RESIDENTIAL WATER DEMAND: A QUANTILE REGRESSION APPROACH

by

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

Quantile regression has been introduced into residential water demand. Differences between quantile regression and conditional mean regression are found on extreme quantiles. Monotonically increasing price elasticities are found by quantile regression. The hypothesis of a "U-shaped" elasticity pattern can only be partially established for high quantiles. Natural experiments are used to compare price elasticity among comparable cross-sectional subsamples, which empirically indicates: 1) lowering break-over thresholds for block rate makes affected consumers more price elastic; 2) high quantile households are less price elastic in the summer than the winter; and 3) low quantile households and those with smaller yards and pools are more price elastic.

CHAPTER 1

Introduction

Residential water demand analysis generally focuses on the marginal effects of key variables like price, income and weather on household water consumption. Much of the water demand literature also focuses on the price elasticity of demand. Policy makers as well as public and private water companies are critically concerned with the effects of water price on consumption. Tax and price related policies are based on demand analysis to assess changes in household welfare. Business strategies are based on price elasticity of demand to efficiently recover fixed costs incurred. Hence, the quality of demand analysis is the key for formulating successful policies and business strategies.

Water demand analysis has been popular for decades. Previous research primarily concerns several key issues including specification, elasticity and simultaneity. Studies on specification discuss the choice of price specification and other variables such as income, weather, housing characteristics and household composition. Price elasticity and income elasticity have been studied in terms of short-run vs. long-run adjustments and seasonal fluctuation. Simultaneity is another issue involved in water demand literature because quantities consumed determine marginal price under a block rate structure. When simultaneity has been detected empirically [1], instrumental variable techniques have been introduced to overcome the problematic estimation. Estimation approaches such as maximum likelihood and generalized method of moments have been applied using instrumental variables.

Although recent literature has shed considerable light on residential water demand, still more can be done to enrich understanding. Most water demand research has employed conditional mean regression, which is optimized by minimizing sum of least squares (LS) in cross-sectional samples. LS provides a view of how representative households behave regarding residential water consumption. However, LS has weaknesses in terms of inefficient estimation (heteroskedasticity), sensitivity to outliers, and incomplete characterization of conditional distributions of the dependent variables. Improvements in making the estimation robust to household heteoroskedasticity, in assigning less weight to extreme observations and in providing a comprehensive understanding of the dependent variable can bring new insights to water demand research.

In order to make contributions in these regards, this paper introduces quantile regression (QR) to residential water demand analysis. Technically, QR is robust to most kinds of heteroskedasticity and relaxes the LS assumption of independent, identical (i.i.d) and normally distributed errors [9]. The optimization strategy in QR is to minimize the sum of weighted absolute values of residuals. This approach assigns less weight to extreme observations so that it is more desirable for residential water data with right skewedness [18]. Moreover, QR provides different coefficients for the chosen quantiles of the dependent variable, because different equations are estimated [23, 24]. These varied coefficients provide extra information which is not captured by conditional mean regression.

Interestingly, QR has been applied to estimate household-level water consumption data provided by EPCOR Utility Inc. located in Phoenix, AZ. The EPCOR data were divided into several comparable subsamples according to year, month and meter size. Estimating each subsample separately, the robust difference between QR and conditional mean regression was verified. Moreover, natural experiments have been used to detect the different influences of price change, seasonality, groupwise usage level[1] and economic status[2] across varied consumption levels. The empirical results can be summarized as follows: 1) conditional mean regression does not characterize the marginal effect of price for consumers with extreme water usage; 2) QR provides a monotonically increasing price elasticity curve, and the "U-shaped"

[1]In what follows, the groupwise usage level specifically refers to the general difference in usage between households with different meter sizes. For more details see Table 3.2.

