-Ain region is characterized by an arid climate with rare rainfall throughout the year and high relative humidity in the summer. The temperature can reach 10℃ in the winter and 51℃ in the summer. The maximum average annual rainfall can reach 120 mm, while relative humidity ranges between 13% and 88% throughout the year (Younis, 2016).

Al-Ain distribution company (AADC) supplies water for more than 92,400 facilities in the Al Ain region. Of these facilities, the main consumers are immovable residential buildings that can be classified as apartments, villas, and Shaabia (old villa). Figure 9 shows a trend in bulk water consumption and the non-revenue water (NRW) in the Al Ain region with an increase in average water tariff (of the two consumption blocks) for expats and nationals in the region. The total amount of water supplied by the company has started to decrease since 2015. This coincides with the introduction of cost recovery pricing (block tariff) in the same year. Even though this indicates that pricing had an impact on consumption, further analysis is needed to estimate the effect of different factors on water consumption.

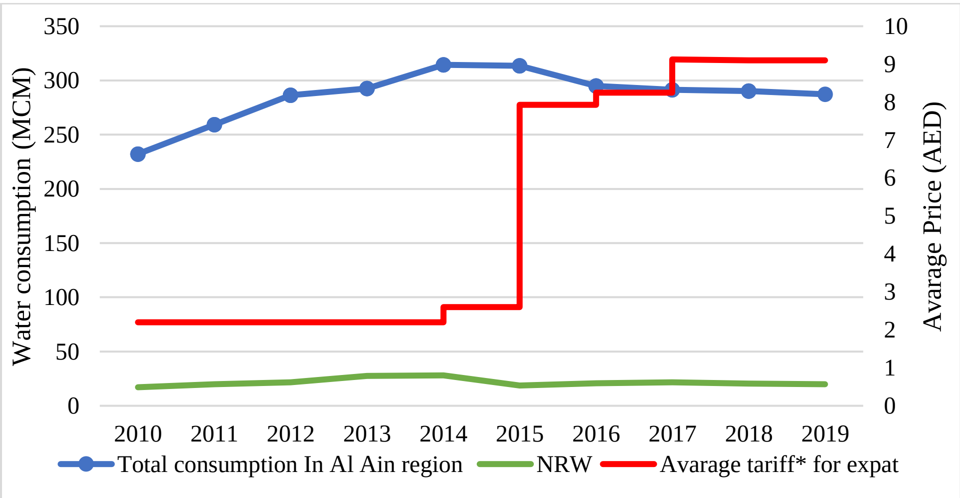


Figure 9: Bulk water consumption in the Al Ain region and average water prices (*Statistical Yearbook of Abu Dhabi*, 2020; *Water & Electricity Tariffs*, 2017).

*Average tariff: is the average of the two blocks (LCB, and HCB) for expats.

3.3 Water consumption and pricing data

Water consumption data can be divided into two main types. The bulk water consumption data, and monthly recorded water consumption data. The bulk water consumption data is defined as the total water supplied by the water distribution company to a network, whereas monthly consumption data is measured as the water quantity recorded by the water meter for individual property in a 30 days period. Many researchers study bulk data and only a few study monthly consumption data due to privacy or legal barriers and difficulty in collecting a representative sample size. It is more suitable to use monthly data when studying the price elasticity of demand for many reasons. In bulk data, the separation between different users is not possible. Agricultural, commercial, governmental, industrial, public service, and residential properties would be treated as similar entities. This type of analysis (using bulk data) obscures the fact that the nature of water consumption differs between these sectors.

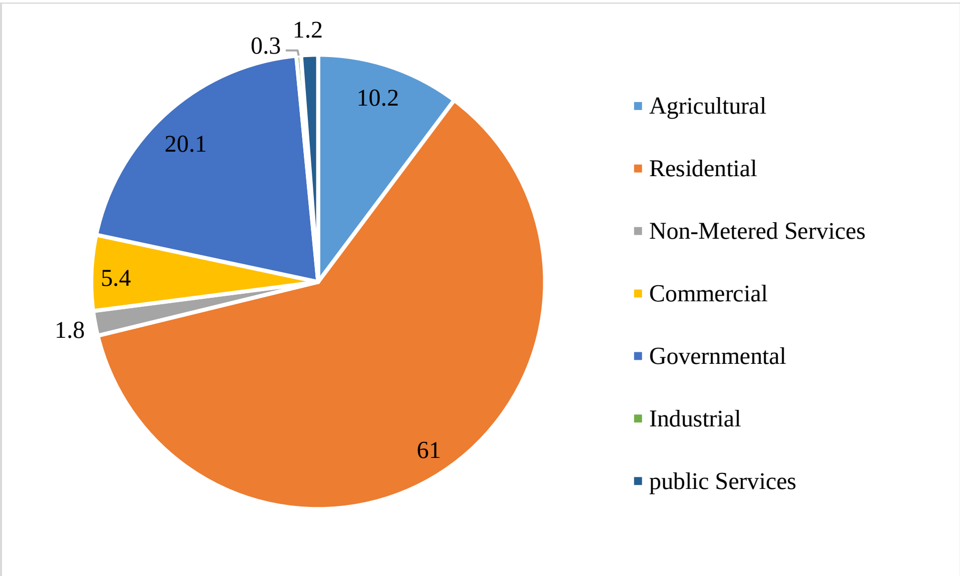


Figure 10: Average percentage of water consumption in different sectors in the Al Ain region from 1998 to 2019.

As can be seen in Figure 10 above, 61% of total water consumption is used by the residential sector, while other areas consumed about 39% of the remaining water consumption. Also, the water leakage in the Al Ain region range between 7% to 20% of total water production (*Statistical Yearbook of Abu Dhabi*, 2017; Younis, 2016). Figure 11 below shows that water consumption across the different sectors fluctuated in the Al Ain region with a steady population increase between 1998 and 2019. This percentage decrease since 2014 can be returned to the various government plans and strategies (water-saving devices, new tariffs, and others) to enhance water-saving behavior in various sectors. It is essential to consider this potential decrease in residential water consumption in any future bulk water demand analysis.

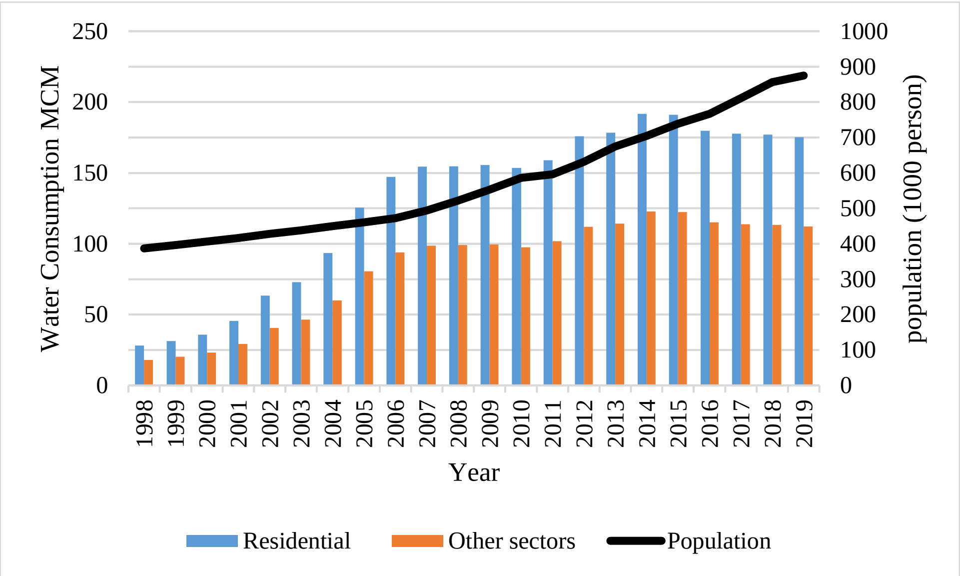


Figure 11: The water demand for residential and other sectors from 1998 to 2019 in Al Ain region (*Statistical Yearbook of Abu Dhabi*, 2017; UN DESA, 2019; Younis, 2016).

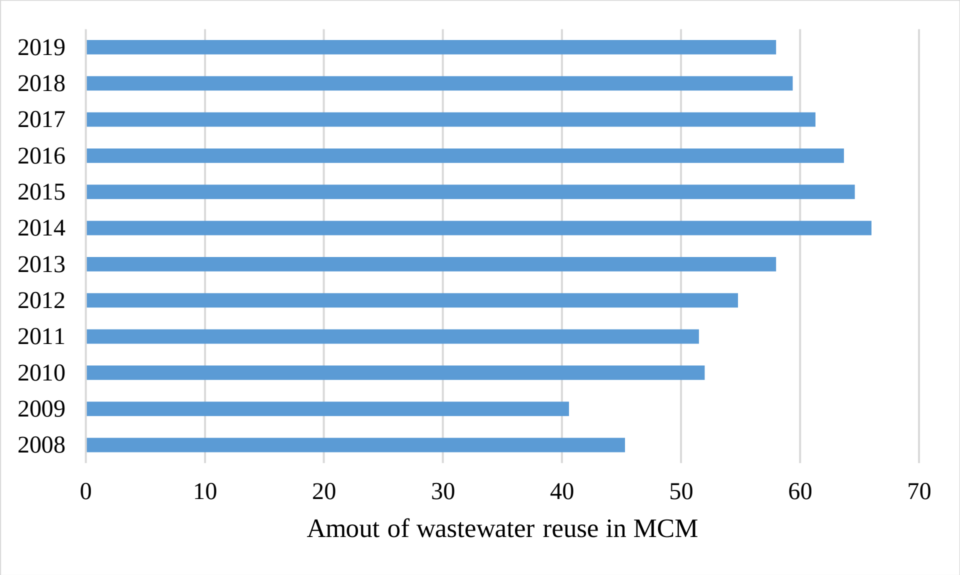


Figure 12: The amount of wastewater reuse in MCM in the Al Ain region from 2008 until 2019 (*Waste Water*, 2019; *Statistical Yearbook of Abu Dhabi*, 2017).

Moreover, a study using bulk water consumption may not take into consideration the amount of wastewater reused in different sectors. Figure 12 shows that the amount of wastewater reused increased from 45.3 MCM in 2008 to 61.3 MCM in 2017 in the Al Ain region (*Statistical Yearbook of Abu Dhabi*, 2020). Besides, the monthly consumption forecasted using bulk water data cannot be reliable because the explanatory variables will not be properly represented. Because of that, this study uses real monthly meter data reading. Nevertheless, it is important to take into consideration the reading dates, as the reading is taken at a different time each month.

Table 11 below shows the meter reading in the period between 6/12/2016 and 14/01/2017 for a certain household. There is a 12-meter reading that has been taken in the year 2017. The monthly readings are calculated based on average daily consumption. For instance, the meter reading for January was taken from two reading periods. The first reading period was between 6/12/2016 and 16/01/2017 which represent the water consumption in the first 16 days of the month. The second reading period was taken between 16/1/2016 and 15/02/2017 which represent the rest of the month. The average daily consumption calculated in the two different reading then the number of days is multiplied by the average daily consumption to calculate the amount of water consumed in January as explained in the following equation:

$$\left(16 \times \frac{43}{41}\right) + \left((31 - 16) \times \frac{29}{30}\right) = 31.3\ m^3 \tag{22}$$

Table 11: Water reading example for a household in the period of 2017.

User ID	**Last Read.**	**New Read.**	**Bill Quant. (m^3)**	**Number OF Days**
0065700931	6/12/2016	16/01/2017	43.00	41.00
0065700931	16/01/2017	15/02/2017	29.00	30.00
0065700931	15/02/2017	15/03/2017	27.00	28.00
0065700931	15/03/2017	16/04/2017	31.00	32.00
0065700931	16/04/2017	12/05/2017	22.00	26.00
0065700931	12/05/2017	19/07/2017	71.00	68.00
0065700931	19/07/2017	17/08/2017	28.00	29.00
0065700931	17/08/2017	18/09/2017	28.00	32.00
0065700931	18/09/2017	16/10/2017	23.00	28.00
0065700931	16/10/2017	15/11/2017	26.00	30.00
0065700931	15/11/2017	14/01/2018	28.00	60.00

The water bill paid by the consumer can be divided into service costs (desalination production, transmission, and distribution) and water consumption price. The desalination cost equal to 4 AED/m^3 where Transmission and supply equal to 3.5 AED/m^3 (Abu Qdais & Al Nassay, 2001; Srouji, 2017). The tariff defined by the Al Ain distribution company (AADC) has changed much time between 2014 and 2017.

Different water price allocated to residential sectors depending on three main factors:

1. Consumer nationality
2. Property type
3. Amount of consumption

The amount of consumption follows a block rate tariff where the price of water unit change depending on consumption level. It can be claimed that consumer behavior is affected by higher service costs. However, the studies show that the unit cost of desalinated water decreases in alignment with higher water production quantities (Shatat et al., 2013). Moreover, the energy consumption and accordingly the desalination unit cost has dropped dramatically through the years (Shatat et al., 2013). Thus, it is more logical to return the changes in consumer behavior to the changes in water tariff rather than the changes in service costs.

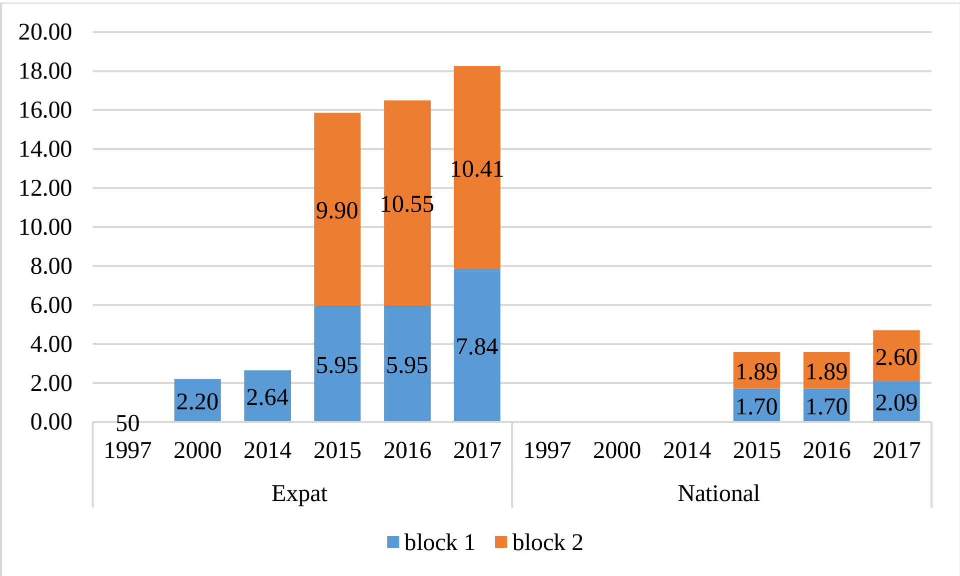


Figure 13: Water prices in Abu Dhabi region from 1997 to 2017 (Abu Qdais & Al Nassay, 2001; *Desalinated Water*, 2017; Srouji, 2017).

Figure 13 shows that for national, the water was free of charge until 2015. On the other hand, expat charges 50 AED regardless of their consumption amount until 2000. The block price tariff started in 2015 continue to increase until 2017. The second block tariff applied if the consumption exceeds 700 L/day for an apartment and 7000 L/day for a villa.

The block price tariff depends on the consumption amount which creates an endogeneity problem. The method applied by Abrams et al., 2012 can be implemented to avoid any relationship between variables and error terms. In his method, block 1 and block 2 have been selected as an instrument for the average price in the GMM model. Choosing block 1 and block 2 as instruments fit the definition of exogenous variables because they break the causal relationship between variables and error term in many water consumption models (Kumaradevan, 2013).

3.4 Obtaining identifying gaps in data of other determinants

A variety of data were collected from several sources AADC (personal communication and website), SCAD (online reports), and a survey. AADC provided meter readings, bill amounts, nationality, location, and property types for the residential sector in the Al Ain region for the years 2016 and 2017. Meter reading transformed into a monthly basis using Excel code. Then monthly bill has been recalculated dependent AADC pricing system. Data for the Al Ain region bulk water consumption and weather characteristics (temperature, rainfall, and relative humidity) were extracted directly from SCAD annual reports for the years 2016 and 2017 *Statistical Yearbook of Abu Dhabi*, 2017; 2018). The literature proposes forms of weather variables methods to be used with the selected model. These forms include the monthly average weather values (Martínez-Espiñeira, 2002), the maximum weather values (Martínez-Espiñeira, 2007), the deviation from average weather values (Abrams et al., 2012), and the weather block values (Arbues & Villanua, 2006). In this study, the average weather values will be used because of its use by many researchers and also for easy interpretation of coefficient values in the model.

After applying restriction, filtering, organizing, and filling the missing data process on AADC and SCAD data source, a survey was conducted on 500 households across Al Ain region to compile the missing data regarding property and family characteristics. The final step is data processing, which includes coding the data before it can be imported to STATA software.

3.5 The selection of households for study

Through the study period, people could change their household for many reasons. To avoid having false data, consumers that have continuous data with the same ID in 2016 and 2017 have selected to be studied. Besides, a group of selection criteria was used to ensure that the sample households used in the analysis will result in reliable and balanced panel data. The criteria used were:

- The selected households should have water consumption data in at least 20 of the 24 monthly data for the study period (years 2016 and 2017).
- The type of household should be a villa or apartment and should not change throughout the period. Some households changed due to expansion, and were designated as a villa, these were excluded from the study.

  The following restrictions have been placed to ensure that the same family uses the same household size in the entire study period.
- The consumer ID should not change from the beginning of January 2016 to the end of December 2017.

- The water consumption amount should not have a sudden decrease by the have or rise by double between meter-readings.
- The household should consume water by 0.5 m^3 at a minimum in 92% of the study period.
- Households that have a range between 2 and 19 rooms have been chosen to be included in the data set.

Moreover, the following filtration points have been applied to confirm data reliability.

- The households that have any supply source other than AADC were detached.
- The households without location have withdrawn from the data set.
- The households with a meter-reading period of more than 60 days were removed.

3.6 The use of a questionnaire to collect missing data

The data collected from AADC and SCAD need to be combined with other types of data to include all factors that have an effect on residential water consumption. The missing data have been collected through a designed phone survey distributed to 500 households as appear in appendix A below. In addition, a survey was designed to collect additional data on household characteristics relevant to this study (Table 12). The survey was distributed to selected households based on the selection criteria discussed in the previous section. The questions have been designed and tested and redesigned to collect the information with the highest possible accuracy. For instance, the exact property size question has been changed to the number of rooms, bathrooms, and kitchens when a lot of respondents reply with an arbitrary answer indicating uncertainty. Further, questions regarding swimming pool, garden, tenant, or owned and water-saving devices have been designed to yes and no questions when many respondents omit to answer these questions. Further, questions regarding swimming pool, garden, tenant, or owned and water-saving devices have been designed to yes and no questions when many respondents ignore these questions. The surveyor should consider the respondent's education, time availability, language, and his privacy. This has led to changing income questions to category type. Furthermore, simplifying many other questions and conducting the survey in English or Arabic language as an option.

Consumers' characteristics play an important role in water consumption. Generally, larger families or families that include children and elderly members consume a higher quantity of water. However, other factors that have not been examined by many researchers could affect consumer behavior. Factors such as the number of females, males, education level, and the number of family members go to work. All this information has been included in the survey question to test their contribution to the model.

Household income is one of the significant factors that are included in many water price elasticity researches. Generally, a household with a high income shows less sensitivity to a higher level of water prices. Also, substantial household income displays a higher level of consumption if compared with the households in the same year. However, a similar method to (Agthe & Billings, 2002) where people have asked about their level of income rather than the exact number they earn monthly in the survey question. The income has been divided into 4 levels as flowing:

1. First level: family earn less than 10 thousand AED
2. Second level: family earn between 11-20 thousand AED
3. Third level: family earn between 21-30 thousand AED
4. Fourth level: family earn more than 31 thousand AED

Household size, garden size, the existence of a swimming pool, and water-saving devices are essential factors in defining the level of water demand. Usually, the size of a household has the most significant effect on water consumption. People have also asked for the household size in terms of the number of rooms, bathrooms, and kitchen to ease the answer. logically, larger homes with a larger number of bathrooms tend to have a higher level of water consumption.

Table 12: Description of the key survey variables.

Variables	**Description**
Income	The total family income category (10, 11-20, 21-30, >30)
Nationality	Nationality of the family members.
Males	The number of males in the household.
Females	The number of females in the household.
Children	Number of children (age < 18) in the household
Elderly	Number of Elderly (< 60 years) in the household.
Working	The number of working family members in the household.
Higher education	Number of the family member that complete university level or higher
Rooms	The number of rooms in the household.
Bathrooms	Number of Bathrooms in the household.
Kitchens	Number of Kitchens in the household.
House age	The Household Age in years.
Tenant or owner	Type of household Owner (Dummy=0 if Tenant or Dummy=1 if Owner)
Swimming pool	Dummy=1if there is a swimming pool, =0 if otherwise.
Garden	Dummy=1 if there is Garden, =0 if otherwise.
Garden Size	The size of the Garden in square meter
Water-saving device	Dummy=1if there is a water-saving device, =0 if otherwise.

3.7 The scale and range of determinants of water consumption

The data processing went through various steps that begin with the selection stage and end with data analysis. In the data selection step, the apartment and villa data will be separated from other consumption data type. Then, restrictions criteria will be applied to select the households that have a good representation of residential consumption. This step followed by organizing the data in an excel sheet and filling the missing data from different data sources. Finally, data coding is a necessary step to prepare the data for the analysis step.

The data statistics were obtained using excel equations. Table 13 below shows all data set variables and statistical summary that has been used in the final result of the analysis procedure.

Table 13: Statistical summary for the data set.

Variable Name	**Description**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Unit**
Consumption	Daily water consumption per capita	0.02* 0.01**	9.05 7.18	0.54 0.49	0.36 0.29	m^3/day/capita
Average Price	The price paid per cubic meter	1.70 2.09	5.95 7.84	3.81 4.93	2.13 2.88	AED/ m^3
Average Temperature	The average monthly temperature	18.20 19.30	37.6 38.6	28.41 29.13	6.61 6.85	°C
Average Humidity	The average monthly relative humidity value	23.20 26.30	59.0 60.4	41.45 39.24	11.27 12.21	%
Average Rainfall	The average monthly rainfall value	0.00 0.00	83.7 50.6	9.80 8.58	22.51 14.01	mm
Number of persons	Total number of persons in the home	1.00	18.0	5.99	3.27	Person
Males	Total number of Males in the home	0.00	12.0	2.80	1.75	Person
Females	Total number of Females in the home	0.00	10.0	3.17	2.15	Person
Children	The total number of children in the home.	0.00	9.00	2.48	1.88	Person
Elders	Total number of Elders in the home	0.00	3.00	0.40	0.80	Person
Work	The total number of working family members in the home.	0.00	13.0	1.72	1.37	Person
Education	The total number of Educated family members in the home.	0.00	10.0	1.52	1.02	Person

Note:*The value in the year 2016,**The value in the year 2017 .