[2]In what follows, the groupwise economic status specifically refers to the difference in yard size, pool size, pool ownership between households with different meter sizes. For more details see Table 3.2.

price elasticities hypothesis can only be partially verified for the high quantiles; 3) the increase in block prices that occurred in the EPCOR data in 2008 fails to make households overall more price elastic, but lowering break-over threshold makes affected households more price elastic; 4) only high water consumers are more price elastic in summer than winter; and 5) households with lower usage and lower economic status are more price elastic.

This paper proceeds as follows. Section 2 presents the literatures on residential water demand, conditional QR and discusses the motivation for introducing QR. Sections 3 discusses the data generating process. Section 4 describes the empirical model, hypotheses, and results. Section 5 discusses policy implication.

CHAPTER 2

Literature Review

The literature devoted to estimating residential water demand is vast. In those articles, specification, elasticity and simultaneity have been discussed. The majority of these studies apply conditional mean regression optimized by minimizing squared errors using cross-sectional data. However, LS has weaknesses in terms of inefficient estimation (heteroskedasticity), sensitivity to outliers, and incomplete characterization of conditional distributions of the dependent variable. These weaknesses can be overcome by QR to provide new insight into water demand studies. This chapter reviews previous research in residential water demand, compares conditional mean regression to conditional quantile regression, and presents motivation for introducing QR.

2.1 Residential Water Demand

Previous water-demand research and similar electricity-demand research generally adopts the following generalized form:

$$Quantity = f(Own\,Price, Income, Other\,Variables).$$

The primary concerns are the nature of water demand, specification, elasticity, functional form and simultaneity, which are discussed below.

2.1.1 The Nature of Water Demand

Most previous research assumes that water is normal good with no substitutes. The demand for water can be divided into non-discretionary and discretionary demand. Non-discretionary demand refers to the basic portion of water consumption, which is independent of price [16]. Discretionary demand refers to water consumption above non-discretionary usage. Discretionary demand is assumed to vary for long-run demand analysis, but determined by a fixed stock of water-using technology in the short-run. The majority of previous studies focus on short-run demand under block rate structure. Most U.S residential water is priced with a block schedule containing a fixed charge and marginal price varying by level of consumption [33]. This makes water consumption a function of varied price, which is different from classic demand analysis where marginal price is exogenous.

2.1.2 Model Specification

The non-exogenous price has generated numerous debates on whether a combination of marginal price with Nordin's "rate structure premium" variable or average price should be the price variable. Taylor [41] proposes that marginal price captures the substitution effect and income effect of a price change on the last block. The income effect for the rest of the blocks can be measured by their average price or total expenditure. Nordin [32] proposes the "rate structure premium" to avoid the situations that same average price and total expenditure are caused coincidentally by different senarios. The "rate structure premium" is defined to be the difference between what consumers have paid and what they would have paid if their water consumption were charged at last block's marginal price. Nordin expects that the coefficient of "rate structure premium" has the opposite sign but same magnitude as the coefficient of income. However, there has been little success in empirical verification of this hypothesis [30].

The alternative price variable is average price proposed by Foster and Beattie[13]. They argue that the perfect-information assumption made by Taylor and Nordin may not be realistic. Their argument accords with a survey made by Stratus Consulting Inc.[40], which indicates only 7 percent of consumers were concerned and aware of their water price. Foster and Beattie[13] have verified empirically that there is no statistically significant difference between the two specifications and the average price specification is superior according to a higher R-squares. Moreover, Shin [38] speculates that benefit of finding out the marginal price may be lower than the cost of determining the marginal price. A slightly different price specification considered is lagged average price, which has at least two advantages. First, lagged average price can be calculated relatively easily from information given on the water bill, which is more likely to affect consumption [5, 10, 31]. Secondly, lagged average price can mitigate the simultaneity between quantity and average price calculated on quantity, because it is predetermined [4, 10].

Water-demand research has gradually reached an agreement that the appropriate price specification is an empirical question. Thus, empirical tests are introduced in water and electricity demand analysis to examine how consumers respond to various price specifications. Opaluch [34] introduces a linear form empirical test, which has been improved by Griffin and Chang [19] as

$$Q = \beta_0 + \beta_1 AP + \beta_2(MP - AP) + \cdots.$$

Two hypotheses tests involving β_1 and β_2 determine price to which consumers respond to (see Table 2.1). Although this test is innovative, it does not specify a function of both marginal and average price for consumers to respond.