Table 13: Statistical summary for the data set (Continued).

Variable Name	**Description**	**Min.**	**Max.**	**Mean**	**Std. Dev.**	**Unit**
Rooms	The total number of rooms in the household.	2.00	17.0	6.29	2.86	Room
Bathroom	The total number of bathrooms in the household.	1.00	15.0	4.72	2.65	Bathroom
Kitchens	Total numbers of kitchens in the household.	1.00	5.00	1.25	0.57	Kitchen
Garden Size	Approximate garden size	0.00	240	8.63	28.1	m^2

Note:*The value in the year 2016,**The value in the year 2017 .

There are 9,600 observations for each variable in the data set. The data has 24 time period and 18 entities which categorize the data under long panel data. The households with missing values have been filtered to avoid any weakness in the data. The coding procedure was performed before analyzing the data using STATA software.

The household size varies from 2 to 17. The standard deviation for the number of rooms is 2.8 and the mean equal to 6.3 which refers to the variety of household sizes in this data set. The average per capita daily water consumption equal to 0.49 m^3 in 2017, while the average per capita daily bulk water consumption in the Al Ain region equal to 0.65 m^3 in the same year (*Statistical Yearbook of Abu Dhabi*, 2017; Younis, 2016). The average per capita daily water consumption is lower by 25% of average per capita daily bulk water consumption which illustrates the differences between bulk water consumption and real water consumption. However, the stander deviation represents 67% and 59% of the mean in 2016 and in 2017, which demonstrates the enormous difference in water consumption in the sample. This variation is expected because different household types (Villa, apartment, garden, and swimming pool) have been included in the data set.

3.8 Water consumption model

Water consumption can be affected by different types of variables. From the literature review, the following variables were classified as the most important elements that alter water consumption and can be used to model explanatory variables.

- Recorded monthly water consumption
- Water price structure
- Consumer's characteristics
- Monthly weather characteristics
- Household characteristics

The demand model for water consumption function is stated as,

$$\begin{aligned} lnC_{it} = \theta + \beta_1 P_{it} + \beta_2 VA_i \\ + \beta_3 NE_i + \beta_4 A_i + \beta_5 MT_i + \beta_6 T_t + \beta_7 TB_t + \beta_8 H_t \\ + \beta_9 HB_t + \beta_{10} R_t + \beta_{11} RB_t + \beta_{12} F_i + \beta_{13} M_i + \beta_{14} E_i \\ + \beta_{15} Ch_i + \beta_{16} W_i + \beta_{17} Ed_i + \beta_{18} G_i + \beta_{19} S_i \\ + \beta_{20} TO_i + \beta_{21} NO_i + \beta_{22} WS_i + \beta_{23} I_i + \beta_{24} M_{it} + u_{it} \end{aligned} \quad (23)$$

$$u_{it} = \eta_i + \varepsilon_{it} \quad (24)$$

Where,

C = Monthly water consumption of 'i' household in the month'''t'

θ = Equation constant value

β =Coefficient for variable x

P_{it} =average daily price for household 'i' in month 't'.

VA_i =Villa or apartment dummy variable for household 'i'.

NE_i =National or expat resident dummy variable for household 'i'.

A_i =Area dummy variable for household 'i'.

MT_i =Meter type dummy variable for household 'i'.

T_t =Temperature variable in month ‘t’.

TB_t =Temperature block dummy variable in month ‘t’.

H_t =Humidity dummy variable in month ‘t’.

HB_t =Humidity block dummy variable in month ‘t’.

R_t =Rainfall dummy variable in month ‘t’.

RB_t =Rainfall block dummy variable in month ‘t’.

F_i =Number of females in a household ‘i’.

M_i =Number of males in a household ‘i’.

E_i =Number of Elders in a household ‘i’.

Ch_i =Number of children in a household ‘i’.

W_i = Number of the working members in a household ‘i’.

Ed_i = Number of family members that have a bachelor’s degree or above in household ‘i’

G_i = Garden size for household ‘i’.

S_i = existence of swimming pool in a household ‘i’.

TO_i = Tenant or owned property dummy variable for household ‘i’

NO_i = new or old property dummy variable for household ‘i’.

WS_i = existence of water-saving-device dummy variable in a household ‘i’

I_i = Income level dummy variable for household ‘i’.

M_{it} = Month (Jan …Dec).

u_{it} = Error term.

Chapter 4: Results and Analysis

4.1 Introduction

The data analysis went through various steps to calculate the elasticity of demand and come up with an approach that describes the reality of water consumption in Al Ain region. In this chapter, the results of the analysis will be illustrated and interpreted in detail. The four types of estimation methods chosen will be discussed and influencing factors will be identified. Figure 14 below summarized the structure of this chapter.

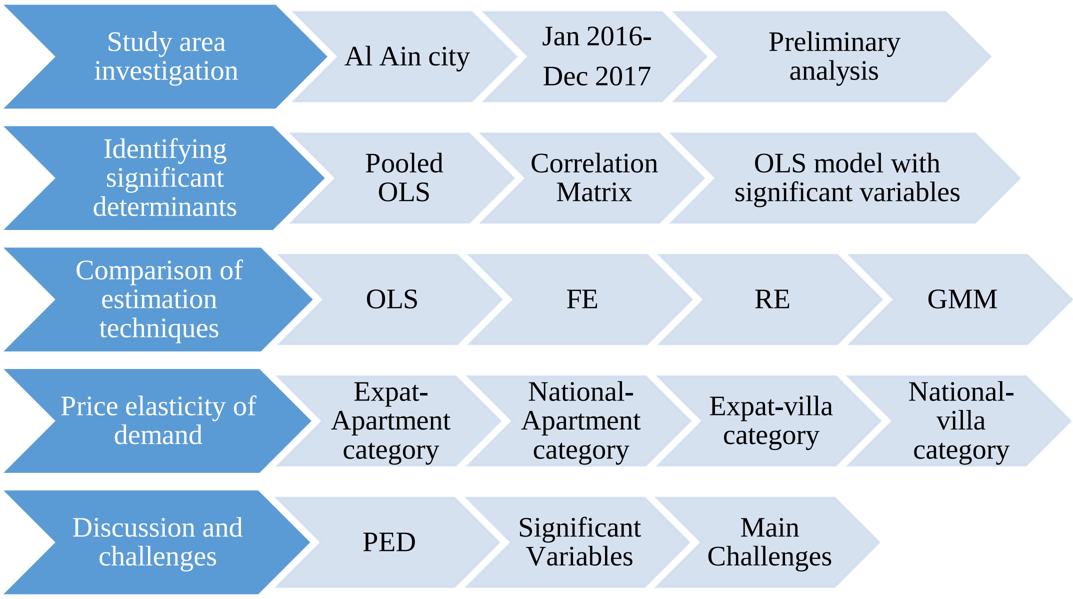


Figure 14: Summary of the structure of Chapter 4.

4.2 Results of study area investigation

A preliminary analysis displayed that the water consumption in Al Ain region decreased in 2017 compared to 2016 as shown in Figure 15. However, the corresponding average monthly bills paid by the consumers were higher in 2017 than in 2016 as shown in Figure 16. In general, the monthly values for average water consumption were higher during the summer months compared to winter months in both years, which probably drove the consumers to focus on reducing the consumption during the summer months. Therefore, the differences between monthly consumption from 2016 compared to 2017 were higher in the summer months as shown in Figure 15. For example, the first three months of 2017 showed a percentage change equal to +3%, -3%, and +1% respectively whereas the rest of the year show a higher negative percentage change that varies between -2% in April to -15% in August, October, and December. It also appears from Figure 16, that it took the consumers one billing cycle to realize the impact of the change in tariff, this is probably why the drop in the average monthly bill was not observed until February of 2017. In January 2017, the average bill paid by consumers was higher by 23% compared to the same period in 2016. The average bill paid had a percentage change that varied between +13% to +20% in the period between February to May in 2017 whereas the rest of the year have values varied between +2% in October to +7% in June, July, and August.

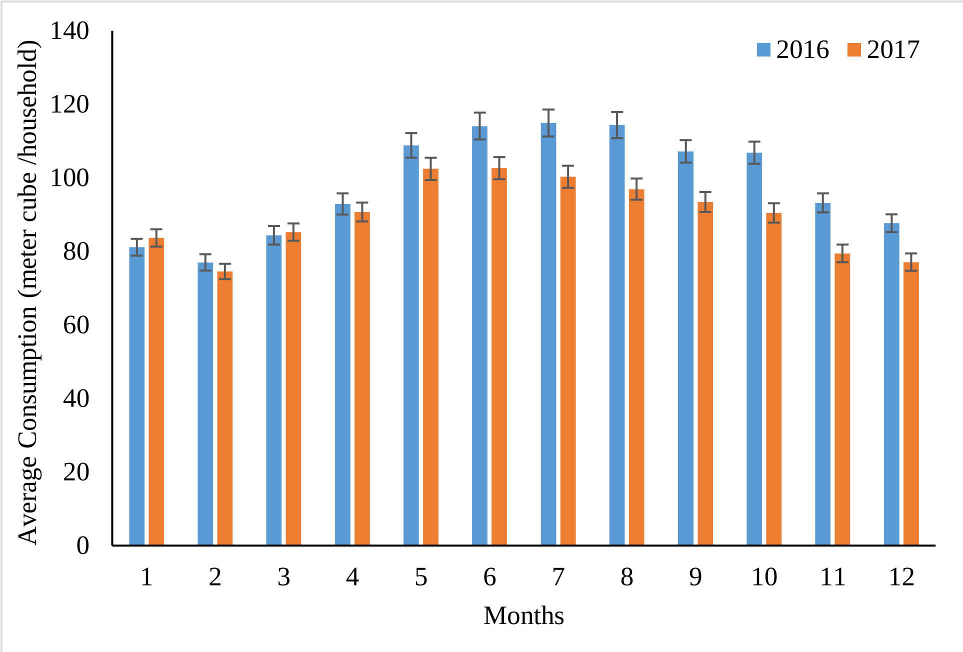


Figure 15: The total means of water consumption for 400 households from January 2016 to December 2017 in Al Ain region.

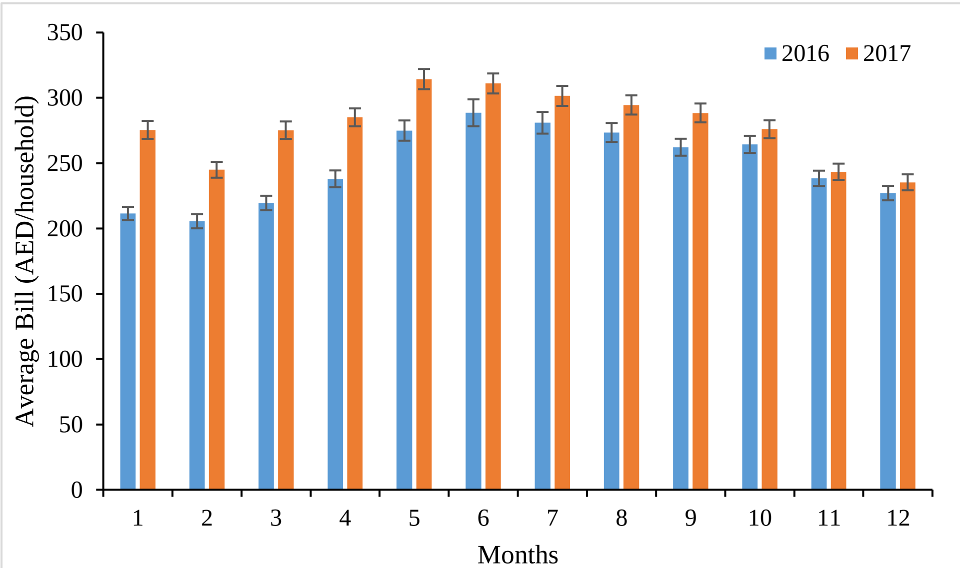


Figure 16: The total average bill paid by 400 households for water consumption from January 2016 to December 2017 in Al Ain region.

Further analysis shows that there was a considerable difference in consumption between apartments and villas as shown in Figure 17. Further, the Villas with national residents have very high consumption compared with other categories due to probable outside activities such as a large-sized garden, a swimming pool, and a small farm located within the property. Comparing the consumption based on block categories, there is on average 50.3% of monthly consumption in the Apartment category consumed in block 2 regardless of the type of resident as shown in Figure 18. On another hand, only on average 22.8% of monthly consumption in the Villa category belonged to block 2 irrespective of the resident type as illustrated in Figure 18. Besides, the percentage of expats that had their water consumption falling within block 1 level has increased in 2017 by 6% and 2% for apartment and villa categories respectively as Figure 18 shows. In contrast, the percentage of nationals living in apartments that consume within block 1 level has decreased from 64% to 25% between 2016 and 2017, whereas, the percentage of nationals living in villas and consume water within the block1 category remained the same, at 60%, in both years.

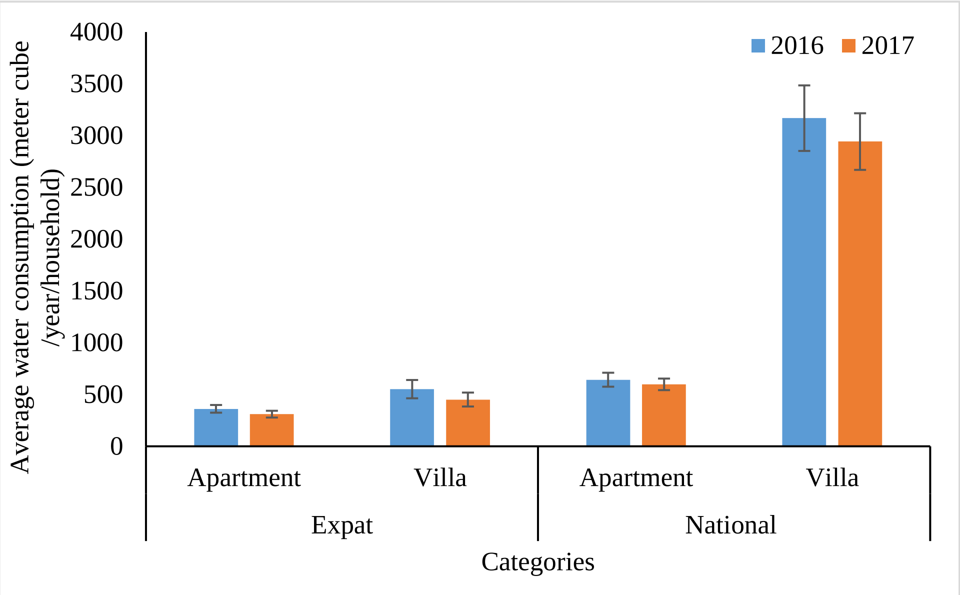


Figure 17: Comparison of the average yearly water consumption for 400 households belonging to different categories, in 2016 and 2017.

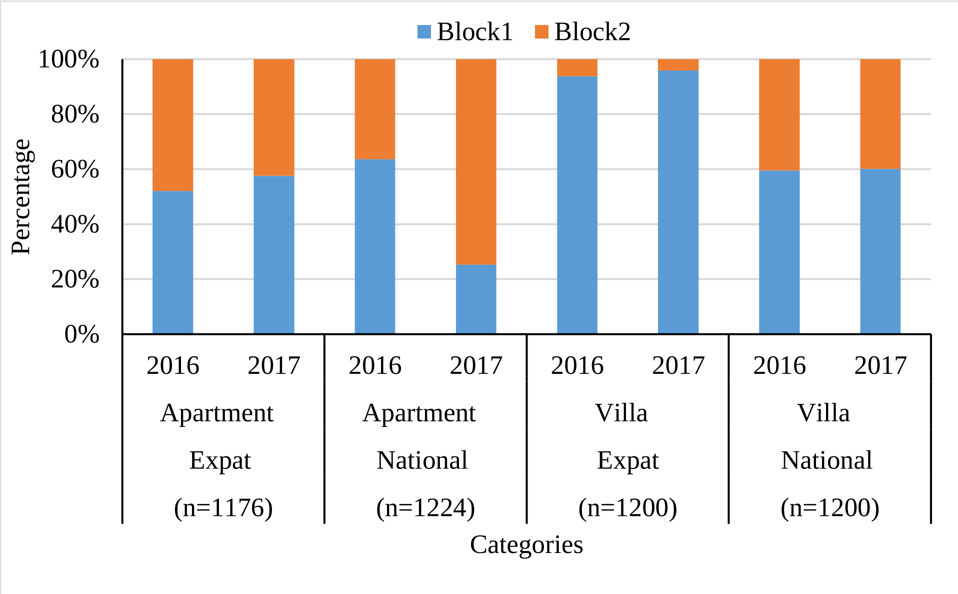


Figure 18: Percentages of monthly water consumption for each household category that belongs to Block 1 or Block 2 tariff (n=number of households × 12 months).

The distribution of households sampled in this study is shown in Table 14. In general, the city of Al Ain has a higher number of properties around the city center (districts of Wasat Al Madina, Al Jimi, Al Khibeesi, Al Mutarad, and Al Muwaiji). The households sampled in this study successfully reflected the distribution of properties. Table 1 shows that the sampled households from the districts located around the city center account for 49.1% of the total sample distribution, whereas, less dense districts such as Ain Al Fayda, Al Bateen, Al Foah, Al Maqam, and Ghireebah located in city border account for 8.1% of total sampled households. The remaining 42.8% belonged to households from other districts inside and surrounding Al Ain.

Table 14: Percentages of sampled households across different districts (n=400).

District	Pct.	District	Pct.	District	Pct.
Wasat Al Madina	11.5%	Al Masoudi	0.8%	Um Ghafa	1.0%
Ain Al Fayda	0.8%	Industrial Area	2.1%	Asharej	3.5%
Al Jimi	16.5%	Al Mutarad	6.3%	Shi'bat Al Wutah	2.3%
Al Khabisi	0.3%	Al Mutaw'ah	1.8%	Ghireebah	1.5%
Al Bateen	2.0%	Al Muwaiji	8.8%	Al Hili	3.5%
Aloha	0.3%	Al Qou'a	0.6%	Ain Al Faydah	1.0%
Ghrebah	2.0%	Al Qattarah	1.0%	Mazyad	0.3%
Al Foah	2.3%	Al Sarooj	3.0%	Nahil	0.5%
Al Hiyar	0.3%	Al Rawdah Al Sharqiyah	1.5%	Ni'mah	1.0%
Al Jahili	0.8%	Al Shiwayb	0.3%	Rimah	0.3%
Al Khibeesi	6.0%	Al Tawia	2.3%	Shiab Al Ashkhar	0.6%
Al khaznah	0.5%	Al Wiqan	0.3%	Sweihan	0.3%
Al Maqam	1.5%	Al Yahar	3.5%	Um Ghafa	0.3%
Al Markhaniya	2.5%	Al Dhahir	1.8%	Zakhir	4.8%

As mentioned earlier, the weather in the UAE has a considerable effect on water consumption. Summer months exhibit an increase in water consumption as shown in Figure 19. Data on the fluctuation in weather variables such as temperature, relative humidity, and rainfall was collected to be used as explanatory variables for changes in weather, this is consistent with previous literature (Abrams et al., 2012; Martínez-Espiñeira, 2002; Martins & Fortunato, 2007). The changes in weather cause noticeable fluctuation in water consumption particularly in households that include outdoor activities such as gardening (Schleich & Hillenbrand, 2009). Water consumption is shown to increase in the summer due to high temperatures and a decrease in rainfall events. The temperatures in the Al Ain region recorded a high of (°C) in 2016 and (°C) in 2017. Similarly, high levels of relative humidity and scarce rainfall in the two years of study contribute to water consumption as shown in Figure 19.

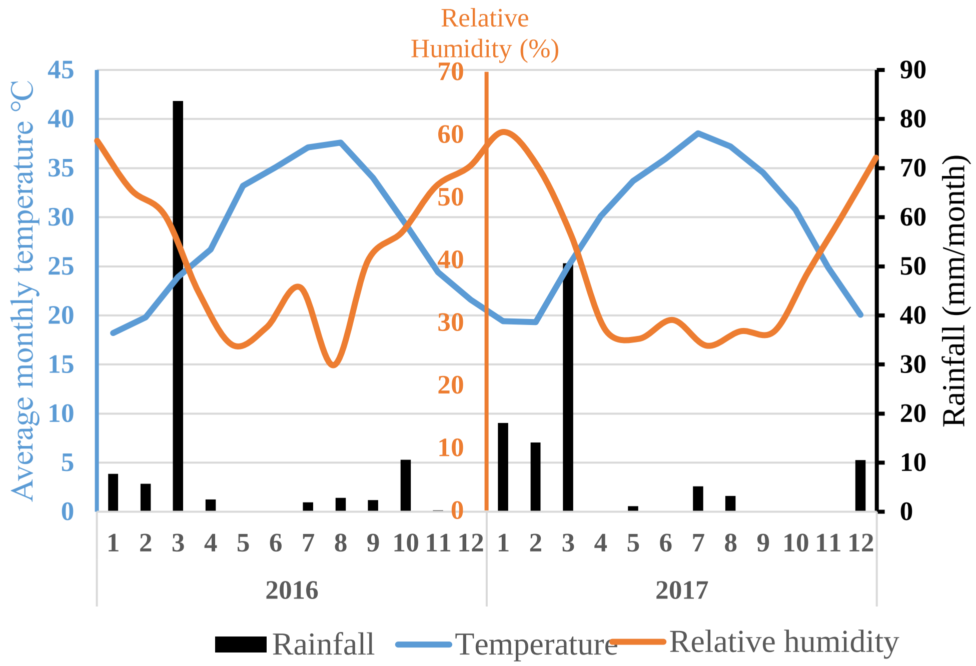


Figure 19: Monthly weather trends in Al Ain for 2016 and 2017 (FCSA, 2018; Statistical Yearbook of Abu Dhabi, 2018).

The survey also gave insights into other important household characteristics relevant to water consumption. These characteristics generally belong to demographical features such as nationality, gender, age, education level, and income level. Other characteristics represent proxy indicators to household size, such as the number of rooms and facilities in a household.

One of the key demographic characteristics that could influence water consumption is household habits (Fielding et al., 2012; Kumaradevan, 2013). It was assumed that household water consumption habits are directly related to the origin region where households develop their habits, therefore, the household’s ethnic categories were used as a proxy of the household's habit. In the sampled households, UAE nationals represented 50% of the residents of the sampled households whereas the other residents belonged to the major ethnic categories such as Arab region, Indian sub subcontinent, Southeast Asia, Western, African, and South America representing 30.3%, 6.8%, 2.8%, 3.3%, 6%, and 1% respectively. Figure 20 shows that water consumption for national's households was the highest whereas westerns have the lowest water consumption. Further, other ethnic groups show similar water consumption levels except for South America where the sample is too small to be representative.

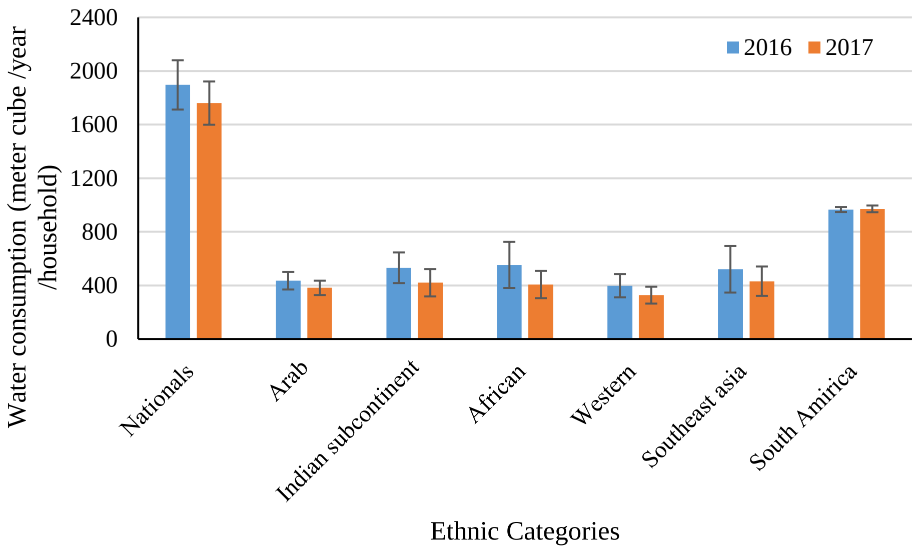


Figure 20: The average yearly water consumption for different ethnic categories in 2016 and 2017.

Figure 21 illustrates the distribution of several demographical features across the sampled households. The average number of expats per household was equal to 5 ± 3 whereas the average number of national per household was equal to 7 ± 4. From Figure 21(a) it appears that the median of the number of males in a household was 2. Similarly, there were 2 females per household in most of the sample, while 36 households had no females at all, Figure 21(b). Also, Figure 21(c) shows that there are 107 households that have 2 children whereas there are 71 households without children residents. Furthermore, there are 294 of the households' sample that has no elderly living within whereas there are 76 households that have 2 elderly living with the family. Finally, in most of the households, there is 1 working family member and at least 2 members hold a bachelor's degree or above as in Figure 21(e) and (f).

These descriptors of demographic characteristics often appear in literature to have an impact on the level of water consumption. The effect of gender on water consumption was studied by previous researchers, where there were considerable consumption differences between adults of the two genders (ages between 16 and 55 years), research results indicated that males consume more water than females (Hossain et al., 2013). Furthermore, similar research concluded that consumer age had an impact on consumption, particularly for age extremes representing elders and children (Hossain et al., 2013; Martinez-Espineira, 2003).

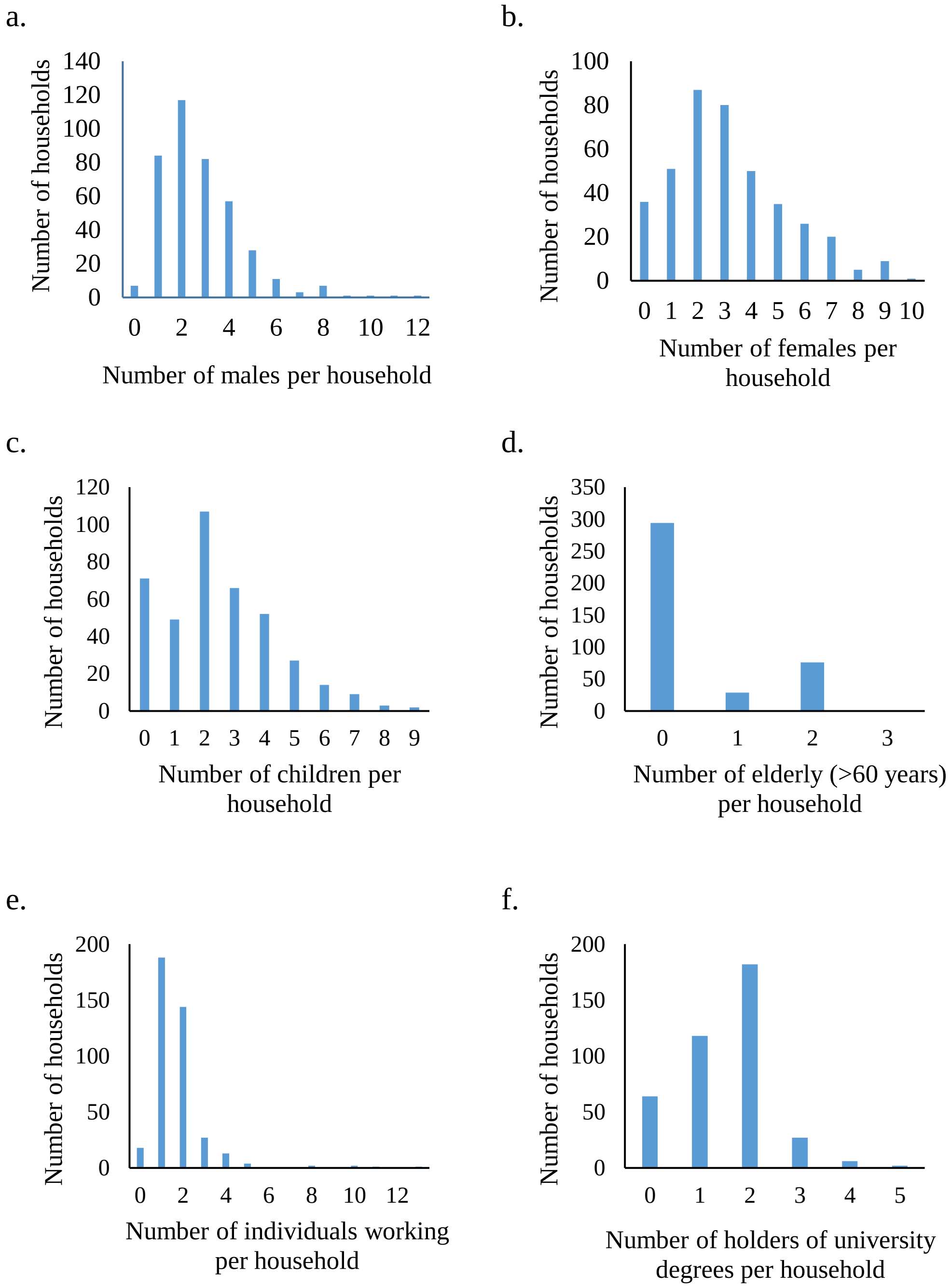
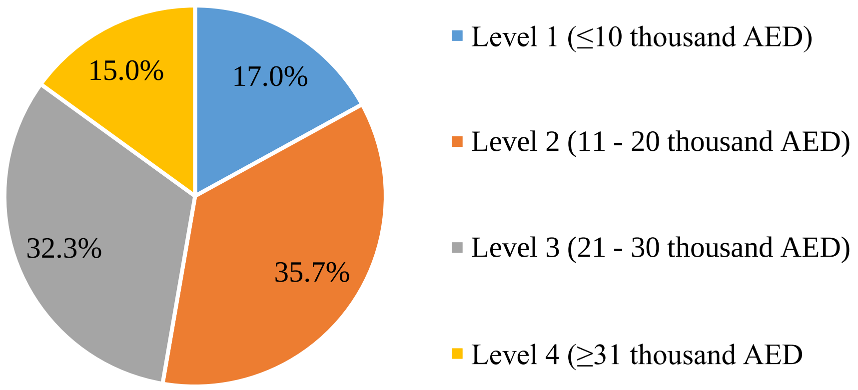


Figure 21: Results of consumer characteristics survey (n=400) (a) Males distribution (b) Females distribution (c) Children distribution (d) Elderly distribution (e) Working family members distribution (f) Distribution of Bachelor degree holder or higher.

Another key demographic feature that has a direct impact on consumption in general and water consumption in particular is that of income level (Fielding et al., 2012). The sample collected shows that around half of sampled households earned income categorized in level 1 and level 2 as Figure 22 shows. Also, 15% of the sampled households earned more than 31 thousand AED/month, and around 32% earned



between 21 to 30 thousand AED/month.

Figure 22: Percentage distribution of sample households across the four income levels (n=400).

Proxy indicators used to gauge residence size are critical in describing residential water consumption (Agthe & Billings, 2002; Mansur & Olmstead, 2012). Figure 23(a) below shows that majority of sampled apartments contain 3 to 4 rooms whereas villas contain 7 rooms. In addition, the number of bathrooms corresponds well with the number of rooms, 76 of the sampled apartments contain 3 bathrooms whereas villas contain 7 rooms (Figure 23). The majority of properties include 1 bathroom and a small percentage of households have more than 2 bathrooms (Figure 23).

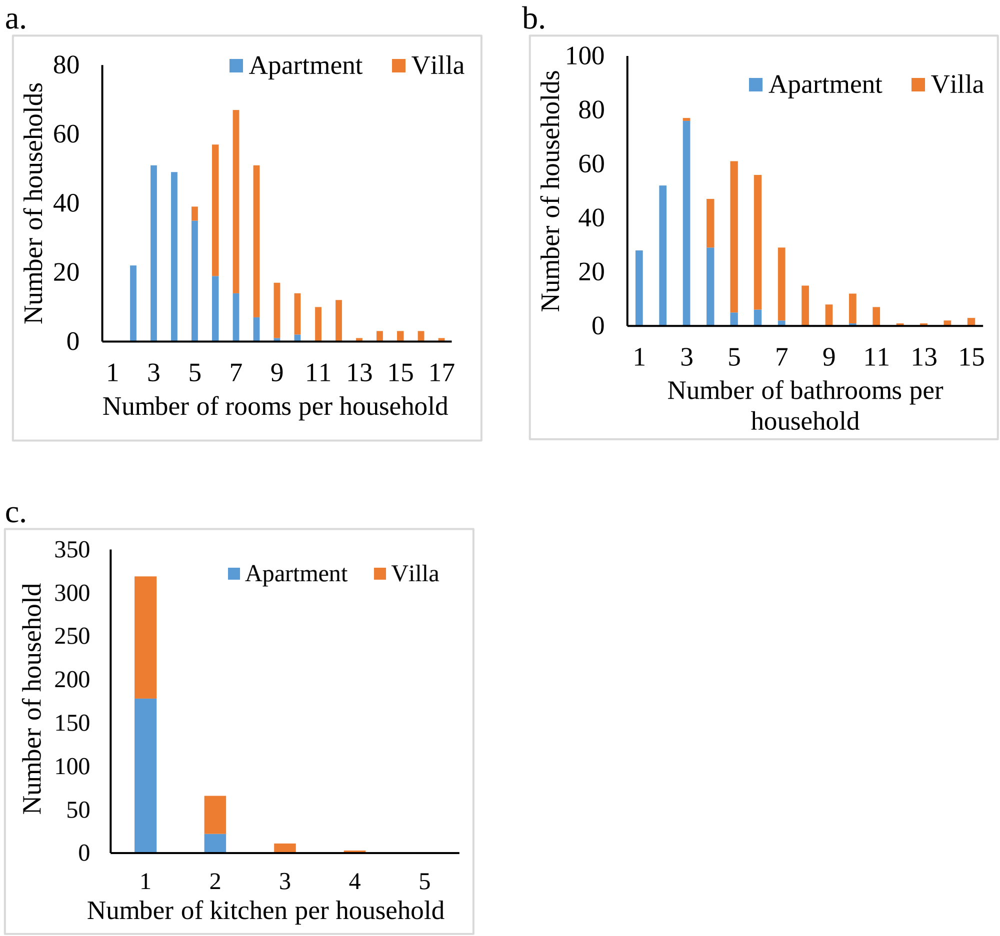
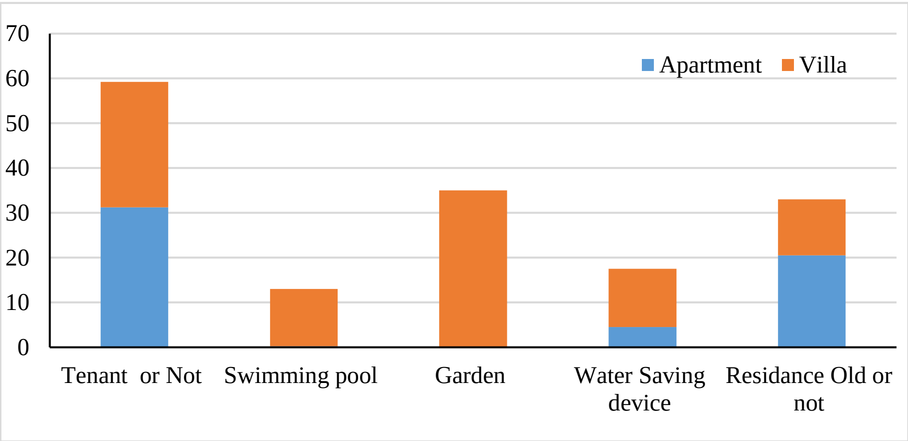


Figure 23: Results of size proxy determinants from the surveyed houses (n=400) (a) Number of rooms distribution (b) Number of baths distribution (c) Number of kitchens distribution.

In general luxury household facilities, such as larger garden size and the existence of swimming pools, will increase water consumption, whereas, water-saving devices will decrease consumption. Figure 24(a) below shows that 35% of the sampled properties contain a garden and only 12.75% contains a swimming pool. Figure 24(a) also shows that only 17.5% of households sample have installed water-saving devices. From various literature, it is expected that such saving devices would reduce water consumption (Agthe & Billings, 2002). Moreover, around 40% of the sample owns the properties they are living in and the remaining are tenants. This factor would overlap with the nationality variable since only UAE nationals can own the residential properties in Abu Dhabi Emirate. Descriptors of household size and facilities are unlikely to change with time, nevertheless, it should be included in the water consumption model to calculate their effect.

a.



b.

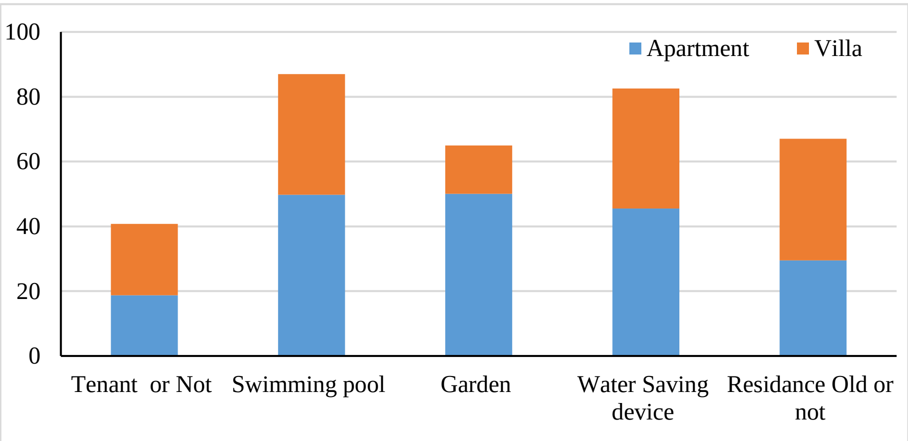


Figure 24: Distribution of property characteristics for the sampled households in percentages. (a) represents residents that have answered Yes and (b) represent residents that have answered No.

4.3 Identifying significant determinants of water consumption in Al Ain

The pooled OLS technique was used as a starting point in the estimation process to identify the most significant determinants of water consumption. An initial model was developed to include all the variables related to the potential determinants. The model is shown in Equation 25 below and the explanation of the variables used in the estimation step is given underneath. Further, the preliminary analysis for the pooled OLS result can be seen in Table 15. The model run utilized the collective characteristics of the sampled 400 households in Al Ain region over 24 periods (monthly readings for two years):

$$\begin{aligned} lnC_{it} = \alpha &+ \beta_1 lnPrice_{it} + \beta_2\, Average\ Temperature_{it} \\ &+ \beta_3\, Average\ Humidity_{it} + \beta_4\, Average\ Rainfall_{it} \\ &+ \beta_5 Income(N)_i + \beta_6 Male_i + \beta_7 Female_i \\ &+ \beta_8 Children_i + \beta_9 Elderly_i + \beta_{10} Education\ _i \\ &+ \beta_{11} Work\ _i + \beta_{12} Nationality(N)_i \\ &+ \beta_{13}\, Resident\ Type(N)_i + \beta_{14}\, Residence\ Type(N)_i \\ &+ \beta_{15}\mathrm{Residence\ Age(N)}\ _i \\ &+ \beta_{16} Residence\ Ownership(N)\ _i + \beta_{17} Rooms\ _i \\ &+ \beta_{18}\mathrm{Bathrooms}_i + \beta_{19}\mathrm{Kitchens}_i \\ &+ \beta_{20} Swimming\ pool(N)\ _i + \beta_{21}\mathrm{Garden(N)}\ _i \\ &+ \beta_{22}\mathrm{Water-saving\ device(N)}_i + u_{it} \end{aligned} \tag{25}$$

$$u_{it} = \eta_i + \varepsilon_{it} \tag{26}$$

Where,

C_{it}	= Daily average water consumption per cubic meter in month ‘t’ for household ‘i’.
C_{it-1}	= Daily average water consumption per cubic meter in month ‘t-1’ for household ‘i’.
$Price_{it}$	= Daily average price per cubic meter in month ‘t’ for household ‘i’.
$Average\ Temperature_{it}$	= The average temperature in a month ‘t’ for household ‘i’.
$Average\ Humidity_{it}$	= The average relative humidity in a month ‘t’ for household ‘i’.
$Average\ Rainfall_{it}$	= The average rainfall in a month ‘t’ for household ‘i’.

$Income\ (N)_i$	= The income level for household 'i' and N values of (1) for income ≤ 10 thousand AED. (2) for income range between 11 to 20 thousand AED. (3) for income range between 21 to 30 thousand AED. (4) for income ≥ 31 thousand AED.
$Adult_i$	= The number of Adults for household 'i'.
$Male_i$	= The number of males for household 'i'.
$Female_i$	= The number of females for household 'i'.
$Children_i$	= The number of children ≤18 years for household 'i'.
$Elderly_i$	= The number of Elderly ≥60 years for household 'i'.
$Education\ _i$	= The numbers of residents have a bachelor's degree or higher for household 'i'.
$Work\ _i$	= The numbers working family members in a household 'i'.
$Nationality\ (N)_i$	= The Residents nationality for household 'i' with (N) values equal to (1) for UAE national, (2) for Arab, (3) for Indian sub subcontinent, (4) for African, (5) for Southeast Asia, (6) for Western and (7) for South American.
$Resident\ Type\ (N)_i$	= The family in 'i' household with values of (N) equal to (1) for expat category and value of (2) for the national category.
$Residence\ Type\ (N)_i$	= The family in 'i' household with (N) value equal to (1) for apartment category and (2) for villa category.
$Residence\ Age\ (N)_i$	= The residence age for household 'i' With (N) Value equal to (1) for old and (2) for new.

$Residence\ Ownership\ (N)_i$	= The ownership of residence for household 'i' with (N) equal to (1) for the tenant and (2) for the owner.
$Rooms_i$	= The number of rooms in a household 'i'.
$Bathrooms_i$	= The number of bathrooms in a household 'i'.
$Kitchens_i$	= The number of kitchens in a household 'i'.
$Swimming\ pool\ (N)_i$	= The household 'i' with (N) value equal to (1) for having not having a swimming pool and (2) for having a swimming pool.
$Garden\ (N)\ _i$	= The family in 'i' household with (N) value equal to (1) for not having a garden and (2) for having a garden.
$Water\ saving\ device\ (N)_{it}$	= The family in 'i' household with (N) value equal to (1) for not installing water-saving devices and (2) for installing water-saving devices.
u_{it}	= Error term
η_i	= Time invariant household effect
ε_{it}	= Random noise

Table 15: The summary results for the initial comprehensive model using pooled OLS estimation technique.

Variable	**coefficient**	**std. error**	**p-value**
const	0.5986	0.2621	0.0224**
Ln Price	-0.1803	0.0266	0.0000***
Average Temperature	0.0044	0.0028	0.1228
Average Humidity	-0.0003	0.0016	0.8580
Average Rainfall	-0.0005	0.0004	0.2437
Income (1)	-0.1704	0.0304	0.0000***
Income (2)	-0.1388	0.0206	0.0000***
Income (4)	0.2819	0.0269	0.0000***
Males	0.1608	0.0076	0.0000***
Females	0.1833	0.0087	0.0000***
Children	0.0255	0.0094	0.0069***
Elderly	-0.0649	0.0126	0.0000***
Education	0.0471	0.0091	0.0000***
Work	-0.0036	0.0076	0.6350

Note:***,**,* are P-value significant at the 1%,5% and 10% level respectively where P<=0.1*,P<=0.05** and P<=0.01 ***.

Table 15: The summary results for the initial comprehensive model using pooled OLS estimation technique (Continued).

Variable	coefficient	std. error	p-value
Nationality (1)	-0.0725	0.2127	0.7333
Nationality (2)	0.1816	0.1510	0.2290
Nationality (3)	0.0985	0.1531	0.5201
Nationality (4)	0.0851	0.1531	0.5783
Nationality (5)	0.1693	0.1575	0.2825
Nationality (6)	0.1703	0.1563	0.2758
Resident Type (1)	-0.2406	0.1555	0.1217
Residence (1)	0.1734	0.0293	0.0000***
Residence Age (1)	0.0748	0.0174	0.0000***
Residence Ownership (1)	-0.3728	0.0288	0.0000***
Rooms	-0.0538	0.0113	0.0000***
Bathrooms	0.0609	0.0130	0.0000***
Kitchens	-0.1589	0.0222	0.0000***
Swimming Pool (1)	-0.3498	0.0318	0.0000***
Garden (1)	-0.8556	0.0345	0.0000***
Water Saving Devices (1)	0.1551	0.0213	0.0000***
R-squared	0.6809	-	-

Note:***,**,* are P-value significant at the 1%,5% and 10% level respectively where P<=0.1*,P<=0.05** and P<=0.01 ***.

Examining the results shown in Table 15, it appears that the property district had no significant effect on consumption, which is expected since all properties are located in the same region. In addition, high correlations exist between a number of variables (Table 16), for example, the variable “nationality” and “resident type” (Expat or National) were closely correlated, and thus only one variable was chosen to remain in the model. Similarly, the high correlation between “residence ownership” variables and “resident type” is due to the laws in the emirate where only nationals can own properties. Also, if you are an expat adult, it is most likely to be working, and since expats represent 80% of the population this resulted in a high correlation between the number of “Adult” variable and the number of working family members “Work” (Table 16).