Table 2.1: Opaluch Test

Case	β_1	β_2	$\beta_1 = \beta_2$	**Response**
(1)	$= 0$	$= 0$	Yes	No Response
(2)	$\neq 0$	$= 0$	No	AP
(3)	$\neq 0$	$\neq 0$	Yes	MP
(4)	Undetermined	$\neq 0$	No	Mixed Price or Weak Data

Shin [38] introduces the concept of perceived price to estimate electricity demand under decreasing block rate, which permits a price perception parameter to be estimated explicitly with a dynamic log-log model as

$$lnQ_t = \beta_0 + \beta_1 lnQ_{t-1} + \beta_2 lnMP_t + \beta_3 \cdot k \cdot ln(\frac{AP_t}{MP_t}) + \cdots.$$

Hypothesis tests about the perception parameter k indicates consumers' behavior (see Table 2.2). Nieswiadomy and Molina [31] have applied Shin's test to their household-level data in Denton, Texas. They found consumers with increasing block rates were more likely react to marginal price, while consumers with decreasing block rates more likely to react to average price. Ray [36] has applied Shin's test to EPCOR data on Phoenix water consumption, finding the k value is statistically different from 0 and 1, which implies consumers respond to a mixture of marginal price and average price.

Table 2.2: Shin Test

Case	k	**Response**
(1)	$k = 0$	MP
(2)	$k = 1$	AP
(3)	$0 < k < 1$	Perceived Price between MP and AP
(4)	$k > 1$	Perceived Price above AP

Income has been included as an explanatory variable in most previous research because income is an element of classic demand analysis. Two common income variables are annual per capita income [19] and assessed home value [11, 22, 31]. The lack of availability of income data is the main reason for using assessed home value. Assessed housing value is a good proxy because banks typically do not allow a mortgage payment above one third of monthly income [30]. Although mortgage policy has changed dramatically in the last two decades, the fact that mortgage eligibility is calculated based on income remains the same. Additionally, assessed value correlates to household preferences for home lifestyle [4] and household size.

The effect of weather on water consumption has gained attention recently because of public concerns about global climate change. Various weather variables have been studied in recent literature. Average temperature [39] and precipitation [12, 13] are the variables first introduced. Then considering consumers' limited interest in collecting exact weather information, the number of days in which temperature exceeds a certain level and the number of rainy day have been included [26]. Another variable is evapotranspiration less rainfall [21, 30, 31]. Evapotranspiration is a comprehensive measure determined by four factors: solar radiation, wind, humidity and temperature [7, 8], which may be more desirable than including those four weather variable separately. Seasonality is another issue to be concerned with because outdoor water usage displays seasonal patterns.

Other variables such as property characteristics and household composition have been discussed as well. Nauges and Thomas [29] found housing features like garden size and number of bathrooms are relevant to residential water consumption. In subsequent research, interaction terms between property characteristics such as size of yard or pool with weather variables were found to be statistically significant [36]. Household composition such as age and cultural background also affect water consumption. A higher proportion of younger people in a community may lead to higher water consumption [29]. Communities with a higher proportion of elderly inhabitants tend to consume more water for gardening [27]. Besides age factors, percentage of Hispanic origin population has also been considered to measure the effect of cultural background on water consumption [16, 19].

2.1.3 Elasticity

Elasticity is another important topic in residential water demand analysis. The main focus is price elasticity rather than income elasticity for several reasons. First, because water consumption is a small proportion of household expenditures, short-run income elasticity has a very small magnitude [44]. Second, block rate structure potentially encompasses the income effect because it changes the budget constraint. Disentangling the income effect caused by block rate structure from the one caused by income presents extra difficulties. Third, water price is the main instrument of water economic policy, so price, not income, is of primary concern for policy-making. Hence, most previous research focused on price elasticity, which is a key determinant of the efficacy of price-related water policies [15].