Furthermore, there is a high negative correlation between average temperature and average humidity (Table 16). The high correlation affects the significance of the two variables. Al-Ain city is a dry area with rare rainfall events thus it is logical to find the average rainfall variable insignificant. Various temperature variables such as the monthly maximum temperature, the monthly average temperature, temperature blocks, and temperature deviation from average were individually tested against water consumption, and temperature deviation has been found to be the most representative variable to be used in the further analysis as shown in Table 16.

Finally, a high correlation was found between the number of rooms, bathrooms, and kitchens in a household (Table 16). This is supported by design facts wherein the number of bathrooms and kitchens is proportional to the number of rooms in a house. In the same manner, The correlation coefficient between the number of rooms and the number of adults was high since both indicate the household size. Finally, the existence of a garden was used instead of stipulating the garden size since the respondents were often incapable of estimating their garden size.

Table 16: The correlation Matrix for model variables.

	N	RT	TO	AT	AH	AR	NR	NB	NK	MT	TD	TB	
N	1.0												-1
RT	0.8	1											-0.8
TO	0.6	0.8	1										-0.6
AT	0.0	0.0	0	1									-0.4
AH	0.0	0.0	0	-0.9	1								-0.2
AR	0.0	0.0	0	-0.3	0.3	1							0
NR	0.2	0.2	0.4	0	0.0	0	1						0.2
NB	0.2	0.3	0.4	0	0.0	0	1.0	1					0.4
NK	0.2	0.2	0.3	0	0.0	0	0.7	0.7	1				0.6
MT	0.0	0.0	0	1	-0.9	-0.3	0.0	0.0	0.0	1			0.8
TD	0.0	0.0	0	0.7	-0.7	-0.3	0.0	0.0	0.0	0.7	1		1
TB	0.0	0.0	0	0.8	-0.7	-0.2	0.0	0.0	0.0	0.8	0.5	1	

Where N: Nationality; RT: Residential Type; TO: Tenant or Owned; AT: Average Temperature; AH: Average Humidity; AR: Average Rainfall; NR: Number of Rooms; NB: Number of Bathrooms; NK: Number of Kitchens; MT: Maximum Temperature; TD: Temperature Deviation; TB: Temperature Blocks.

The pooled OLS model has been enhanced by considering only uncorrelated factors as Equation 27 indicates. The pooled OLS technique was used by many researchers to study the price elasticity of demand on water consumption (Dhungel & Fiedler, 2014; Schleich & Hillenbrand, 2009; Kumaradevan, 2013; Martínez-Espiñeira, 2007). The results of the regression indicate that several variables had an insignificant effect. These are Humidity, rainfall, number of males, females, and working family members, nationality, residence age, residence ownership, and number of rooms, bathrooms, and kitchens. Contrarily, a summary of significant variables according to the pooled OLS results can be seen in Table 17. The F test shows that the variation in the independent variable is significant to explained variability in water consumption. The constant value can be explained as the value of water consumption when all other independent variables are equal to zero, which represents the minimum consumption to satisfy basic needs. The OLS model assumes that error variance is independent of the explanatory variable (homoscedasticity). To check this assumption, the Breusch–Pagan test is applied to the model. The test result of the P-value rejects the null hypothesis of homoscedasticity and presents heteroskedasticity in the model. The results in Table 17 show that “Price”, as expected, negatively impacts water consumption. Other variables that reduce consumption include income level 1 and 2, resident type 1, the nonexistence of swimming pool and garden, whereas variables that increase water consumption were: average temperature, income level 4, the number of adult, children, elderly, and educated residents, residence type 1 and the nonexistence of water-saving device.

$$lnC_{it} = \alpha + \beta_1 lnPrice_{it} + \beta_2\ Average\ Temperature_{it} + \beta_3 Income\ (N)_i + \beta_4 Adult_i + \beta_5 Children_i + \beta_6 Elderly_i + \beta_7 Education\ _i + \beta_8\ Resident\ Type\ (N)_i + \beta_9\ Residence\ Type\ (N)_i + \beta_{10} Swimming\ pool\ (N)\ _i + \beta_{11}\text{Garden (N)}\ _i + \beta_{12}\text{Water} - \text{saving device (N)}_i + \ u_{it} \tag{27}$$

$$u_{it} = \eta_i + \varepsilon_{it} \tag{28}$$

Table 17: The results for the refined model using pooled OLS estimation technique.

Variable	**coefficient**	**std. error**	**p-value**
Constant	0.3047	0.0561	0.0000***
Ln Price	-0.1820	0.0268	0.0000***
Average Temperature	0.0053	0.0011	0.0000***
Income (1)	-0.1447	0.0296	0.0000***
Income (2)	-0.1449	0.0203	0.0000***
Income (4)	0.2445	0.0271	0.0000***
Adult	0.1494	0.0054	0.0000***
Children	0.2045	0.0059	0.0000***
Elderly	0.0864	0.0122	0.0000***
Education	0.0347	0.0089	0.0001***
Resident Type (1)	-0.3340	0.0384	0.0000***
Residence Type (1)	0.1314	0.0204	0.0000***
Swimming Pool (1)	-0.3812	0.0312	0.0000***
Garden (1)	-0.8260	0.0325	0.0000***
Water Saving Devices (1)	0.1812	0.0205	0.0000***
R-squared	0.6693	-	-

Note:***,**,* are P-value significant at the 1%,5% and 10% level respectively where P<=0.1*,P<=0.05** and P<=0.01 ***.

4.4 Comparison of estimation techniques

Four estimation techniques were applied to Equation 27 to avoid producing biased estimates and compare results with previous research (Kumaradevan, 2013). A panel data set was constructed by pooling the household characteristics over 24 months. (Baltagi, 2016) has listed many benefits behind using panel such as measuring the effects that cannot be measured using pure cross-sectional and time-series data. The collected data is strongly balanced since all 400 households have complete data set across the 24 months (Baltagi, 2016).

Fixed Effect (FE) estimation permits individual-specific effects to be correlated with the independent variable. The individual-specific effect will be included as intercepts where each individual has its own intercept in the equation. This term is calculated to include the variation that cannot be explained by other independent variables (Allison, 2009). In other words, the technique assumes that the individual (household) effect may alter or bias the outcome and should be controlled. Estimating the net effect on the dependent variable requires eliminating the time-invariant characteristics because it cannot fit the assumption. The other important assumption of FE is that the error term and constant (that contain individual characteristics and time-invariant variables) should have an independent relationship. If there is a relationship between the error term and constant, then the FE can give false inferences and the data can be modelled with other techniques such as random-effect.

The test summary for the FE result appears in Table 18. The overall variability in consumption against time (24 months) and different households was equal to 0.3863. The major part of consumption variability was due to variability across households. The variation across households was equal to 0.4655 and variability within the individual household over the time period (24 months) was equal to 0.0193. The result of the F test (p-value less than 0.05) indicates that the model parameters differ from zero (i.e. a representative model). Moreover, the Error term, u_{it} = 0.5176, shows a correlation with the independent variable in the fixed-effect model. Moreover, The error value u_{it} shows that the FE model is appropriate to be used with this data (Xiao, 2016). The ρ (rho) which called infraclass correlation shows that 80.6% of the variance is due to the differences across panels (households). All the variables show high significance. The parameter signs were as expected to know knowledge. The water consumption increases with higher average temperature which indicates high consumption in summer compared to winter months.

The Wald test was performed for the FE model to reject the null hypothesis that assumes homoskedasticity due to contemporaneous correlation (correlation between error terms at the same time period) and the variability in standard error between different households (Groupwise heteroskedasticity).

$$lnC_{it} = \alpha + \beta_1 lnPrice_{it} + \beta_2\, Average\, Temperature_{it} + u_{it} \quad (29)$$

$$u_{it} = \eta_i + \varepsilon_{it} \quad (30)$$

Table 18: Results summary for model 3 using the fixed-effect technique.

Variables	**coefficient**	**std. error**	**p-value**
Constant	0.7957	0.1729	0.0000***
Ln Price	-0.2048	0.0205	0.0000***
Average Temperature	0.0499	0.0062	0.0000***
R-square	0.3863	-	-

Note:***,**,* are P-value significant at the 1%,5% and 10% level respectively where P<=0.1*,P<=0.05** and P<=0.01 ***.

The random effect (RE) model assumes that individual-specific effects are random (Allison, 2009). it distributed independently of the independent variable and it is included in the error term. This will result in a model where different households have equal slop and error terms. in other words, the assumption in RE is that consumption is not correlated with household variation, which makes it possible to estimate time-invariant variables. Generally, it is important to identify the variables that could or could not affect consumption to use RE correctly. This assumption may not be valid in many cases which could produce a biased estimation model. The highest advantage in the RE result is that it can be used as a generalized result where it could be applied beyond the sample that it was built on.

RE-based estimation results are shown in Table 19 and 20. Model equation (31) can explain the variability in consumption data by 65.7%, whereas the reduced model equation (33) gives a 63.5% explanation of variability. The R-square value in the model equation (33) is comparable with R-square in previous studies that have ranged between 0.30 to 0.70 (Martínez-Espiñeira, 2007; Martins & Fortunato, 2007; Schleich & Hillenbrand, 2009). Results show that the variability in consumption was mainly due to variation in household characteristics, which is similar to findings from the FE technique. Moreover, the estimated parameters were relatively close to the OLS result. All variables have expected signs with respect to their effect on water consumption. The RE assumes that the correlation between different households u_{it} and independent variables was equal to zero and the F test rejects the null hypothesis which indicates coefficients values differ from zero. The value of ρ (rho) was 0.5623 in the unrefined model equation (31) indicating that a good fraction of variance was due to the individual effect. In other words, the variability within a household is smaller than the variability between different households. Because of that, it was concluded that the preferred estimation model was OLS.

The Breusch and Pagan Lagrange Multiplier (LM) test for random effects was performed on the RE result. The null hypothesis in LM test assumes that the variance of random effect was equal to zero, where different households have equal intercept. Being unable to reject the null hypothesis means it is acceptable to estimate the parameters using pooled OLS. The LM test in the study rejects the null hypothesis which makes the random or fixed effect a possible estimation method for the data. On the other hand, the null hypothesis in the Hausman test assumes that both (FE and RE) models can be used to estimate the data parameters. The RE is assuming that the effect is orthogonal to the independent variable whereas the effect of FE is not. The null hypothesis was not rejected which indicates that RE estimation results are consistent and that it can be used to estimate the model's parameters. Finally, although the Hausman test suggested the suitability of RE or FE models, it is important to address the endogeneity problem in the data.

$$\begin{aligned} lnC_{it} = \alpha &+ \beta_1 lnPrice_{it} + \beta_2\ Average\ Temperature_{it} \\ &+ \beta_3 Income\ (N)_i + \beta_4 Adult_i + \beta_5 Children_i \\ &+ \beta_6 Elderly_i + \beta_7 Education\ _i \\ &+ \beta_8\ Resident\ Type\ (N)_i + \beta_9\ Residence\ Type\ (N)_i \\ &+ \beta_{10}\text{Residence Age(N)}\ _i + \beta_{11} Swimming\ pool\ (N)\ _i \\ &+ \beta_{12}\text{Garden (N)}\ _i + \beta_{13}\text{Water} - \text{saving device (N)}_i \\ &+\ u_{it} \end{aligned} \tag{31}$$

$$u_{it} = \eta_i + \varepsilon_{it} \tag{32}$$

Table 19: Results summary for model 4 using random effect technique.

Variables	**coefficient**	**std. error**	**p-value**
Constant	0.2296	0.2023	0.2570
Ln Price	-0.2048	0.0205	0.0000***
Average Temperature	0.0499	0.0062	0.0000***
Income (1)	-0.1881	0.1149	0.1020
Income (2)	-0.1872	0.0784	0.0170**
Income (4)	0.3562	0.1018	0.0000***
Adult	0.1464	0.0211	0.0000***
Children	0.1989	0.0231	0.0000***
Elderly	0.1249	0.0465	0.0070***
Education	0.0117	0.0342	0.7320
Resident Type (1)	-0.2700	0.0790	0.0010***
Residence Type (1)	0.0745	0.0781	0.3400
Residence Age (1)	0.0452	0.0669	0.4990
Swimming pool (1)	-0.6051	0.1096	0.0000***
Garden (1)	-0.6212	0.1088	0.0000***
Water Saving Device (1)	0.1595	0.0794	0.0450**
R-square	0.6570	-	-

Note:***,**,* are P-value significant at the 1%,5% and 10% level respectively where P<=0.1*,P<=0.05** and P<=0.01 ***,The rho = 0.5623.

$$
\begin{aligned}
lnC_{it} = \alpha + \beta_1 lnPrice_{it} + \beta_2\ Average\ Temperature_{it} \\
+ \beta_3 Income\ (N)_i + \beta_4 Adult_i + \beta_5 Children_i \\
+ \beta_6 Elderly_i + \beta_7 Swimming\ pool\ (N)\ _i \\
+ \beta_8 \text{Garden (N)}\ _i + \beta_9 \text{Water} - \text{saving device (N)}_i \\
+\ u_{it}
\end{aligned} \tag{33}
$$

$$
u_{it} = \eta_i + \varepsilon_{it} \tag{34}
$$

Table 20: Results for model 5 using random effect techniques.

Variables	**coefficient**	**std. error**	**p-value**
Constant	-0.6787	0.0999	0.0000***
Ln Price	-0.2429	0.0190	0.0000***
Average Temperature	0.0054	0.0008	0.0000***
Income (1)	-0.2664	0.0954	0.0052***
Income (2)	-0.1890	0.0740	0.0107**
Income (4)	0.2683	0.1006	0.0077***
Adult	0.1677	0.0189	0.0000***
Children	0.1899	0.0205	0.0000***
Elderly	0.1008	0.0441	0.0223**
Swimming pool (2)	0.3662	0.1153	0.0015***
Garden (2)	0.8086	0.1187	0.0000***
Water Saving Device (2)	-0.2079	0.0753	0.0058***
R-square	0.6358	-	-

Note:***,**,* are P-value significant at the 1%,5% and 10% level respectively where P<=0.1*,P<=0.05** and P<=0.01 ***.

The GMM model can provide a better estimation when an endogeneity problem exists, this results from correlations such as that between the water price and the amount of water consumed. Moreover, the first lag of consumption generally has a high correlation with the history of consumption. To solve such a problem, an ‘xtabond2’ command in Stata software was used. The result summary for the two-step difference GMM technique is shown in Table 21. The function can handle the data of nature similar to the one under this study (400 houses analyzed over 24 periods). The ‘xtabond2’ function was used to analyze the following situations in the data:

1. N>>T where N is the number of households (400) and T is the time periods (24).
2. Linear relationship.
3. Current consumption is affected by consumer consumption history.
4. Endogeneity between variables.
5. Standard error variability over time (heteroskedasticity).
6. Autocorrelation between observation (OLS assumes independence of observation).

$$lnC_{it} = \alpha + \beta_1 lnPrice_{it} + \beta_2\ Average\ Temperature_{it} +\ u_{it} \tag{35}$$

$$u_{it} = \eta_i + \varepsilon_{it} \tag{36}$$

Table 21: Results summary for model 6 using a two-step difference GMM technique.

Variables	**coefficient**	**std. error**	**p-value**
Ln Price	-0.2047	0.0644	0.0020***
Average Temperature	0.0499	0.0077	0.0000***
Number of instruments	3.0000	-	-
F (3, 400)	38.080	-	-
Prob > F	0.0000	-	-

Note:***,**,* are P-value significant at the 1%,5% and 10% level respectively where P<=0.1*,P<=0.05** and P<=0.01 ***.

The ‘noleveleq’ and ‘xtabond2’ options in STATA can be used to perform a one-step difference GMM, two-step difference GMM, one-step system GMM, and two-step system GMM. The difference between difference GMM and System GMM is that difference GMM alters endogeneity through handling all regressors thru differencing and remove fixed effect while system GMM modifies endogeneity by including a high number of instrument and change the instrument to exogenous ones with fixed effects (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998). Generally, it is standard to use two-step procedures to produce a more efficient GMM estimator and improve the associated tests (Hwang & Sun, 2018). Choosing the correct model between difference and system GMM can enhance the consistency and efficiency of the model. There are two rules of thumb to choose between difference and system GMM. The first rule is that the closer the parameter of the lag of consumption is to one indifference GMM, the higher the bias and the lower the efficiency level in the model, and it would thus be better to perform the system GMM (Blundell & Bond, 1998). Moreover, the parameters for the lag of consumption in OLS and FE can be used as upper-bound and lower-bound for a lag of consumption in difference GMM. The second rule of thumb is that if the coefficient of consumption lags in difference GMM is closer to lower-bound, then the model is downward biased (weak instrument) and it is better to perform System GMM (Bond et al., 2001). Table 22 summarizes the result for lag estimation coefficients.

Table 22: Summarized result for the first lag of consumption in a different method

Estimators	**Coefficients**
Pooled OLS	0.8384
Fixed Effects	0.6265
One-step Diff. GMM	0.6223
Two-step Diff. GMM	0.7197
One-step System GMM	0.6931
Two-step System GMM	0.7204

As can be seen from Table 22 that the system GMM and difference GMM give very similar results. The estimation result for the two-step difference GMM with the first lag of consumption can be seen in Table 23. There is a noticeable similarity between FE results and GMM. All the parameters' coefficients have the expected signs. The time-invariant variables were omitted from the model because the difference between the current value and previous values for the same variable will be zero. This procedure will not affect the coefficient estimation for another coefficient of independent variables (Roodman, 2009).

$$lnC_{it} = \alpha + \beta_1 C_{it-1} + \beta_2 lnPrice_{it} + \beta_3\ Average\ Temperature_{it} + \ u_{it} \quad (37)$$

$$u_{it} = \eta_i + \varepsilon_{it} \quad (38)$$

Table 23: The results for model 7 of the two-step difference GMM technique including the first lag of consumption.

Variables	**coefficient**	**std. error**	**p-value**
Constant	0.6873	0.1054	0.0000***
First lag of consumption	0.7205	0.0289	0.0000***
Ln Price	-0.1840	0.0256	0.0000***
Average Temperature	0.0225	0.0046	0.0000***
Number of instrument	27	-	-
F (3, 400)	2031.7	-	-
Prob > F	0.0000	-	-

Note:***,**,* are P-value significant at the 1%,5% and 10% level respectively where P<=0.1*,P<=0.05** and P<=0.01 ***.

Table 24 below summarizes the system GMM results. First, the number of households (N) is larger than the time-span (T). Moreover, an instrumental variable was used to solve the endogeneity problem. Also, the instrument exogenous with error term where the null hypothesis for the Hansen J – test with value 0.005 shows that the instrument used in this model was valid. The F test rejects the null hypothesis which indicates that the regressors used are jointly significant. Besides, The value for AR(2) shows that there is no autocorrelation problem in the data. Finally, the number of instruments used is less than the number of households.

Table 24: System GMM results

Month dummies	Yes
Number of observations	9200
N/T	400/23
Groups/Instruments	400/27
AR(2)	0.262
Hansen statistics	0.005
F statistics	2031.7

4.5 Price elasticity of demand for water in Al Ain

The log-log interpretation (price elasticity of demand) for OLS results was equal to -0.1820. This can be interpreted as for every 1% increase in price, the water consumption amount would decrease by 0.1820 % when all other variable remains at the same level as shown in Table 17. This also means that the higher water price did not lead to effective consumption reduction in the short run. The long-run value that includes the first lag of consumption was equal to -0.1631/(1-0.7561)= -0.6687 which implies a low variability between consumption periods. In the same manner, the consumption lag can be explained as price elasticity where if the consumption increases by 1% in the previous month, it will result in decreasing consumption by 0.67% in the next month keeping all variables at the same level (Appendix B). On the other hand, the price coefficient in the short-run for the FE model was equal to -0.2048 (Table 18) which can be interpreted as a higher impact of price on consumption compared with the coefficient obtained from the OLS. Contrarily, the long-run price coefficient was equal to -0.5510 which implies low variability between consecutive consumption periods (Appendix B).

The price coefficient for the RE model in the short-run was -0.2429 (Table 19) exhibiting an even higher impact of price on consumption than that estimated using OLS and FE. The long-run price coefficient was -0.6687 which indicates higher variability to consumption period compared with FE. The 95% confidence interval includes the OLS value in the RE model (Appendix B). This can be because the OLS technique ignores variation in consumption that cannot be explained by the independent variables whereas RE assumes the unexplained variation to be random (suggests a complete exogenous model). On the other hand, the FE add this variation from different household as a constant amount to the intercept.

The price coefficient for the two-step difference GMM model in the short-run has a value of -0.2047 which is close to the FE result (Table 21). It could be interpreted that a price increase of 1%, results in a decrease of 0.2047% on average. The long-run price coefficient in the model that includes lag of consumption was -0.6402 which implies lower variability between consumption periods compared to FE (Appendix B).

A comparison between the price elasticity for different resident types (expat vs. national) and residence types (apartment vs. villa) shows that an increase in price by 1% for an expat living in an apartment would decrease the consumption by 0.23% (Table 25). In general, an expat’s water consumption is estimated to decrease by 0.21% compared with a UAE national whose reduction in consumption is estimated at 0.16% for each 1% increase in price (Table 25). Another important comparison was made between households that have different income levels. Table 25 shows a decrease in the effect of tariff changes on reduction in consumption with higher income levels, it can be noted that the higher the income the less influence of price change on consumption.

Overall, the Expat-Apartment category shows higher price elasticity due to the lower-income level, higher tariff rate, and smaller consumption limit in block 1. Compared with PEDs that were calculated by Srouji, 2017, the price elasticities in this study are smaller (Table 25); this could be due to consumer adaptation to earlier water price changes in 2015. Contrarily, an increase in water price by 1% was estimated to decrease the water consumption for a UAE national living in an apartment by 0.18% which is more than that estimated by Srouji (2017). Reduction in water consumption in villas was estimated to be as high as 0.19% for Expats and as low as 0.11% for UAE nationals. These values were lower than those reported by Srouji (2017), however, their study did not consider other significant factors that could affect consumer behavior as much as price changes.

Table 25: Price elasticity for different consumption category.

Consumption category	**This study**	**Srouji, 2017**
Expat-Apartment	-0.23	-0.34
National-Apartment	-0.18	-0.14
Expat-villa	-0.19	-0.33
National-villa	-0.11	-0.31
Expat	-0.21	-
National	-0.16	-
Apartment	-0.22	-
Villa	-0.18	-
Income level 1	-0.31	-
Income level 2	-0.29	-
Income level 3	-0.21	-
Income level 4	0.47	-

4.6 Discussion

This research surveyed households to collect data rather than relying on the proxy of bulk water data to obtain better results and understand water consumption behavior in the residential sector. The first research goal was to find factors that significantly affect residential water consumption. The significant variables were summarized in Table 20.

The price elasticity using the four estimation techniques ranged between -0.243 to -0.170 for the semi-log models which indicated that water consumption is rather priced inelastic. The results are comparable with (Schleich & Hillenbrand, 2009) and (Mansur & Olmstead, 2012) who found price elasticity of water consumption in a semi-log model was equal to -0.230 and -0.326 respectively. Additionally, the value of price elasticity in the long-term varies between -1.039 to -0.551 using the four estimation techniques. These values are higher than the short-term values which coincide with several previous studies (e.g. Arbúes et al., 2004; Martínez-Espiñeira, 2007; Musolesi & Nosvelli, 2007; Nauges & Thomas, 2003). The price inelasticity may due to the small share of water cost in the total household expenditure. This is true in many high-income countries compared with other lower-income countries in the region. Another reason behind the inelasticity of consumption to water prices observed in this study could be attributed to the impact of earlier water tariff changes that occurred in 2015 and the consumer adaptation to these tariff changes over the past years. Other researchers attribute the inelasticity in water consumption to the continuing government subsidy (reaching between 65.8% to 72.5% in 2015) for the high-income UAE nationals which discourages the consumer to value water for its real cost (*New slabs, rates for water, electricity for 2015*, 2014; Srouji, 2017).

The price elasticity of demand was found to be greater among expats in Al Ain compared with nationals (Table 25). This can be attributed to the higher tariff rate for the expats which encourages them to reduce their water consumption. The lower water tariff for the UAE nationals may have caused the lower price elasticity and higher water consumption. The effect of lower water consumption limit (block 1) can be observed to appear clearly in the higher price elasticity for the apartment category compared with villas (Table 25). The price coefficient is even a significant positive value for high-income levels (level 4) and a gradually decreasing significant negative coefficient for other income levels (Table 25). This coincides with finding from a study in Cyprus which found that higher water prices are more effective with low-income households (Hajispyrou et al., 2002). Moreover, households with higher incomes are likely to consume more water than those with lower incomes. The same result was found by (Arbúes et al., 2004) where a semi-log model was used to investigate price and income elasticity in the city of Zaragoza, Spain. (Schleich & Hillenbrand, 2009) suggested that a higher consumption that correlates with greater income households is a result of consuming water through complementary commodities such as gardens, sauna, dishwashers, and swimming pools. This is mainly because the share of water expenditure will be more tolerated in households that have higher incomes (Arbués et al., 2003). Moreover, similar empirical data from a survey on residential water demand showed an inelasticity of water demand against income variation and coefficients lower than one for income variables, which agrees to findings of this research (Worthington & Hoffman, 2008).

The household demographic factors all had a positive significant effect on water consumption. Consumption was estimated to be positive for the adults, children, and elderly respectively (Table 20). This result is confirmed with the reported average water consumption in the Abu Dhabi region which reached 1.10 m^3/day/capita (*Statistical Yearbook of Abu Dhabi*, 2017). Moreover, empirical data in previous studies indicate the significant positive effect of family size on household water consumption (Arbúes et al., 2004; Mansur & Olmstead, 2012; Martins & Fortunato, 2007; Worthington & Hoffman, 2008). In addition, other studies found that households that contain younger people have higher levels of consumption (Martinez-Espineira, 2003; Mazzanti & Montini, 2006; Nauges & Thomas, 2000). This mainly was attributed to frequent laundry runs and excessive water usage in outdoor leisure activities (Nauges & Thomas, 2000). In contrast, the elderly have lower per capita water consumption compared to adults as shown by previous studies referring to their lower consumption (Martinez-Espineira, 2003; Martínez-Espiñeira, 2002; Martins & Fortunato, 2007; Mazzanti & Montini, 2006). Other studies argued that older people use more water because they spend a longer time at home and their health issues may lead them to use the bathroom frequently whereas children use less water in hygiene and washing compared with adults (Schleich & Hillenbrand, 2009).

As expected, the existence of a garden and a swimming pool was found to have a significantly positive (increase) impact on water consumption, whereas the existence of a water-saving device has a significantly negative impact. These results are compatible with the results found in the literature. Similarly, the average ambient temperature had a significantly positive effect on residential water consumption (increases). Although Most previous researches show similar results for the temperature effect (Martinez-Espineira, 2003; Martínez-Espiñeira, 2002, 2007; Martins & Fortunato, 2007), Arbues and Villanua, 2006 found that water consumption would decrease by 1.39% for temperatures higher than 18°C in Zaragoza city, Spain because residents stayed outside the city in the summer and there is a significant outdoor activity which is not the case in Al Ain region. Contrarily, the relative humidity and rainfall had an insignificant effect on water consumption. This may be due to rare rainfall events in the region and the dominance of the temperature effect among weather variables. The temperature effect was highest for UAE nationals living in villas compared with other groups which are similar to the findings of previous studies indicating that high-income households are the only category affected by climate variation (Martinez-Espineira, 2003).

This can be explained by the expected increase in water consumption for maintaining gardens and swimming pools that probably exist in high-income villas. This result is also supported by other researchers who found that affluent households consume more water compared with others (Harlan et al., 2009; Kowalski & Marshallsay, 2005).

Chapter 5: Conclusions and Implications

5.1 Introduction

Water consumption in the UAE has reached high levels because of government subsidy and arid weather conditions. The new water price policies were implemented to reduce water consumption to an acceptable level and achieve sustainability. Few studies in the region take water price elasticity of demand into consideration. Most studies rely on bulk water data where the variability between households was neglected. This study went beyond the norm to study the influence of consumer and household characteristics, price changes, and weather variables on water consumption.

5.2 Research outcomes

Panel data for water consumption and other factors were individually recorded for 400 households in Al Ain region for the period between January 2016 to December 2017. Four techniques: OLS, FE, RE, and GMM were used to estimate the coefficients of independent variables and compare their results. A refined regression model was obtained to demonstrate the relationship between the significant independent variables and water consumption, which can be expressed as:

$$\begin{aligned} lnC_{it} = \alpha &+ \beta_1 lnPrice_{it} + \beta_2\ Average\ Temperature_{it} \\ &+ \beta_3 Income\ (N)_i + \beta_4 Adult_i + \beta_5 Children_i \\ &+ \beta_6 Elderly_i + \beta_7 Swimming\ pool\ (N)\ _i \\ &+ \beta_8 \text{Garden (N)}\ _i + \beta_9 \text{Water} - \text{saving device (N)}_i \\ &+\ u_{it} \end{aligned} \tag{39}$$

$$u_{it} = \eta_i + \varepsilon_{it} \tag{40}$$

The OLS estimation results showed highly significant coefficients at a 5% significance level. The Breusch–Pagan test is applied to the OLS model. The test result of the P-value rejects the null hypothesis of homoscedasticity and presents heteroskedasticity in the model. The fixed effect estimation results showed highly significant coefficients at a 5% significance level. The independent variables had the expected signs except for the time-invariant variables, which were omitted from the FE model.

The employed estimation methods FE and GMM were limited in evaluating the time-invariant variables. A proposed solution to this issue can be to collect a higher number of household samples and categorize them into segments. Each segment contains several households that have similar characteristics. For example. households that have a similar number of family members, similar property size, and a similar level of income would be pooled in the same segment.

5.3 Research implications and challenges

Few studies have looked into details of the factors that have a significant effect on water consumption in the UAE. This research studied, in particular, the impact of price changes on water consumption. Moreover, it gives a deeper insight into the factors that have a more significant effect on lowering water usage in the UAE. Also, it gives the stakeholders the tools to build good strategies to lower water consumption. It also allows them to examine the effect of their decisions based on the regression equations and forecasting applied in this research.

Several difficulties were encountered during this study, the main difficulty was in obtaining reliable meter readings. Meter readings were taken on different dates and cover different periods. Some houses would have 4 readings a year whereas others have 12 readings a year (monthly readings). However, this is common in large cities, and researchers are thus forced to ignore this reading variability and assume even distribution of the reading amount across the time periods to be able to analyze the data. This kind of irregular data makes it hard to formulate a pre-set code to calculate monthly water consumption for households. In addition, it makes it difficult to connect the selected variables with consumption periods to examine the time effect on both variables simultaneously. This challenge was addressed by creating a code that reads the different periods and transforms them into monthly consumption. It was also necessary to limit the sample to houses that have at least 20 readings.

Another issue was choosing the appropriate form to represent the different variables. There is a wide range of selection procedures for each stage in this research. Figure 25 summarizes the range of options for each different modelling component. Generally, choosing the appropriate component depends on the type of available data, research objectives, time frame for the study, and nature of the study area. These are the four main factors that could affect the selection procedure.

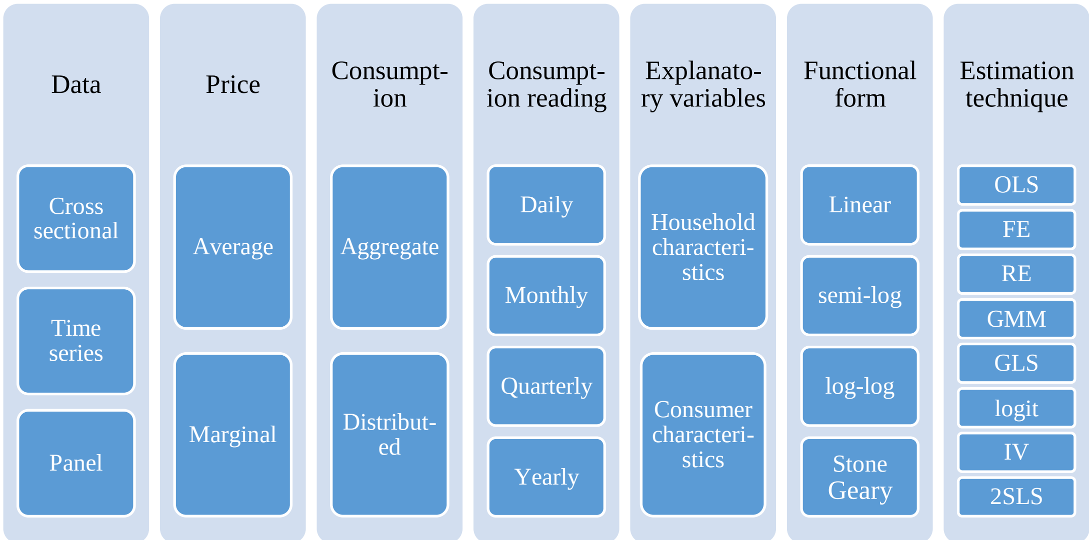


Figure 25: A summary of the available options in investigating water consumption

Besides, one of the study limitation related to the data acquisition, while structured interviews helped overcome this data accessibility, the small sample size (400 houses) could give weak relationships and misrepresent the population leading to misleading results. In addition, surveys have inherent challenges and limitations due to the inconsistency in the measures applied to collect the data. For example, if an important question was not properly understood, then the answer would probably be not representative. Also, surveys are difficult to conduct in a multicultural country like the UAE where the language barrier represents a real challenge in data collection. Finally, there are only a few detailed studies on this topic in the UAE and this made it difficult to compare the results with previous research.

Finally, privacy issues with data collection through surveys and consumption data from the distribution company. Since the survey was voluntary, several respondents were not comfortable to give information that they deemed confidential. To overcome this problem, the survey questions were changed to be more generalized and categorical rather than being specific. One problem that remained unresolved is that respondents could have still given an incorrect answer because of their inability to assess some property characteristics such as the number of people living in the house or the size of the garden.

5.4 Policy implications

Cooperation between water distribution companies and research centers is essential to achieve more reliable results in assessing the impact of pricing on water consumption. For example, household characteristics, consumer characteristics could be routinely collected using a survey distributed through the company’s payment channel. Detailed data for water consumption would then be available for researchers through an online platform. The UAE government has established bayan as a governmental data platform, but the data on the portal is more of a summary rather than detailed data that can be used as a basis for research.

Ultimately, an effective water pricing policy should achieve equality between the different consumers and enhance the overall country's welfare. This can be done if the price structure takes into consideration the different consumer segments. A proposed study could come up with a dynamic price system that changes according to consumer characteristics. This dynamic structure can consider factors such as luxury amenities, family size, income level, etc. The idea can be studied and required data can be provided through the cooperation with the water distribution companies and their new smart metering initiative that is being implemented throughout the country.

5.5 Future research direction

The non-Pricing tools such as Engineering solution, Education and awareness reduces the water consumption in different places (Cominola et al., 2015; *DEWA Installs 595,755 Smart Water Meters*, 2018; Lee et al., 2011; Strong & Goemans, 2014; Turner et al., 2012). The evaluation of long term evaluation the non-pricing tools is still ambiguous and further assessment is needed. This would discourage a wider adaptation for such tools. Thus, a platform that include water provider, governmental authorities and researchers are essential to improve the assessment of different water management tools. Besides, this would also enhance the researchers' results focused on determinants that lead to better water-saving behaviours.

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Appendices

Appendix A

Meter #:

This questionnaire is designed to collect information about your household characteristics to improve water service plans. The collected information will be used to analyze the factors influencing water consumption. The results will guide the government's efforts to in reducing household water demand.

(Note: In order to protect the privacy of individuals, no names or any other similar information are requested)

Indicator	**Unit**	**Question**	**Response**
Nationality of tenants	Nationality	What is the nationality of household residents?	
Monthly Household Income	AED/month	What is your estimation for the household member average income?<10 , 11-20 , 21-30 , >30	
Total number of persons in households	Persons	What is the total number of persons in the household?	
Number of Males	Persons	How many male in the household?	
Number of Females	Persons	How many females in the household?	
Children less than 18 years	Persons	How many children (<18) in the household?	
Elderly more than 60 years	Persons	How many Elderly (more than 60 years) in household?	
Number of working family members	Persons	How many members are working in the household?	
People with higher education degrees	Persons	How many members carry higher education in the household?	
Number of household rooms	#	How many rooms in the house hold?	
Number of household bathrooms	#	How many bathrooms in the household?	
Number of household kitchens	#	How many Kitchens in the household?	

House age	Years	Could you estimate the household age in years?	
Tenant or owner	Y/N	Are you owner or tenant?	
Has swimming pool	Y/N	Do you have swimming pool or not in your household?	
Has garden	Y/N	Do you have garden in your household or not?	
If Yes, what is the size of green area	M^2 or m by m	Can you estimate the green area in meters?	
Water saving devices	Y/N	Do you have water saving device in your household? Ex: efficient showerheads, automatic faucet... etc.	

رقم العداد :

تم تصميم هذا الاستبيان لجمع معلومات حول خصائص منزلك لتحسين خطط خدمة المياه. سيتم استخدام المعلومات التي تم جمعها لتحليل العوامل التي تؤثر على استهلاك المياه. ستوجه النتائج جهود الحكومة لإدارة أفضل لقطاع توزيع المياه (ملاحظة: حرصا على خصوصية الأفراد لا يتم طلب أسماء الأفراد أو أي معلومة مشابهة أخرى).

العوامل	الوحدة	السؤال	الإجابة
جنسية ساكني المنزل	الجنسية	ماهي جنسية ساكني المنزل	
الدخل الشهري للمنزل	درهم \ الشهر	ماهو تقديرك لمتوسط دخل الفرد؟ <10 , 11-20 , 21-30 , >30	
العدد الإجمالي للأفراد في المنزل	أفراد	كم يبلغ العدد الإجمالي للأفراد في المنزل ؟	
عدد الرجال	أفراد	كم يبلغ العدد الإجمالي للرجال في المنزل ؟	
عدد النساء	أفراد	كم يبلغ العدد الإجمالي للنساء في المنزل ؟	
عدد الأطفال الذين تقل أعمارهم عن 18 عاما	أفراد	كم يبلغ العدد الإجمالي للأطفال في المنزل الذين تقل أعمارهم عن 18 سنة ؟	
عدد كبار السن الذين تتجاوز	أفراد	كم يبلغ العدد الإجمالي لكبار السن في المنزل الذين تزيد أعمارهم عن 60 سنة	

أعمارهم 60 عاما			
عدد الأفراد الذين يعملون في المنزل	أفراد	كم يبلغ عدد الأفراد المنخرطين في سوق العمل في المنزل؟	
عدد الأفراد الحاصلي على درجات التعليم العالي	أفراد	كم يبلغ عدد الأفراد الحاصلين على درجات التعليم العالي في المنزل ؟	
عدد غرف المنزل	عدد #	كم يبلغ عدد الغرف في المنزل ؟	
عدد الحمامات في المنزل	عدد #	كم يبلغ عدد الحمامات في المنزل ؟	
عدد المطابخ في المنزل	عدد #	كم يبلغ عدد المطابخ في المنزل ؟	
عمر التقديري للمنزل	سنين	كم يبلغ العمرالتقديري للمنزل ؟	
ملك أو إيجار	نعم \ لا	هل أنت مستأجر ؟	
إمتلاك حمام سباحة	نعم \ لا	هل يوجد حمام سباحة في المنزل	
إمتلاك حديقة	نعم \ لا	هل يوجد حديقة في المنزل ؟	
أذا كان الجواب نعم ، حجم المساحة المزروعة في الحديقة	متر مربع أو مترx متر	كم تبلغ حجم المساحة المزروعة في الحديقة بالمتر المربع ؟	
أجهزة توفير المياه	نعم \ لا	هل تمتلك أيا من أجهزة توفير المياه في المنزل ؟ مثال: رشاشات موفرة للمياه، صنبور مياه يعمل بشكل أوتوماتيكي (الأستشعار)....إلخ	

Appendix B

Model 1: Pooled OLS, using 9598 observations
Included 400 cross-sectional units
Time-series length: minimum 22, maximum 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.598632	0.262095	2.284	0.0224	**
LnAveragePricePerDay	−0.180336	0.0265653	−6.788	<0.0001	***
AverageTemperature_oC	0.00438650	0.00284251	1.543	0.1228	
Average_Humidity	−0.000287314	0.00160634	−0.1789	0.8580	
Avarage_Rainfall_mm	−0.000483687	0.000414875	−1.166	0.2437	
DIncome_1	−0.170371	0.0304112	−5.602	<0.0001	***
DIncome_2	−0.138798	0.0206176	−6.732	<0.0001	***
DIncome_4	0.281915	0.0269014	10.48	<0.0001	***
Numbe_Males	0.160751	0.00764451	21.03	<0.0001	***
Numbe_Females	0.183295	0.00873034	21.00	<0.0001	***
Children_18_years	0.0254757	0.00942707	2.702	0.0069	***
Elderly_More_60_years	−0.0648758	0.0126457	−5.130	<0.0001	***
Num_Higher_Education	0.0471434	0.00908389	5.190	<0.0001	***
Number_Working_Family	−0.00361366	0.00761116	−0.4748	0.6350	
DC_Nationality_1	−0.0724757	0.212680	−0.3408	0.7333	
DC_Nationality_2	0.181649	0.150993	1.203	0.2290	
DC_Nationality_3	0.0985112	0.153146	0.6433	0.5201	
DC_Nationality_4	0.0850895	0.153056	0.5559	0.5783	
DC_Nationality_5	0.169263	0.157493	1.075	0.2825	
DC_Nationality_6	0.170343	0.156302	1.090	0.2758	
DResidential_Type_1	−0.240649	0.155478	−1.548	0.1217	
DHoushold_Type_1	0.173361	0.0293245	5.912	<0.0001	***
DHouse_Age_1	0.0747767	0.0173826	4.302	<0.0001	***
DTenant_Owner_1	−0.372761	0.0288067	−12.94	<0.0001	***
Num_Rooms	−0.0538013	0.0112834	−4.768	<0.0001	***
Num_Bathrooms	0.0608536	0.0129701	4.692	<0.0001	***
Num_Kitchens	−0.158897	0.0221703	−7.167	<0.0001	***
DSwimming_Pool_1	−0.349764	0.0318149	−10.99	<0.0001	***
DGarden_1	−0.855573	0.0345457	−24.77	<0.0001	***

DWater_Saving_Devices_1	0.155142	0.0212660	7.295	<0.0001	***

Mean dependent var	0.263842	S.D. dependent var	1.273216
Sum squared resid	4964.912	S.E. of regression	0.720353
R-squared	0.680867	Adjusted R-squared	0.679900
F(29, 9568)	703.9041	P-value(F)	0.000000
Log-likelihood	−10455.67	Akaike criterion	20971.34
Schwarz criterion	21186.41	Hannan-Quinn	21044.29
rho	0.831842	Durbin-Watson	0.324032

Model 2: Pooled OLS, using 9598 observations
Included 400 cross-sectional units
Time-series length: minimum 22, maximum 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.304721	0.0560713	5.435	<0.0001	***
LnAveragePricePerDay	−0.181962	0.0268437	−6.779	<0.0001	***
AverageTemperature_oC	0.00531207	0.00110944	4.788	<0.0001	***
DIncome_1	−0.144695	0.0296349	−4.883	<0.0001	***
DIncome_2	−0.144907	0.0203444	−7.123	<0.0001	***
DIncome_4	0.244542	0.0271426	9.010	<0.0001	***
Adult	0.149363	0.00541547	27.58	<0.0001	***
Children_18_years	0.204519	0.00593869	34.44	<0.0001	***
Elderly_More_60_years	0.0864180	0.0121722	7.100	<0.0001	***
Num_Higher_Education	0.0347429	0.00894235	3.885	0.0001	***
DResidential_Type_1	−0.333964	0.0384409	−8.688	<0.0001	***
DHoushold_Type_1	0.131359	0.0203780	6.446	<0.0001	***
DSwimming_Pool_1	−0.381174	0.0312159	−12.21	<0.0001	***
DGarden_1	−0.826034	0.0325476	−25.38	<0.0001	***
DWater_Saving_Devices_1	0.181206	0.0205401	8.822	<0.0001	***