Price elasticity is calculated differently depending on the functional form. For a linear demand model price elasticity is calculated using a constant price coefficient estimated by conditional mean regression. The average price elasticity is commonly calculated on sample average quantity and price to obtain a single price elasticity. The price elasticity for each customer can be calculated with actual quantity and average price with the single price coefficient on conditional mean but matching an individual customer's quantity and average price with a single slope coefficient may not make sense. The reason is that the price coefficient estimated on sample average may not represent the behaviors of households with extreme water consumption. The Log-log functional form only provides a single constant price elasticity for all customers.

The water demand literature has gradually reached a consensus on price elasticity. First, price elasticity and income elasticity are inelastic because water expenditure is a small component of household expenditure [4, 44]. Secondly, long-run price elasticity is more elastic than short-run due to the fact that long-run demand allows the discretionary demand to change once water-consuming technology changes [6]. Last, some studies provide empirical evidence that elasticity differs because of seasonality [16, 35] and income class [37].

2.1.4 Functional Form and Simultaneity

Other studies have shed light on functional form and simultaneity. In terms of the functional forms, linear [30], semi-log [3] and log-log [29] demand function dominate water demand analysis, while recently the Stone-Geary demand function has been introduced [2, 16, 28]. The Stone-Geary demand function has been commonly used to estimate demand of durable goods, which estimates subsistence-level demand and the rest of demand separately. Studies in water demand estimate a utility function of the form

$$lnU = \sum_{i=1}^{n} \beta_i ln(q_i - \gamma_i)$$

where subsistence-level usage has been separated from total usage by "marginal budget share" (β_i) and "subsistence level usage" (γ_i). The price slope in the Stone-Geary demand function can be interpreted as marginal effect of price beyond the fixed proportion of necessary purchases.

Simultaneity is a main challenge in water demand analysis since both average price and marginal price are functions of quantity consumed. Early research estimated water demand functions using linear regression. However, LS requires there be no correlation between the errors and explanatory variables, which may be violated as in the case of block rate structure for residential water. Agthe et.al [1] employed a Hausman [20] test to detect possible simultaneity. The Hausman test results indicated the existence of simultaneity, which implies alternative estimation approaches should be considered to mitigate this problem.

Subsequent efforts to overcome simultaneity start with applying instrumental variable techniques. Wilder and Willenborg [43] suggests a two-stage least squares technique. In the first stage, average price is regressed on other instrumental variables to get predicted values. These predicted values are used as a regressor in the second stage. Another approach is a two-stage probit approach introduced by Terza [42]. In his method, observed electricity demand was first regressed on actual marginal prices that the household would face at different level. Then the actual rate schedule and predicted quantity demand were used to obtain marginal price. Maximum likelihood [21] and generalized method of moments [14] have been applied with instrumental variables.

2.2 Mean Regression vs. Quantile Regression

Conditional mean regression has been applied to most cross-sectional data for residential water demand analysis. Estimated coefficients indicate how representative households behave in residential water consumption. Although conditional mean regression is a good approach, it has weaknesses which may lead to inefficient estimation, sensitivity to extreme observations, and incomplete characterization of the conditional distribution of the dependent variable.

Conditional mean regression may lead to inefficient estimation because of the LS assumption on errors. LS assumes i.i.d distributed errors to guarantee Gauss-Markov theorem, which ensures the estimated coefficients are unbiased and efficient. However, the i.i.d assumption contradicts the household varied water consumption behavior and the normally distributed error assumption does not fit the right skewedness in residential water consumption distribution [16]. The violation of these assumptions results in unbiased but inefficient estimation of coefficients, which may hinder making correct inferences.

The second problem for conditional mean regression is LS optimization strategy. LS assigns more weight to extreme observations than non-extreme observations. The larger weight comes from the criterion being minimized, i.e. sum of squared residuals. Extreme water consumption is likely to be caused by unusual factors such as vacancy or family gathering. These factors add limited information in characterizing representative household behaviors in daily water consumption. Hence, assigning too much weight to extreme observations is not appropriate.