Mean dependent var	0.263842	S.D. dependent var	1.273216
Sum squared resid	5144.293	S.E. of regression	0.732676
R-squared	0.669337	Adjusted R-squared	0.668854
F(14, 9583)	1385.581	P-value(F)	0.000000
Log-likelihood	−10626.00	Akaike criterion	21281.99
Schwarz criterion	21389.53	Hannan-Quinn	21318.47

rho	0.837701	Durbin-Watson	0.312757

Stata Code

```
  ___  ____  ____  ____  ____ (R)
 /__    /   ____/   /   ____/
___/   /   /___/   /   /___/   16.0   Copyright 1985-2019 StataCorp LLC
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Notes:
      1.  Unicode is supported; see help unicode_advice.
      2.  Maximum number of variables is set to 5000; see help set_maxvar.

. use "C:\Users\bara alrefai\OneDrive\Thesis\data file\first attampt.dta"

. import delimited "C:\Users\bara alrefai\OneDrive\Thesis\New data\STATA.csv", clear
(45 vars, 9,600 obs)

. gen deta1= ym( year , month )

. format %tmNN/CCYY deta1

. xtset id deta1
       panel variable:  id (strongly balanced)
```

```
        time variable:  deta1, 01/2016 to 12/2017

                delta:  1 month


. gen lag1_lncon= lnconsumption[_n-1]

(1 missing value generated)

. regress lnconsumption lnavaregeprice adtemp adult children_18_years
elderly_more_60_years num_higher_education expat app swim_no garden_no wsaving_no old
incom1 incom2 incom4 jan feb mar apr may jun jul aug sep oct nov dec

note: jun omitted because of collinearity


      Source |       SS           df       MS      Number of obs   =     9,598
-------------+----------------------------------   F(26, 9571)     =    706.54
       Model |  10228.4111        26  393.400426   Prob > F        =    0.0000
    Residual |  5329.08465     9,571  .556794969   R-squared       =    0.6575
-------------+----------------------------------   Adj R-squared   =    0.6565
       Total |  15557.4957     9,597  1.62107906   Root MSE        =    .74619


--------------------------------------------------------------------------------------
        lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------------+---------------------------------------------------------------
       lnavaregeprice |  -.1729733   .0274729    -6.30   0.000    -.2268259   -.1191207
               adtemp |    .026773   .0178009     1.50   0.133    -.0081205    .0616665
                adult |   .1465704   .0056019    26.16   0.000     .1355895    .1575513
    children_18_years |   .2003178   .0061982    32.32   0.000      .188168    .2124676
elderly_more_60_years |   .1249555   .0123368    10.13   0.000     .1007727    .1491383
 num_higher_education |    .011886   .0090745     1.31   0.190     -.005902    .0296739
                expat |  -.3120501    .039724    -7.86   0.000    -.3899175   -.2341827
                  app |    .072492   .0207262     3.50   0.000     .0318641    .1131198
              swim_no |  -.6119875   .0294044   -20.81   0.000    -.6696264   -.5543486
            garden_no |  -.5882756   .0358546   -16.41   0.000    -.6585583    -.517993
           wsaving_no |   .1604656   .0210662     7.62   0.000     .1191714    .2017598
                  old |   .0434981    .017755     2.45   0.014     .0086946    .0783016
               incom1 |  -.1819256   .0306545    -5.93   0.000    -.2420149   -.1218363
               incom2 |   -.185439   .0208083    -8.91   0.000    -.2262276   -.1446504
               incom4 |   .3604669   .0271206    13.29   0.000     .3073047    .4136291
                  jan |  -.0731094   .0563937    -1.30   0.195     -.183653    .0374343
```

```
                feb |  -.0781515   .0563777    -1.39   0.166    -.1886637    .0323606

                mar |  -.0569508   .0518742    -1.10   0.272    -.1586352    .0447337

                apr |  -.0224951   .0415296    -0.54   0.588    -.1039018    .0589116

                may |   .0115338   .0394764     0.29   0.770    -.0658483    .0889159

                jun |          0  (omitted)

                jul |  -.0345842   .0448829    -0.77   0.441    -.1225641    .0533958

                aug |  -.0489849   .0451342    -1.09   0.278    -.1374576    .0394877

                sep |   .0081762   .0443901     0.18   0.854    -.0788377    .0951901

                oct |  -.0080765   .0446531    -0.18   0.856     -.095606    .0794529

                nov |  -.0205398   .0571115    -0.36   0.719    -.1324905    .0914109

                dec |  -.0709899   .0510329    -1.39   0.164    -.1710252    .0290453

              _cons |   .3768843   .1640972     2.30   0.022      .055219    .6985496

------------------------------------------------------------------------------------

. regress lnconsumption lag1_lncon lnavaregeprice adtemp adult children_18_years
elderly_more_60_years num_higher_education expat app

> swim_no garden_no wsaving_no old incom1 incom2 incom4


      Source |       SS           df       MS      Number of obs   =     9,597

-------------+----------------------------------   F(16, 9580)     =   3905.93

       Model |  13489.5751        16  843.098445   Prob > F        =    0.0000

    Residual |  2067.85098     9,580  .215850833   R-squared       =    0.8671

-------------+----------------------------------   Adj R-squared   =    0.8669

       Total |  15557.4261     9,596  1.62124074   Root MSE        =     .4646


------------------------------------------------------------------------------------

        lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]

----------------------+-------------------------------------------------------------

           lag1_lncon |   .7560901   .0061466   123.01   0.000     .7440415    .7681387

       lnavaregeprice |  -.1630819   .0170321    -9.57   0.000    -.1964685   -.1296953

               adtemp |   .0265317    .005748     4.62   0.000     .0152643     .037799

                adult |    .038112   .0035977    10.59   0.000     .0310598    .0451643

   children_18_years |   .0540678   .0040385    13.39   0.000     .0461514    .0619842

elderly_more_60_years |   .0304018   .0077196     3.94   0.000     .0152696    .0455339

 num_higher_education |    .001346   .0056508     0.24   0.812    -.0097308    .0124227

                expat |   .0944983   .0248767     3.80   0.000     .0457348    .1432618

                  app |   .0414751   .0129079     3.21   0.001     .0161729    .0667773

              swim_no |  -.1531958    .018684    -8.20   0.000    -.1898203   -.1165713
```

```
           garden_no |  -.1599111   .0225938    -7.08   0.000    -.2041997   -.1156225
          wsaving_no |   .0409386   .0131524     3.11   0.002     .0151572      .06672
                 old |   .0110893   .0110583     1.00   0.316    -.0105873    .0327659
              incom1 |  -.0717567   .0191083    -3.76   0.000     -.109213   -.0343004
              incom2 |  -.0559863   .0129986    -4.31   0.000    -.0814663   -.0305063
              incom4 |   .1078339   .0170105     6.34   0.000     .0744898    .1411781
               _cons |   .0028287   .0536989     0.05   0.958    -.1024326    .1080899
------------------------------------------------------------------------------------
```

```
. regress lnconsumption lnavaregeprice adtemp adult children_18_years
elderly_more_60_years num_higher_education expat app swim_no garden_no wsaving_no old
incom1 incom2 incom4

      Source |       SS           df       MS      Number of obs   =     9,598
-------------+----------------------------------   F(15, 9582)     =   1224.08
       Model |   10222.673        15  681.511534   Prob > F        =    0.0000
    Residual |  5334.82272     9,582  .556754615   R-squared       =    0.6571
-------------+----------------------------------   Adj R-squared   =    0.6566
       Total |  15557.4957     9,597  1.62107906   Root MSE        =    .74616


------------------------------------------------------------------------------------
       lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------------+--------------------------------------------------------------
      lnavaregeprice |  -.1726376   .0273538    -6.31   0.000    -.2262569   -.1190183
              adtemp |   .0499709    .009226     5.42   0.000      .031886    .0680559
               adult |   .1465731   .0056017    26.17   0.000     .1355926    .1575535
   children_18_years |   .2003144    .006198    32.32   0.000     .1881651    .2124637
elderly_more_60_years |   .1249536   .0123363    10.13   0.000     .1007718    .1491354
 num_higher_education |   .0118794   .0090742     1.31   0.191    -.0059079    .0296668
               expat |  -.3124562   .0395954    -7.89   0.000    -.3900716   -.2348408
                 app |   .0724932   .0207255     3.50   0.000     .0318669    .1131195
             swim_no |  -.6119797   .0294033   -20.81   0.000    -.6696164    -.554343
           garden_no |    -.58831   .0358523   -16.41   0.000    -.6585881   -.5180319
          wsaving_no |   .1604736   .0210654     7.62   0.000     .1191809    .2017662
                 old |   .0435042   .0177542     2.45   0.014     .0087022    .0783061
              incom1 |  -.1819019   .0306533    -5.93   0.000    -.2419889    -.121815
              incom2 |  -.1854417   .0208075    -8.91   0.000    -.2262288   -.1446546
              incom4 |   .3604698   .0271196    13.29   0.000     .3073096      .41363
               _cons |   .1829126   .0862063     2.12   0.034     .0139301    .3518952
```

```
------------------------------------------------------------------------------

. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lnconsumption

         chi2(1)      =    77.66
         Prob > chi2  =   0.0000

. xtreg lnconsumption lnavaregeprice adtemp adult children_18_years
elderly_more_60_years num_high
> er_education expat app swim_no garden_no wsaving_no old incom1 incom2 incom4, fe
note: adult omitted because of collinearity
note: children_18_years omitted because of collinearity
note: elderly_more_60_years omitted because of collinearity
note: num_higher_education omitted because of collinearity
note: expat omitted because of collinearity
note: app omitted because of collinearity
note: swim_no omitted because of collinearity
note: wsaving_no omitted because of collinearity
note: old omitted because of collinearity
note: incom1 omitted because of collinearity
note: incom2 omitted because of collinearity
note: incom4 omitted because of collinearity

Fixed-effects (within) regression               Number of obs     =      9,598
Group variable: id                              Number of groups  =        400

R-sq:                                           Obs per group:
     within  = 0.0193                                         min =         22
     between = 0.4655                                         avg =       24.0
     overall = 0.3863                                         max =         24
```

```
                                                F(3,9195)          =      60.46
corr(u_i, Xb)  = 0.5176                         Prob > F           =     0.0000

------------------------------------------------------------------------------------
       lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------------+--------------------------------------------------------------
      lnavaregeprice |  -.2048134   .0204959    -9.99   0.000      -.24499   -.1646369
              adtemp |   .0499284    .006169     8.09   0.000     .0378357    .0620211
               adult |          0  (omitted)
    children_18_years |          0  (omitted)
elderly_more_60_years |          0  (omitted)
 num_higher_education |          0  (omitted)
               expat |          0  (omitted)
                 app |          0  (omitted)
             swim_no |          0  (omitted)
           garden_no |  -.6824561   .1801886    -3.79   0.000    -1.035666   -.3292465
          wsaving_no |          0  (omitted)
                 old |          0  (omitted)
              incom1 |          0  (omitted)
              incom2 |          0  (omitted)
              incom4 |          0  (omitted)
               _cons |   .7956737    .172933     4.60   0.000     .4566867    1.134661
---------------------+--------------------------------------------------------------
             sigma_u |  1.0177075
             sigma_e |  .49888717
                 rho |  .80625476   (fraction of variance due to u_i)
------------------------------------------------------------------------------------
F test that all u_i=0: F(399, 9195) = 72.23                 Prob > F = 0.0000

. estimates store fixed

. xttest3

Modified Wald test for groupwise heteroskedasticity
```

```
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (400)  =   3.4e+05

Prob>chi2 =      0.0000

. xtreg lnconsumption lnavaregeprice adtemp adult children_18_years
elderly_more_60_years num_high

> er_education expat app swim_no garden_no wsaving_no old incom1 incom2 incom4, re

Random-effects GLS regression                   Number of obs     =      9,598

Group variable: id                              Number of groups  =        400

R-sq:                                           Obs per group:

     within  = 0.0193                                         min =         22

     between = 0.7696                                         avg =       24.0

     overall = 0.6570                                         max =         24

                                                Wald chi2(15)     =    1466.48

corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000

------------------------------------------------------------------------------

        lnconsumption |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

----------------------+-------------------------------------------------------

       lnavaregeprice |  -.2035438   .0204116    -9.97   0.000    -.2435499   -.1635377

               adtemp |   .0499528   .0061681     8.10   0.000     .0378636     .062042

                adult |   .1463977   .0211192     6.93   0.000     .1050049    .1877905

   children_18_years |   .1989013   .0230903     8.61   0.000     .1536451    .2441574

elderly_more_60_years |   .1248951      .0465     2.69   0.007     .0337569    .2160334

 num_higher_education |     .01174   .0342172     0.34   0.732    -.0553245    .0788045

                expat |  -.2700253   .0790439    -3.42   0.001    -.4249485    -.115102

                  app |   .0745033   .0780541     0.95   0.340    -.0784799    .2274866

              swim_no |   -.605069   .1095867    -5.52   0.000    -.8198551    -.390283
```

```
           garden_no |  -.6212107   .1087647    -5.71   0.000    -.8343856   -.4080358
          wsaving_no |   .1595195   .0794331     2.01   0.045     .0038336    .3152055
                 old |   .0451871   .0668584     0.68   0.499    -.0858529     .176227
               incom1 |  -.1881423   .1148908    -1.64   0.102    -.4133242    .0370396
               incom2 |  -.1872095    .078372    -2.39   0.017    -.3408159   -.0336032
               incom4 |   .3561679   .1018412     3.50   0.000     .1565628     .555773
                _cons |   .2296006   .2023473     1.13   0.257    -.1669927     .626194
---------------------+----------------------------------------------------------------
             sigma_u |  .56544456
             sigma_e |  .49888717
                 rho |  .56229084   (fraction of variance due to u_i)
--------------------------------------------------------------------------------------
--

. estimates store random

. xttest0

Breusch and Pagan Lagrangian multiplier test for random effects

        lnconsumption[id,t] = Xb + u[id] + e[id,t]

        Estimated results:
                         |       Var     sd = sqrt(Var)
                ---------+-----------------------------
                lnconsu~n |   1.621079       1.273216
                        e |   .2488884       .4988872
                        u |   .3197275       .5654446

        Test:   Var(u) = 0
                             chibar2(01) = 33666.00
                          Prob > chibar2 =   0.0000

. hausman fixed random
```

```
                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------+----------------------------------------------------------------
lnavaregep~e |   -.2048134    -.2035438       -.0012696        .0018567
      adtemp |    .0499284     .0499528       -.0000244        .0001092
   garden_no |   -.6824561    -.6212107       -.0612454        .1436598
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        0.64
                Prob>chi2 =      0.8870

.  xtreg lnconsumption lag1_lncon lnavaregeprice adtemp adult children_18_years
elderly_more_60_years num_higher_education expat app s
> wim_no garden_no wsaving_no old incom1 incom2 incom4, re

Random-effects GLS regression                   Number of obs     =      9,597
Group variable: id                              Number of groups  =        400

R-sq:                                           Obs per group:
     within  = 0.3040                                         min =         22
     between = 0.9841                                         avg =       24.0
     overall = 0.8671                                         max =         24

                                                Wald chi2(16)     =   62494.89
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000

--------------------------------------------------------------------------------------
       lnconsumption |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+----------------------------------------------------------------
```

```
         lag1_lncon |  .7560901   .0061466   123.01   0.000     .744043    .7681372
     lnavaregeprice | -.1630819   .0170321    -9.57   0.000   -.1964643   -.1296995
             adtemp |  .0265317    .005748     4.62   0.000    .0152658    .0377976
              adult |   .038112   .0035977    10.59   0.000    .0310607    .0451634
  children_18_years |  .0540678   .0040385    13.39   0.000    .0461524    .0619832
elderly_more_60_years |  .0304018   .0077196     3.94   0.000    .0152715     .045532
 num_higher_education |   .001346   .0056508     0.24   0.812   -.0097294    .0124213
              expat |  .0944983   .0248767     3.80   0.000    .0457409    .1432557
                app |  .0414751   .0129079     3.21   0.001    .0161761    .0667741
            swim_no | -.1531958    .018684    -8.20   0.000   -.1898157   -.1165759
          garden_no | -.1599111   .0225938    -7.08   0.000   -.2041941   -.1156281
         wsaving_no |  .0409386   .0131524     3.11   0.002    .0151604    .0667168
                old |  .0110893   .0110583     1.00   0.316   -.0105846    .0327632
             incom1 | -.0717567   .0191083    -3.76   0.000   -.1092083   -.0343051
             incom2 | -.0559863   .0129986    -4.31   0.000   -.0814631   -.0305095
             incom4 |  .1078339   .0170105     6.34   0.000     .074494    .1411739
              _cons |  .0028287   .0536989     0.05   0.958   -.1024193    .1080766
---------------------+----------------------------------------------------------------
            sigma_u |         0
            sigma_e | .41916255
                rho |         0   (fraction of variance due to u_i)
--------------------------------------------------------------------------------------
```

```
. xtabond2 lnconsumption  lnavaregeprice adtemp garden_no , iv( lnavaregeprice adtemp
garden_no ) noleveleq nodiffsargan robust small

Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.


Dynamic panel-data estimation, one-step difference GMM
------------------------------------------------------------------------------
Group variable: id                              Number of obs      =      9200
Time variable : deta1                           Number of groups   =       400
Number of instruments = 3                       Obs per group: min =        23
F(3, 400)     =     27.65                                      avg =     23.00
Prob > F      =     0.000                                      max =        23
--------------------------------------------------------------------------------
```

```
               |              Robust
 lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
lnavaregeprice |  -.5769816   .0911691    -6.33   0.000     -.756212   -.3977511
        adtemp |   .0275744   .0053144     5.19   0.000     .0171268    .0380221
     garden_no |  -.5904277   .2194846    -2.69   0.007    -1.021915   -.1589401
--------------------------------------------------------------------------------
Instruments for first differences equation
  Standard
    D.(lnavaregeprice adtemp garden_no)
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -4.54  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =  -4.31  Pr > z =  0.000
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(0)    =   0.00  Prob > chi2 =      .
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(0)    =   0.00  Prob > chi2 =      .
  (Robust, but weakened by many instruments.)
```

```
. xtabond2 lnconsumption  lnavaregeprice adtemp garden_no , iv( lnavaregeprice adtemp
garden_no ) noleveleq nodiffsargan twostep robust orthogonal small

Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.


Dynamic panel-data estimation, two-step difference GMM
------------------------------------------------------------------------------
Group variable: id                              Number of obs      =      9200
Time variable : deta1                           Number of groups   =       400
Number of instruments = 3                       Obs per group: min =        23
F(3, 400)     =     38.08                                      avg =     23.00
Prob > F      =     0.000                                      max =        23
--------------------------------------------------------------------------------
               |             Corrected
 lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
```

```
lnavaregeprice |    -.20468   .0643768    -3.18   0.002    -.3312393   -.0781208

        adtemp |   .0499783   .0077071     6.48   0.000     .0348269    .0651297

     garden_no |  -.6824395   .0943785    -7.23   0.000    -.8679794   -.4968996

--------------------------------------------------------------------------------

Instruments for orthogonal deviations equation

  Standard

    FOD.(lnavaregeprice adtemp garden_no)

------------------------------------------------------------------------------

Arellano-Bond test for AR(1) in first differences: z =  -4.61  Pr > z =  0.000

Arellano-Bond test for AR(2) in first differences: z =  -3.90  Pr > z =  0.000

------------------------------------------------------------------------------

Sargan test of overid. restrictions: chi2(0)    =   0.00  Prob > chi2 =      .

  (Not robust, but not weakened by many instruments.)

Hansen test of overid. restrictions: chi2(0)    =   0.00  Prob > chi2 =      .

  (Robust, but weakened by many instruments.)


. xtabond2 lnconsumption  lnavaregeprice adtemp garden_no , iv( lnavaregeprice adtemp
garden_no )

> nodiffsargan robust orthogonal small

Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.


Dynamic panel-data estimation, one-step system GMM

------------------------------------------------------------------------------

Group variable: id                              Number of obs      =      9600

Time variable : deta1                           Number of groups   =       400

Number of instruments = 4                       Obs per group: min =        24

F(3, 399)     =    269.37                                      avg =     24.00

Prob > F      =     0.000                                      max =        24

--------------------------------------------------------------------------------

               |               Robust

 lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]

---------------+----------------------------------------------------------------

lnavaregeprice |  -.5196176   .0584385    -8.89   0.000    -.6345034   -.4047317

        adtemp |   .0488196   .0078499     6.22   0.000     .0333873     .064252
```

```
     garden_no |  -2.200662   .1123193   -19.59   0.000    -2.421473    -1.97985

         _cons |   2.582766   .1147108    22.52   0.000     2.357253    2.808279

--------------------------------------------------------------------------------

Instruments for orthogonal deviations equation

  Standard

    FOD.(lnavaregeprice adtemp garden_no)

Instruments for levels equation

  Standard

    lnavaregeprice adtemp garden_no

    _cons

------------------------------------------------------------------------------

Arellano-Bond test for AR(1) in first differences: z =  -4.52  Pr > z =  0.000

Arellano-Bond test for AR(2) in first differences: z =  -4.33  Pr > z =  0.000

------------------------------------------------------------------------------

Sargan test of overid. restrictions: chi2(0)    =   0.00  Prob > chi2 =      .

  (Not robust, but not weakened by many instruments.)

Hansen test of overid. restrictions: chi2(0)    =   0.00  Prob > chi2 =      .

  (Robust, but weakened by many instruments.)

. xtabond2 lnconsumption  lnavaregeprice adtemp garden_no , iv( lnavaregeprice adtemp
garden_no )

> nodiffsargan twostep robust orthogonal small

Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.


Dynamic panel-data estimation, two-step system GMM

------------------------------------------------------------------------------

Group variable: id                               Number of obs      =      9600

Time variable : deta1                            Number of groups   =       400

Number of instruments = 4                        Obs per group: min =        24

F(3, 399)     =    269.37                                       avg =     24.00

Prob > F      =     0.000                                       max =        24

--------------------------------------------------------------------------------

               |              Corrected

 lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]

---------------+----------------------------------------------------------------
```

```
lnavaregeprice |  -.5196176   .0584385    -8.89   0.000    -.6345034   -.4047317

        adtemp |   .0488196   .0078499     6.22   0.000     .0333873     .064252

     garden_no |  -2.200662   .1123193   -19.59   0.000    -2.421473    -1.97985

         _cons |   2.582766   .1147108    22.52   0.000     2.357253    2.808279

--------------------------------------------------------------------------------

Instruments for orthogonal deviations equation

  Standard

    FOD.(lnavaregeprice adtemp garden_no)

Instruments for levels equation

  Standard

    lnavaregeprice adtemp garden_no

    _cons

------------------------------------------------------------------------------

Arellano-Bond test for AR(1) in first differences: z =  -4.52  Pr > z =  0.000

Arellano-Bond test for AR(2) in first differences: z =  -4.33  Pr > z =  0.000

------------------------------------------------------------------------------

Sargan test of overid. restrictions: chi2(0)    =   0.00  Prob > chi2 =      .

  (Not robust, but not weakened by many instruments.)

Hansen test of overid. restrictions: chi2(0)    =   0.00  Prob > chi2 =      .

  (Robust, but weakened by many instruments.)


. xtabond2 lnconsumption  lnavaregeprice adtemp garden_no jan feb mar apr may jun jul
aug sep oct

> nov dec , iv( lnavaregeprice adtemp garden_no jan feb mar apr may jun jul aug sep
oct nov dec) n

> oleveleq nodiffsargan twostep robust orthogonal small

Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.

nov dropped due to collinearity

Warning: Two-step estimated covariance matrix of moments is singular.

  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimation.


Dynamic panel-data estimation, two-step difference GMM

------------------------------------------------------------------------------

Group variable: id                             Number of obs      =      9200
```

```
Time variable : deta1                          Number of groups   =       400
Number of instruments = 14                     Obs per group: min =        23
F(14, 400)    =     11.21                                     avg =     23.00
Prob > F      =     0.000                                     max =        23
------------------------------------------------------------------------------
               |              Corrected
  lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
lnavaregeprice |  -.2054041   .0652935    -3.15   0.002    -.3337653   -.0770428
        adtemp |   .0258998    .010788     2.40   0.017     .0046916    .0471081
     garden_no |   -.680881    .104615    -6.51   0.000    -.8865449   -.4752171
           jan |   -.051664   .0223652    -2.31   0.021     -.095632   -.0076959
           feb |  -.0561233   .0244055    -2.30   0.022    -.1041024   -.0081442
           mar |  -.0343112   .0250691    -1.37   0.172    -.0835949    .0149724
           apr |   .0010165   .0288004     0.04   0.972    -.0556025    .0576355
           may |   .0351098    .029627     1.19   0.237    -.0231343     .093354
           jun |   .0239893   .0359627     0.67   0.505    -.0467103    .0946889
           jul |  -.0124741   .0276304    -0.45   0.652    -.0667932    .0418449
           aug |  -.0269799   .0271714    -0.99   0.321    -.0803966    .0264368
           sep |   .0304869   .0228691     1.33   0.183    -.0144718    .0754457
           oct |   .0135719   .0172751     0.79   0.433    -.0203895    .0475333
           dec |  -.0504482   .0143811    -3.51   0.001    -.0787203   -.0221762
------------------------------------------------------------------------------
Instruments for orthogonal deviations equation
  Standard
    FOD.(lnavaregeprice adtemp garden_no jan feb mar apr may jun jul aug sep
    oct nov dec)
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -4.59  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =  -3.88  Pr > z =  0.000
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(0)    =   0.00  Prob > chi2 =      .
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(0)    =   0.00  Prob > chi2 =      .
```

```
  (Robust, but weakened by many instruments.)


. xtabond2 lnconsumption lag1_lncon lnavaregeprice adtemp garden_no jan feb mar apr
may jun jul au

> g sep oct nov dec , gmm( lag1_lncon , collapse) iv( lnavaregeprice adtemp garden_no
jan feb mar

> apr may jun jul aug sep oct nov dec) noleveleq nodiffsargan twostep robust
orthogonal small

Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.

nov dropped due to collinearity

Warning: Two-step estimated covariance matrix of moments is singular.

  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimation.


Dynamic panel-data estimation, two-step difference GMM

------------------------------------------------------------------------------

Group variable: id                              Number of obs      =      8800

Time variable : deta1                           Number of groups   =       400

Number of instruments = 36                      Obs per group: min =        22

F(15, 400)    =     65.59                                      avg =     22.00

Prob > F      =     0.000                                      max =        22

--------------------------------------------------------------------------------

               |              Corrected

 lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]

---------------+----------------------------------------------------------------

    lag1_lncon |   .7212078   .0323642    22.28   0.000     .6575826    .7848329

lnavaregeprice |  -.1784795   .0329312    -5.42   0.000    -.2432194   -.1137395

        adtemp |  -.0021567    .008242    -0.26   0.794    -.0183597    .0140463

     garden_no |   -.770475   .1491273    -5.17   0.000    -1.063646   -.4773039

           jan |   .0048882   .0229052     0.21   0.831    -.0401413    .0499178

           feb |   .0098038   .0178884     0.55   0.584    -.0253633    .0449709

           mar |   .0427381   .0181723     2.35   0.019     .0070129    .0784633

           apr |   .0834585   .0205896     4.05   0.000     .0429812    .1239358

           may |   .0779997   .0229658     3.40   0.001     .0328509    .1231485

           jun |   .0651499   .0278698     2.34   0.020     .0103604    .1199394
```

```
         jul |  -.0137091   .0219669    -0.62   0.533    -.0568941    .0294759
         aug |   .0213723    .021749     0.98   0.326    -.0213843    .0641289
         sep |   .0723988   .0195297     3.71   0.000      .034005    .1107925
         oct |   .0419265   .0181387     2.31   0.021     .0062674    .0775855
         dec |   -.020131   .0155001    -1.30   0.195    -.0506029    .0103409
------------------------------------------------------------------------------
Instruments for orthogonal deviations equation
  Standard
    FOD.(lnavaregeprice adtemp garden_no jan feb mar apr may jun jul aug sep
    oct nov dec)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(1/23).lag1_lncon collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -7.69  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =  -1.07  Pr > z =  0.286
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(21)   =  87.93  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(21)   =  40.13  Prob > chi2 =  0.007
  (Robust, but weakened by many instruments.)


. xtabond2 lnconsumption lag1_lncon lnavaregeprice adtemp garden_no jan feb mar apr
may jun jul au
> g sep oct nov dec , gmm( lag1_lncon , collapse) iv( lnavaregeprice adtemp garden_no
jan feb mar
> apr may jun jul aug sep oct nov dec) noleveleq  twostep robust orthogonal small
Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.
nov dropped due to collinearity
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimation.
  Difference-in-Sargan/Hansen statistics may be negative.


Dynamic panel-data estimation, two-step difference GMM
------------------------------------------------------------------------------
```

```
Group variable: id                              Number of obs      =      8800
Time variable : deta1                           Number of groups   =       400
Number of instruments = 36                      Obs per group: min =        22
F(15, 400)    =     65.59                                      avg =     22.00
Prob > F      =     0.000                                      max =        22
--------------------------------------------------------------------------------
               |             Corrected
 lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
    lag1_lncon |   .7212078   .0323642    22.28   0.000     .6575826    .7848329
lnavaregeprice |  -.1784795   .0329312    -5.42   0.000    -.2432194   -.1137395
        adtemp |  -.0021567    .008242    -0.26   0.794    -.0183597    .0140463
     garden_no |   -.770475   .1491273    -5.17   0.000    -1.063646   -.4773039
           jan |   .0048882   .0229052     0.21   0.831    -.0401413    .0499178
           feb |   .0098038   .0178884     0.55   0.584    -.0253633    .0449709
           mar |   .0427381   .0181723     2.35   0.019     .0070129    .0784633
           apr |   .0834585   .0205896     4.05   0.000     .0429812    .1239358
           may |   .0779997   .0229658     3.40   0.001     .0328509    .1231485
           jun |   .0651499   .0278698     2.34   0.020     .0103604    .1199394
           jul |  -.0137091   .0219669    -0.62   0.533    -.0568941    .0294759
           aug |   .0213723    .021749     0.98   0.326    -.0213843    .0641289
           sep |   .0723988   .0195297     3.71   0.000      .034005    .1107925
           oct |   .0419265   .0181387     2.31   0.021     .0062674    .0775855
           dec |   -.020131   .0155001    -1.30   0.195    -.0506029    .0103409
--------------------------------------------------------------------------------
Instruments for orthogonal deviations equation
  Standard
    FOD.(lnavaregeprice adtemp garden_no jan feb mar apr may jun jul aug sep
    oct nov dec)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(1/23).lag1_lncon collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -7.69  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =  -1.07  Pr > z =  0.286
```

```
------------------------------------------------------------------------------

Sargan test of overid. restrictions: chi2(21)   =  87.93  Prob > chi2 =  0.000

  (Not robust, but not weakened by many instruments.)

Hansen test of overid. restrictions: chi2(21)   =  40.13  Prob > chi2 =  0.007

  (Robust, but weakened by many instruments.)


Difference-in-Hansen tests of exogeneity of instrument subsets:

  iv(lnavaregeprice adtemp garden_no jan feb mar apr may jun jul aug sep oct nov dec)

    Hansen test excluding group:     chi2(7)    =   3.73  Prob > chi2 =  0.810

    Difference (null H = exogenous): chi2(14)   =  36.39  Prob > chi2 =  0.001


. gen lag1_lncon=L1.lnconsumption

(400 missing values generated)


. regress lnconsumption lag1_lncon lnavaregeprice adtemp adult children_18_years
elderly_more_60_y

> ears num_higher_education expat app swim_no garden_no wsaving_no old incom1 incom2
incom4


      Source |       SS           df       MS      Number of obs   =     9,199

-------------+----------------------------------   F(16, 9182)     =   5134.54

       Model |  13479.2353        16  842.452209   Prob > F        =    0.0000

    Residual |  1506.53986     9,182   .16407535   R-squared       =    0.8995

-------------+----------------------------------   Adj R-squared   =    0.8993

       Total |  14985.7752     9,198  1.62924279   Root MSE        =    .40506


-----------------------------------------------------------------------------------
--

        lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]

---------------------+-------------------------------------------------------------
--

           lag1_lncon |   .8384445   .0056467   148.48   0.000     .8273756
.8495133

       lnavaregeprice |  -.1678637   .0149864   -11.20   0.000    -.1972405    -
.138487

               adtemp |   .0243413   .0051007     4.77   0.000     .0143428
.0343399
```

```
               adult |   .0244477   .0032155     7.60   0.000     .0181446
.0307508

    children_18_years |   .0345591   .0036162     9.56   0.000     .0274705
.0416477

elderly_more_60_years |   .0193898   .0068781     2.82   0.005     .0059073
.0328724

 num_higher_education |  -.0037748   .0050322    -0.75   0.453     -.013639
.0060894

               expat |   .1205462   .0219572     5.49   0.000     .0775053
.1635871

                 app |   .0099261   .0114995     0.86   0.388    -.0126156
.0324678

             swim_no |  -.0862114   .0166829    -5.17   0.000    -.1189136   -
.0535092

           garden_no |  -.0994056   .0201471    -4.93   0.000    -.1388984   -
.0599129

          wsaving_no |   .0207505   .0117189     1.77   0.077    -.0022211
.0437221

                 old |   .0137773   .0098481     1.40   0.162    -.0055272
.0330818

              incom1 |  -.0239232   .0170279    -1.40   0.160    -.0573017
.0094554

              incom2 |  -.0271438   .0115858    -2.34   0.019    -.0498547    -
.004433

              incom4 |   .0611793   .0151775     4.03   0.000      .031428
.0909306

               _cons |  -.0026613   .0479384    -0.06   0.956    -.0966312
.0913086

------------------------------------------------------------------------------------
--

. xtreg lnconsumption lag1_lncon lnavaregeprice adtemp adult children_18_years
elderly_more_60_years num_higher_education expat app sw

> im_no garden_no wsaving_no old incom1 incom2 incom4, fe

note: adult omitted because of collinearity

note: children_18_years omitted because of collinearity

note: elderly_more_60_years omitted because of collinearity

note: num_higher_education omitted because of collinearity

note: expat omitted because of collinearity

note: app omitted because of collinearity

note: swim_no omitted because of collinearity

note: wsaving_no omitted because of collinearity

note: old omitted because of collinearity
```

```
note: incom1 omitted because of collinearity

note: incom2 omitted because of collinearity

note: incom4 omitted because of collinearity


Fixed-effects (within) regression               Number of obs     =      9,199

Group variable: id                              Number of groups  =        400


R-sq:                                           Obs per group:

     within  = 0.4070                                         min =         22

     between = 0.9579                                         avg =       23.0

     overall = 0.8732                                         max =         23


                                                F(4,8795)         =    1508.84

corr(u_i, Xb)  = 0.6276                         Prob > F          =     0.0000


------------------------------------------------------------------------------------
--

        lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf.
Interval]

---------------------+--------------------------------------------------------------
--

           lag1_lncon |   .6265107   .0082873    75.60   0.000     .6102656
.6427559

       lnavaregeprice |  -.2057601   .0161198   -12.76   0.000    -.2373587   -
.1741615

               adtemp |   .0297875   .0048823     6.10   0.000     .0202171
.0393578

                adult |          0  (omitted)

    children_18_years |          0  (omitted)

elderly_more_60_years |          0  (omitted)

 num_higher_education |          0  (omitted)

                expat |          0  (omitted)

                  app |          0  (omitted)

              swim_no |          0  (omitted)

            garden_no |  -.7126082   .1433655    -4.97   0.000     -.993638   -
.4315784

           wsaving_no |          0  (omitted)
```

```
                 old |          0  (omitted)
              incom1 |          0  (omitted)
              incom2 |          0  (omitted)
              incom4 |          0  (omitted)
               _cons |   .7994289   .1375503     5.81   0.000     .5297982
1.06906
---------------------+----------------------------------------------------------------
--
             sigma_u |  .32278237
             sigma_e |  .38742918
                 rho |  .40972327   (fraction of variance due to u_i)
--------------------------------------------------------------------------------------
--
F test that all u_i=0: F(399, 8795) = 4.11                   Prob > F = 0.0000

. xtreg lnconsumption lag1_lncon lnavaregeprice adtemp adult children_18_years
elderly_more_60_years num_higher_education expat app sw

> im_no garden_no wsaving_no old incom1 incom2 incom4, re


Random-effects GLS regression                   Number of obs     =      9,199
Group variable: id                              Number of groups  =        400


R-sq:                                           Obs per group:
     within  = 0.4036                                         min =         22
     between = 0.9943                                         avg =       23.0
     overall = 0.8995                                         max =         23


                                                Wald chi2(16)     =   82152.71
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000


--------------------------------------------------------------------------------------
--
       lnconsumption |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]
---------------------+----------------------------------------------------------------
--
          lag1_lncon |   .8384445   .0056467   148.48   0.000     .8273771
.8495118
```

```
      lnavaregeprice |  -.1678637   .0149864   -11.20   0.000    -.1972366   -
.1384908

              adtemp |   .0243413   .0051007     4.77   0.000     .0143441
.0343386

               adult |   .0244477   .0032155     7.60   0.000     .0181454
.03075

    children_18_years |   .0345591   .0036162     9.56   0.000     .0274715
.0416467

elderly_more_60_years |   .0193898   .0068781     2.82   0.005      .005909
.0328706

 num_higher_education |  -.0037748   .0050322    -0.75   0.453    -.0136377
.0060881

               expat |   .1205462   .0219572     5.49   0.000     .0775109
.1635814

                 app |   .0099261   .0114995     0.86   0.388    -.0126126
.0324648

             swim_no |  -.0862114   .0166829    -5.17   0.000    -.1189093   -
.0535135

           garden_no |  -.0994056   .0201471    -4.93   0.000    -.1388932   -
.0599181

          wsaving_no |   .0207505   .0117189     1.77   0.077    -.0022181
.0437191

                 old |   .0137773   .0098481     1.40   0.162    -.0055246
.0330792

              incom1 |  -.0239232   .0170279    -1.40   0.160    -.0572973
.009451

              incom2 |  -.0271438   .0115858    -2.34   0.019    -.0498517    -
.004436

              incom4 |   .0611793   .0151775     4.03   0.000     .0314319
.0909267

               _cons |  -.0026613   .0479384    -0.06   0.956    -.0966188
.0912962

----------------------+----------------------------------------------------------
--

             sigma_u |          0

             sigma_e |  .38742918

                 rho |          0   (fraction of variance due to u_i)

-------------------------------------------------------------------------------------
--

. xtabond2 lnconsumption lag1_lncon lnavaregeprice adtemp garden_no , gmm(
lag1_lncon,collapse) iv( lnavaregeprice adtemp garden_no )

> noleveleq nodiffsargan robust small
```

```
Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.

Warning: Two-step estimated covariance matrix of moments is singular.

  Using a generalized inverse to calculate robust weighting matrix for Hansen test.


Dynamic panel-data estimation, one-step difference GMM

------------------------------------------------------------------------------

Group variable: id                              Number of obs      =      8800

Time variable : deta1                           Number of groups   =       400

Number of instruments = 25                      Obs per group: min =        22

F(4, 400)     =    178.53                                      avg =     22.00

Prob > F      =     0.000                                      max =        22

--------------------------------------------------------------------------------

               |               Robust

 lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]

---------------+----------------------------------------------------------------

    lag1_lncon |   .6223142   .0348856    17.84   0.000     .5537322    .6908963

lnavaregeprice |  -.7686031   .1152464    -6.67   0.000    -.9951673   -.5420388

        adtemp |   .0232397   .0064108     3.63   0.000     .0106367    .0358427

     garden_no |  -.6853616   .2109166    -3.25   0.001    -1.100005   -.2707181

--------------------------------------------------------------------------------

Instruments for first differences equation

  Standard

    D.(lnavaregeprice adtemp garden_no)

  GMM-type (missing=0, separate instruments for each period unless collapsed)

    L(1/23).lag1_lncon collapsed

------------------------------------------------------------------------------

Arellano-Bond test for AR(1) in first differences: z =  -7.92  Pr > z =  0.000

Arellano-Bond test for AR(2) in first differences: z =  -1.64  Pr > z =  0.101

------------------------------------------------------------------------------

Sargan test of overid. restrictions: chi2(21)   =  74.52  Prob > chi2 =  0.000

  (Not robust, but not weakened by many instruments.)

Hansen test of overid. restrictions: chi2(21)   =  35.00  Prob > chi2 =  0.028

  (Robust, but weakened by many instruments.)
```

```
. xtabond2 lnconsumption lag1_lncon lnavaregeprice adtemp garden_no ,
gmm(lag1_lncon,collaps) iv( lnavaregeprice adtemp garden_no ) no

> leveleq nodiffsargan twostep robust orthogonal small

Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.

Warning: Two-step estimated covariance matrix of moments is singular.

  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimation.


Dynamic panel-data estimation, two-step difference GMM

------------------------------------------------------------------------------

Group variable: id                              Number of obs      =      8800

Time variable : deta1                           Number of groups   =       400

Number of instruments = 25                      Obs per group: min =        22

F(4, 400)     =    209.31                                      avg =     22.00

Prob > F      =     0.000                                      max =        22

------------------------------------------------------------------------------

               |              Corrected

 lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]

---------------+----------------------------------------------------------------

    lag1_lncon |   .7197087   .0312914    23.00   0.000     .6581925    .7812249

lnavaregeprice |  -.1675645   .0317296    -5.28   0.000    -.2299421   -.1051868

        adtemp |   .0226563   .0046801     4.84   0.000     .0134556    .0318569

     garden_no |  -.7755646   .1528154    -5.08   0.000    -1.075986   -.4751428

------------------------------------------------------------------------------

Instruments for orthogonal deviations equation

  Standard

    FOD.(lnavaregeprice adtemp garden_no)

  GMM-type (missing=0, separate instruments for each period unless collapsed)

    L(1/23).lag1_lncon collapsed

------------------------------------------------------------------------------

Arellano-Bond test for AR(1) in first differences: z =  -7.65  Pr > z =  0.000

Arellano-Bond test for AR(2) in first differences: z =  -1.12  Pr > z =  0.263
```

```
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(21)   =  88.14  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(21)   =  41.94  Prob > chi2 =  0.004
  (Robust, but weakened by many instruments.)


. xtabond2 lnconsumption lag1_lncon lnavaregeprice adtemp garden_no , gmm( lag1_lncon
,collaps) iv( lnavaregeprice adtemp garden_no )
> nodiffsargan robust orthogonal small
Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.
Warning: Two-step estimated covariance matrix of moments is singular.
  Using a generalized inverse to calculate robust weighting matrix for Hansen test.


Dynamic panel-data estimation, one-step system GMM
------------------------------------------------------------------------------
Group variable: id                              Number of obs      =      9200
Time variable : deta1                           Number of groups   =       400
Number of instruments = 27                      Obs per group: min =        23
F(4, 399)     =   2417.02                                      avg =     23.00
Prob > F      =     0.000                                      max =        23
--------------------------------------------------------------------------------
               |               Robust
 lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
    lag1_lncon |   .6931413   .0301945    22.96   0.000     .6337812    .7525014
lnavaregeprice |  -.1966221   .0241245    -8.15   0.000     -.244049   -.1491952
        adtemp |   .0280252   .0050025     5.60   0.000     .0181905    .0378598
     garden_no |  -.6609762   .0814184    -8.12   0.000    -.8210388   -.5009137
         _cons |   .7352268   .1021471     7.20   0.000     .5344131    .9360405
--------------------------------------------------------------------------------
Instruments for orthogonal deviations equation
  Standard
    FOD.(lnavaregeprice adtemp garden_no)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
```

```
    L(1/23).lag1_lncon collapsed

Instruments for levels equation

  Standard

    lnavaregeprice adtemp garden_no

    _cons

  GMM-type (missing=0, separate instruments for each period unless collapsed)

    D.lag1_lncon collapsed

------------------------------------------------------------------------------

Arellano-Bond test for AR(1) in first differences: z =  -8.15  Pr > z =  0.000

Arellano-Bond test for AR(2) in first differences: z =  -1.15  Pr > z =  0.249

------------------------------------------------------------------------------

Sargan test of overid. restrictions: chi2(22)   =  89.56  Prob > chi2 =  0.000

  (Not robust, but not weakened by many instruments.)

Hansen test of overid. restrictions: chi2(22)   =  42.46  Prob > chi2 =  0.005

  (Robust, but weakened by many instruments.)


. xtabond2 lnconsumption lag1_lncon lnavaregeprice adtemp garden_no , gmm( lag1_lncon
,collaps) iv( lnavaregeprice adtemp garden_no )

> nodiffsargan twostep robust orthogonal small

Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.

Warning: Two-step estimated covariance matrix of moments is singular.

  Using a generalized inverse to calculate optimal weighting matrix for two-step
estimation.


Dynamic panel-data estimation, two-step system GMM

------------------------------------------------------------------------------

Group variable: id                              Number of obs      =      9200

Time variable : deta1                           Number of groups   =       400

Number of instruments = 27                      Obs per group: min =        23

F(4, 399)     =   2031.70                                      avg =     23.00

Prob > F      =     0.000                                      max =        23

-------------------------------------------------------------------------------

               |              Corrected

 lnconsumption |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
```

```
---------------+----------------------------------------------------------------
     lag1_lncon |   .7204498   .0288954    24.93   0.000     .6636435     .777256
lnavaregeprice |  -.1840345   .0256443    -7.18   0.000    -.2344494   -.1336196
        adtemp |   .0225133   .0045666     4.93   0.000     .0135357    .0314908
     garden_no |  -.5747727   .0781474    -7.35   0.000    -.7284048   -.4211406
         _cons |   .6873174   .1053922     6.52   0.000      .480124    .8945107
--------------------------------------------------------------------------------
Instruments for orthogonal deviations equation
  Standard
    FOD.(lnavaregeprice adtemp garden_no)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(1/23).lag1_lncon collapsed
Instruments for levels equation
  Standard
    lnavaregeprice adtemp garden_no
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.lag1_lncon collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -7.69  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =  -1.12  Pr > z =  0.262
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(22)   =  89.56  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(22)   =  42.46  Prob > chi2 =  0.005
  (Robust, but weakened by many instruments.)
```

Model 1: Random-effects (GLS), using 2350 observations
Included 98 cross-sectional units
Time-series length: minimum 22, maximum 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.149795	0.343691	−0.4358	0.6630	
LnAveragePricePerDay	−0.225310	0.0240449	−9.370	<0.0001	***
ADTemp	0.0226447	0.0101979	2.221	0.0264	**
Adult	0.118370	0.0340619	3.475	0.0005	***
Children_18_years	0.149853	0.0528820	2.834	0.0046	***
Elderly_More_60_years	0.0742164	0.111079	0.6681	0.5040	
Num_Higher_Education	0.0554120	0.0695674	0.7965	0.4257	
DHouse_Age_1	−0.154201	0.121265	−1.272	0.2035	
DIncome_1	−0.564624	0.270657	−2.086	0.0370	**
DWater_Saving_Devices_1	−0.0519112	0.149169	−0.3480	0.7278	
DIncome_2	−0.435486	0.244290	−1.783	0.0746	*
DIncome_4	0.364155	0.400772	0.9086	0.3635	

Mean dependent var	−0.379726	S.D. dependent var	0.801389
Sum squared resid	949.5439	S.E. of regression	0.637151
Log-likelihood	−2269.734	Akaike criterion	4563.467
Schwarz criterion	4632.613	Hannan-Quinn	4588.650
rho	−0.169248	Durbin-Watson	2.238885

'Between' variance = 0.268522
'Within' variance = 0.166611
mean theta = 0.84118

Joint test on named regressors -
Asymptotic test statistic: Chi-square(11) = 173.437
with p-value = 2.31236e-031

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 9313.96
with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(2) = 0.937642
with p-value = 0.62574

Model 1: Random-effects (GLS), using 2448 observations
Included 102 cross-sectional units

Time-series length = 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.339383	0.786783	−0.4314	0.6662	
LnAveragePricePerDay	−0.183922	0.0762429	−2.412	0.0159	**
ADTemp	0.0304283	0.0133785	2.274	0.0229	**
Adult	0.232550	0.0483522	4.810	<0.0001	***
Children_18_years	0.240297	0.0508373	4.727	<0.0001	***
Elderly_More_60_years	0.0533955	0.0862613	0.6190	0.5359	
Num_Higher_Education	0.0575094	0.0630988	0.9114	0.3621	
DHouse_Age_1	0.00552543	0.113763	0.04857	0.9613	
DSwimming_Pool_1	−0.0824567	0.549213	−0.1501	0.8807	
DWater_Saving_Devices_1	−0.763774	0.505439	−1.511	0.1308	
DIncome_1	−0.174084	0.252549	−0.6893	0.4906	
DIncome_2	0.0107615	0.116624	0.09228	0.9265	
DIncome_4	0.0746571	0.187332	0.3985	0.6902	

Mean dependent var	0.163066	S.D. dependent var	0.960797
Sum squared resid	1240.625	S.E. of regression	0.713644
Log-likelihood	−2641.663	Akaike criterion	5309.325
Schwarz criterion	5384.765	Hannan-Quinn	5336.743
rho	−0.251606	Durbin-Watson	2.400011

'Between' variance = 0.228293
'Within' variance = 0.297509
theta used for quasi-demeaning = 0.773057

Joint test on named regressors -
Asymptotic test statistic: Chi-square(12) = 188.682
with p-value = 7.0132e-034

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 4580.42
with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(1) = 4.24605
with p-value = 0.0393416

Model 1: Random-effects (GLS), using 2400 observations
Included 100 cross-sectional units
Time-series length = 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.401524	0.272328	−1.474	0.1404	
LnAveragePricePerDay	−0.186581	0.0326582	−5.713	<0.0001	***
ADTemp	0.0221830	0.0121452	1.826	0.0678	*
Adult	0.137607	0.0392689	3.504	0.0005	***
Children_18_years	0.258516	0.0344651	7.501	<0.0001	***
Elderly_More_60_years	0.195526	0.0655095	2.985	0.0028	***
Num_Higher_Education	0.0440039	0.0605972	0.7262	0.4677	
DSwimming_Pool_1	−0.465430	0.229049	−2.032	0.0422	**
DGarden_1	−0.778093	0.175823	−4.425	<0.0001	***
DWater_Saving_Devices_1	0.251473	0.106728	2.356	0.0185	**
DHouse_Age_1	0.121668	0.0890573	1.366	0.1719	
DIncome_1	−0.492614	0.190290	−2.589	0.0096	***
DIncome_2	−0.149027	0.103030	−1.446	0.1481	
DIncome_4	0.0582056	0.184044	0.3163	0.7518	

Mean dependent var	−0.258295	S.D. dependent var	1.024630
Sum squared resid	887.2192	S.E. of regression	0.609662
Log-likelihood	−2211.294	Akaike criterion	4450.588
Schwarz criterion	4531.553	Hannan-Quinn	4480.043
rho	−0.194763	Durbin-Watson	2.251468

'Between' variance = 0.148655
'Within' variance = 0.241203
theta used for quasi-demeaning = 0.748354

Joint test on named regressors -
Asymptotic test statistic: Chi-square(13) = 460.527
with p-value = 3.47718e-090

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 3335.86
with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(1) = 0.416483

with p-value = 0.518697

Model 1: Random-effects (GLS), using 2400 observations
Included 100 cross-sectional units
Time-series length = 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.0952468	0.395804	0.2406	0.8098	
LnAveragePricePerDay	−0.110711	0.0928301	−1.193	0.2330	
ADTemp	0.126177	0.0132512	9.522	<0.0001	***
Adult	0.126922	0.0589668	2.152	0.0314	**
Children_18_years	0.135508	0.0464381	2.918	0.0035	***
Elderly_More_60_years	0.0777597	0.0888598	0.8751	0.3815	
Num_Higher_Education	−0.0143705	0.0660392	−0.2176	0.8277	
DHouse_Age_1	0.0804495	0.203336	0.3956	0.6924	
DSwimming_Pool_1	−0.262711	0.146242	−1.796	0.0724	*
DWater_Saving_Devices_1	0.534382	0.126860	4.212	<0.0001	***
DGarden_1	−0.804440	0.181566	−4.431	<0.0001	***
DIncome_2	−0.492199	0.233833	−2.105	0.0353	**
DIncome_3	−0.406719	0.167222	−2.432	0.0150	**

Mean dependent var	1.518931	S.D. dependent var	1.264894
Sum squared resid	1519.008	S.E. of regression	0.797559
Log-likelihood	−2856.559	Akaike criterion	5739.117
Schwarz criterion	5814.299	Hannan-Quinn	5766.469
rho	−0.232992	Durbin-Watson	2.299668

'Between' variance = 0.324486
'Within' variance = 0.284056
theta used for quasi-demeaning = 0.812406

Joint test on named regressors -
Asymptotic test statistic: Chi-square(12) = 375.924
with p-value = 4.69871e-073

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 8243.34
with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(1) = 19.4558

with p-value = 1.02953e-005

Model 1: Random-effects (GLS), using 4750 observations
Included 198 cross-sectional units
Time-series length: minimum 22, maximum 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.411049	0.245191	−1.676	0.0937	*
LnAveragePricePerDay	−0.208359	0.0199380	−10.45	<0.0001	***
ADTemp	0.0224866	0.00794368	2.831	0.0046	***
Adult	0.140215	0.0236857	5.920	<0.0001	***
Children_18_years	0.200326	0.0297034	6.744	<0.0001	***
Elderly_More_60_years	0.134101	0.0597967	2.243	0.0249	**
Num_Higher_Education	0.0384789	0.0440701	0.8731	0.3826	
DHouse_Age_1	0.00964991	0.0734510	0.1314	0.8955	
DIncome_2	0.123371	0.0983238	1.255	0.2096	
DIncome_3	0.415632	0.135280	3.072	0.0021	***
DIncome_4	0.588126	0.205705	2.859	0.0042	***
DSwimming_Pool_1	−0.466148	0.251565	−1.853	0.0639	*
DWater_Saving_Devices_1	0.130019	0.0900045	1.445	0.1486	
DGarden_1	−0.726932	0.206035	−3.528	0.0004	***
DHoushold_Type_1	0.529877	0.0881818	6.009	<0.0001	***

Mean dependent var	−0.318371	S.D. dependent var	0.922876
Sum squared resid	1915.802	S.E. of regression	0.636018
Log-likelihood	−4583.438	Akaike criterion	9196.877
Schwarz criterion	9293.865	Hannan-Quinn	9230.958
rho	−0.184477	Durbin-Watson	2.247729

'Between' variance = 0.21439
'Within' variance = 0.204254
mean theta = 0.804558
Joint test on named regressors -
Asymptotic test statistic: Chi-square(14) = 507.546
with p-value = 2.33045e-099

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 13282.8
with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(2) = 1.42425
with p-value = 0.4906

Model 1: Random-effects (GLS), using 4848 observations
Included 202 cross-sectional units
Time-series length = 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.588019	0.368633	−1.595	0.1107	
LnAveragePricePerDay	−0.159958	0.0590353	−2.710	0.0067	***
ADTemp	0.0777297	0.00942416	8.248	<0.0001	***
Adult	0.177989	0.0361007	4.930	<0.0001	***
Children_18_years	0.164719	0.0347270	4.743	<0.0001	***
Elderly_More_60_years	0.0796904	0.0640641	1.244	0.2135	
Num_Higher_Education	0.00231262	0.0475344	0.04865	0.9612	
DHouse_Age_1	0.0305425	0.105493	0.2895	0.7722	
DIncome_2	0.317960	0.273069	1.164	0.2443	
DIncome_3	0.358447	0.276894	1.295	0.1955	
DIncome_4	0.701144	0.301632	2.325	0.0201	**
DSwimming_Pool_1	−0.250696	0.134396	−1.865	0.0621	*
DWater_Saving_Devices_1	0.464806	0.120625	3.853	0.0001	***
DGarden_1	−0.726137	0.152684	−4.756	<0.0001	***
DHoushold_Type_1	−0.438585	0.130031	−3.373	0.0007	***

Mean dependent var	0.834286	S.D. dependent var	1.310563
Sum squared resid	2861.106	S.E. of regression	0.769332
Log-likelihood	−5600.699	Akaike criterion	11231.40
Schwarz criterion	11328.69	Hannan-Quinn	11265.55
rho	−0.230946	Durbin-Watson	2.327784

'Between' variance = 0.312079
'Within' variance = 0.29237
theta used for quasi-demeaning = 0.806173

Joint test on named regressors -
Asymptotic test statistic: Chi-square(14) = 778.07
with p-value = 5.41395e-157

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 13874.5
with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(1) = 5.30074
with p-value = 0.0213163

Model 1: Random-effects (GLS), using 4798 observations
Included 200 cross-sectional units
Time-series length: minimum 22, maximum 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.551931	0.592972	−0.9308	0.3520	
LnAveragePricePerDay	−0.222207	0.0262090	−8.478	<0.0001	***
ADTemp	0.0264459	0.00844612	3.131	0.0017	***
Adult	0.165380	0.0250734	6.596	<0.0001	***
Children_18_years	0.213689	0.0331255	6.451	<0.0001	***
Elderly_More_60_years	0.0475407	0.0660155	0.7201	0.4714	
Num_Higher_Education	0.0354460	0.0456178	0.7770	0.4371	
DHouse_Age_1	−0.0672079	0.0812983	−0.8267	0.4084	
DIncome_2	0.113803	0.110816	1.027	0.3044	
DIncome_3	0.227560	0.141842	1.604	0.1086	
DIncome_4	0.482929	0.201027	2.402	0.0163	**
DSwimming_Pool_1	−0.328111	0.544743	−0.6023	0.5470	
DWater_Saving_Devices_1	−0.106391	0.137503	−0.7737	0.4391	
DResidential_Type_1	0.000412139	0.108806	0.003788	0.9970	

Mean dependent var	−0.102787	S.D. dependent var	0.926836
Sum squared resid	2259.516	S.E. of regression	0.687174
Log-likelihood	−5001.504	Akaike criterion	10031.01
Schwarz criterion	10121.67	Hannan-Quinn	10062.85
rho	−0.223437	Durbin-Watson	2.345710

'Between' variance = 0.255913
'Within' variance = 0.233308
mean theta = 0.808658

Joint test on named regressors -

Asymptotic test statistic: Chi-square(13) = 371.33
with p-value = 2.50326e-071

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 14060.2
with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(2) = 0.234861
with p-value = 0.889202

Model 1: Random-effects (GLS), using 4800 observations
Included 200 cross-sectional units
Time-series length = 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−2.39673	0.269907	−8.880	<0.0001	***
LnAveragePricePerDay	−0.180172	0.0320001	−5.630	<0.0001	***
ADTemp	0.0738659	0.00899055	8.216	<0.0001	***
Adult	0.144626	0.0355639	4.067	<0.0001	***
Children_18_years	0.198717	0.0306341	6.487	<0.0001	***
Elderly_More_60_years	0.175566	0.0612913	2.864	0.0042	***
Num_Higher_Education	−0.0374142	0.0480417	−0.7788	0.4361	
DHouse_Age_1	0.0619809	0.103593	0.5983	0.5496	
DIncome_2	0.447291	0.237364	1.884	0.0595	*
DIncome_3	0.672984	0.244840	2.749	0.0060	***
DIncome_4	1.25666	0.271802	4.623	<0.0001	***
DSwimming_Pool_2	0.504731	0.119600	4.220	<0.0001	***
DResidential_Type_2	0.728867	0.113983	6.395	<0.0001	***
DWater_Saving_Devices_1	0.408972	0.0973272	4.202	<0.0001	***

Mean dependent var	0.630318	S.D. dependent var	1.454109
Sum squared resid	2723.847	S.E. of regression	0.754327
Log-likelihood	−5451.136	Akaike criterion	10930.27
Schwarz criterion	11020.94	Hannan-Quinn	10962.12
rho	−0.200360	Durbin-Watson	2.248890

'Between' variance = 0.324062
'Within' variance = 0.264442

theta used for quasi-demeaning = 0.818663
Joint test on named regressors -
Asymptotic test statistic: Chi-square(13) = 1019.54
with p-value = 1.11163e-209

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 15733.4
with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(1) = 0.515141
with p-value = 0.472922

Model 1: Random-effects (GLS), using 9598 observations
Included 400 cross-sectional units
Time-series length: minimum 22, maximum 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.0941405	0.166491	0.5654	0.5718	
LnAveragePricePerDay	−0.232681	0.0190871	−12.19	<0.0001	***
ADTemp	0.0501423	0.00617690	8.118	<0.0001	***
Adult	0.161060	0.0189294	8.508	<0.0001	***
Children_18_years	0.212783	0.0217606	9.778	<0.0001	***
Elderly_More_60_years	0.0789781	0.0445116	1.774	0.0760	*
DHoushold_Type_1	0.221630	0.0725522	3.055	0.0023	***
DSwimming_Pool_1	−0.409628	0.115708	−3.540	0.0004	***
DGarden_1	−0.869217	0.119834	−7.253	<0.0001	***
DWater_Saving_Devices_1	0.166410	0.0762603	2.182	0.0291	**
DIncome_2	−0.209932	0.0739981	−2.837	0.0046	***
DIncome_4	0.237780	0.100704	2.361	0.0182	**
DIncome_1	−0.346025	0.0983130	−3.520	0.0004	***

Mean dependent var	0.263842	S.D. dependent var	1.273216
Sum squared resid	5252.454	S.E. of regression	0.740223
Log-likelihood	−10725.85	Akaike criterion	21477.70
Schwarz criterion	21570.90	Hannan-Quinn	21509.31
rho	0.635067	Durbin-Watson	0.699105

'Between' variance = 0.298763

'Within' variance = 0.24925
mean theta = 0.816695
Joint test on named regressors -
Asymptotic test statistic: Chi-square(12) = 1546.8
with p-value = 0

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 31630.4
with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(2) = 13.8101
with p-value = 0.00100269

Model 1: Random-effects (GLS), using 9598 observations
Included 400 cross-sectional units
Time-series length: minimum 22, maximum 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*	
const	0.290944	0.162272	1.793	0.0730	*
LnAveragePricePerDay	−0.236715	0.0191058	−12.39	<0.0001	***
Adult	0.160967	0.0189288	8.504	<0.0001	***
Children_18_years	0.212703	0.0217599	9.775	<0.0001	***
Elderly_More_60_years	0.0793367	0.0445103	1.782	0.0747	*
DHoushold_Type_1	0.219940	0.0725508	3.032	0.0024	***
DSwimming_Pool_1	−0.408947	0.115705	−3.534	0.0004	***
DGarden_1	−0.868131	0.119831	−7.245	<0.0001	***
DWater_Saving_Devices_1	0.166557	0.0762579	2.184	0.0290	**
DIncome_2	−0.208682	0.0739963	−2.820	0.0048	***
DIncome_4	0.237966	0.100701	2.363	0.0181	**
DIncome_1	−0.342563	0.0983126	−3.484	0.0005	***
AverageTemperature_oC	0.00536948	0.000757112	7.092	<0.0001	***

Mean dependent var	0.263842	S.D. dependent var	1.273216
Sum squared resid	5252.547	S.E. of regression	0.740229
Log-likelihood	−10725.94	Akaike criterion	21477.87
Schwarz criterion	21571.07	Hannan-Quinn	21509.48
rho	0.635827	Durbin-Watson	0.698041

'Between' variance = 0.298745
'Within' variance = 0.249687
mean theta = 0.816534

Joint test on named regressors -
Asymptotic test statistic: Chi-square(12) = 1531.12
with p-value = 0

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 31585.8
with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(2) = 13.2038
with p-value = 0.00135777

Model 1: Random-effects (GLS), using 9598 observations
Included 400 cross-sectional units
Time-series length: minimum 22, maximum 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.678703	0.0998910	−6.794	<0.0001	***
LnAveragePricePerDay	−0.242899	0.0190043	−12.78	<0.0001	***
Adult	0.167671	0.0188724	8.884	<0.0001	***
Children_18_years	0.189937	0.0205030	9.264	<0.0001	***
Elderly_More_60_years	0.100793	0.0441142	2.285	0.0223	**
DIncome_2	−0.188960	0.0739935	−2.554	0.0107	**
DIncome_4	0.268270	0.100593	2.667	0.0077	***
DIncome_1	−0.266405	0.0953989	−2.793	0.0052	***
AverageTemperature_oC	0.00537514	0.000757318	7.098	<0.0001	***
DGarden_2	0.808618	0.118669	6.814	<0.0001	***
DSwimming_Pool_2	0.366178	0.115287	3.176	0.0015	***
DWater_Saving_Devices_2	−0.207862	0.0753231	−2.760	0.0058	***

Mean dependent var	0.263842	S.D. dependent var	1.273216
Sum squared resid	5314.417	S.E. of regression	0.744537
Log-likelihood	−10782.13	Akaike criterion	21588.26
Schwarz criterion	21674.30	Hannan-Quinn	21617.45
rho	0.635827	Durbin-Watson	0.698041

'Between' variance = 0.300982
'Within' variance = 0.249687
mean theta = 0.817194
Joint test on named regressors -
Asymptotic test statistic: Chi-square(11) = 1511.22
with p-value = 0

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 31817.1
with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(2) = 18.4892
with p-value = 9.66338e-005

Model 1: Random-effects (GLS), using 1632 observations
Included 68 cross-sectional units
Time-series length = 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−1.28742	0.263888	−4.879	<0.0001	***
LnAveragePricePerDay	−0.309776	0.0281026	−11.02	<0.0001	***
Adult	0.152055	0.0465868	3.264	0.0011	***
Children_18_years	0.143159	0.0611797	2.340	0.0193	**
DHoushold_Type_1	0.743243	0.211477	3.515	0.0004	***

Mean dependent var	−0.677312	S.D. dependent var	0.695911
Sum squared resid	632.3305	S.E. of regression	0.623225
Log-likelihood	−1542.018	Akaike criterion	3094.036
Schwarz criterion	3121.023	Hannan-Quinn	3104.047
rho	0.502438	Durbin-Watson	0.950788

'Between' variance = 0.227649
'Within' variance = 0.175644
theta used for quasi-demeaning = 0.823515
Joint test on named regressors -
Asymptotic test statistic: Chi-square(4) = 144.72
with p-value = 2.75303e-030

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 5575.23

with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(1) = 0.462993
with p-value = 0.496229

Model 1: Random-effects (GLS), using 3432 observations
Included 143 cross-sectional units
Time-series length = 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.765799	0.133749	−5.726	<0.0001	***
LnAveragePricePerDay	−0.286005	0.0297506	−9.613	<0.0001	***
Adult	0.220460	0.0355647	6.199	<0.0001	***
Children_18_years	0.260064	0.0380004	6.844	<0.0001	***
DResidential_Type_1	−0.307757	0.101352	−3.037	0.0024	***

Mean dependent var	−0.256510	S.D. dependent var	0.812726
Sum squared resid	1475.832	S.E. of regression	0.656142
Log-likelihood	−3421.628	Akaike criterion	6853.255
Schwarz criterion	6883.960	Hannan-Quinn	6864.224
rho	0.546094	Durbin-Watson	0.871614

'Between' variance = 0.269391
'Within' variance = 0.170335
theta used for quasi-demeaning = 0.839783

Joint test on named regressors -
Asymptotic test statistic: Chi-square(4) = 208.745
with p-value = 4.94776e-044

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 14398.9
with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(1) = 0.00647542
with p-value = 0.935863

Model 1: Random-effects (GLS), using 3096 observations
Included 129 cross-sectional units
Time-series length = 24

Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*	
const	−0.468728	0.273081	−1.716	0.0861	*
LnAveragePricePerDay	−0.209318	0.0491898	−4.255	<0.0001	***
Adult	0.180953	0.0427231	4.235	<0.0001	***
Children_18_years	0.274276	0.0314606	8.718	<0.0001	***
ADTemp	0.0819215	0.0120460	6.801	<0.0001	***
DGarden_1	−0.625965	0.153356	−4.082	<0.0001	***
DWater_Saving_Devices_1	0.388339	0.134950	2.878	0.0040	***
DSwimming_Pool_1	−0.565468	0.150147	−3.766	0.0002	***
DResidential_Type_1	−0.235164	0.127050	−1.851	0.0642	*

Mean dependent var	0.604103	S.D. dependent var	1.196228
Sum squared resid	1803.534	S.E. of regression	0.764229
Log-likelihood	−3556.552	Akaike criterion	7131.104
Schwarz criterion	7185.445	Hannan-Quinn	7150.619
rho	0.648128	Durbin-Watson	0.675738

'Between' variance = 0.288359
'Within' variance = 0.305897
theta used for quasi-demeaning = 0.794258

Joint test on named regressors -
Asymptotic test statistic: Chi-square(8) = 427.203
with p-value = 2.8236e-087

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 7866.77
with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(1) = 3.14238
with p-value = 0.0762827

Model 1: Random-effects (GLS), using 1440 observations
Included 60 cross-sectional units
Time-series length = 24
Dependent variable: LnConPerDay

	Coefficient	*Std. Error*	*z*	*p-value*

const	1.05074	0.219277	4.792	<0.0001	***
LnAveragePricePerDay	0.465616	0.0777807	5.986	<0.0001	***
Adult	0.122728	0.0311852	3.935	<0.0001	***
ADTemp	0.0921004	0.0194780	4.728	<0.0001	***
DResidential_Type_1	−1.31526	0.201533	−6.526	<0.0001	***
DGarden_1	−1.25810	0.160701	−7.829	<0.0001	***

Mean dependent var	1.836988	S.D. dependent var	1.112281
Sum squared resid	975.7468	S.E. of regression	0.824599
Log-likelihood	−1763.051	Akaike criterion	3538.102
Schwarz criterion	3569.736	Hannan-Quinn	3549.911
rho	0.760674	Durbin-Watson	0.467897

'Between' variance = 0.332956
'Within' variance = 0.372508
theta used for quasi-demeaning = 0.788955

Joint test on named regressors -
Asymptotic test statistic: Chi-square(5) = 151.926
with p-value = 5.19361e-031

Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 3364.42
with p-value = 0

Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(1) = 0.294507
with p-value = 0.587347