Another problem is that conditional mean regression estimated by LS does not fully characterize the conditional distribution of the dependent variable. LS provides constant coefficient for all sample households regardless of their varied consumption levels. A constant coefficient may limit economic inferences. For instance, a constant price coefficient may be restrictive in calculating an accurate price elasticity for an individual household. The reason is that it may be inappropriate to match price coefficient estimated on conditional mean with varied quantity and price. Hence, designing policy and price structure only based on a LS constant coefficient may not be appropriate for all groups of consumers.

To overcome the above problems, QR is applied to residential water demand analysis. QR provides a convenient method for estimating conditional quantile functions. Without strict assumptions on errors, QR is robust to most forms of heteroskedasticity. Its optimization strategy is to minimize the sum of weighted absolute residuals, which assigns less weight to the extreme observations than LS. Moreover, QR allows estimated coefficients to vary by quantiles (τ) of dependent variable. Thus, it is possible that the conditional distribution of water consumption can be characterized.

QR has been successfully applied to other fields. Manning et al. [25] have investigated the impacts of price on alcohol consumption with QR, finding statistically significant difference between moderate drinkers and heavy drinkers. A pronounced "U-shaped" price elasticity was found. Light drinkers, those consuming small quantities very infrequently, do not respond much to changes in the price of alcohol. Heavy drinkers are addicted so they change their alcohol consumption very little, if any, when price changes. Both groups are less responsive to price changes than the moderate consumers of alcohol who drink more frequently but who are not addicted.

Similarly, QR was introduced by Gilpin [17] to education research to observe relationship between teachers' aptitude and salary. The goal of his research was to examine the effect of salary and other factors such as school and community environment on teachers' aptitude. An inverted "U-shaped" salary elasticity to aptitude curve was found. According to Gilpin's interpretation, teachers with different aptitude respond differently to the salary change. Teachers with median level aptitude are more sensitive to the salary change than their lower and higher aptitude counterparts. Teachers with lower quantile aptitude are concerned more about education support from local funds, while teachers with high quantile aptitude are concerned more about community factors such as street crime and students' eligibility for free lunch.

2.3 Motivation for Introducing Quantile Regression

The knowledge of marginal effects of price change, seasonality, water usage level and economic status is helpful in designing effective water policy and price schedules. The efficacy of price-related policy is determined by the magnitude of price elasticity. Academic efforts in this regard must address the peculiarities of block rate structure, which causes simultaneity and affects consumers on different blocks differently. Hence, it is necessary to study marginal effects and price elasticity more specifically on different quantiles to obtain a more comprehensive understanding of block prices.

The encouraging results from applying QR into other fields motivates this paper. Most previous water demand studies on cross-sectional sample estimate a constant price coefficient regardless of household heterogeneities. A constant coefficient is to some extent limited in making economic inference for individual households, in particular for extreme observations. Designing policy and price schedule based upon these results may not be efficient. Therefore, QR is introduced to compare LS results on cross sectional sample. QR can provide results varied across different consumption to give a more complete explanation than conditional mean regression.

QR can also provide more comprehensive knowledge to advance recent studies on the effects of rate structure change, seasonality, groupwise usage level and economic status on price coefficients and price elasticities. The intensity of these effects across varied consumption level remains unknown.

CHAPTER 3

Data

The cross-sectional data used are extracted from a monthly household-level panel dataset from June 2005 to December 2010 (see Table 3.1). These data includes household-level water usage provided by EPCOR Water in Anthem, Phoenix, property characteristics data collected from Maricopa County Assessors' Office and weather data from the Arizona Meteorological Network (AZMET), and Maricopa County Flood Control District (FCD). These data are matched according to billing address of EPCOR water consumers. The daily weather data were also matched with billing dates for each customer.

Table 3.1: Variable Definitions

Source	**Variable**	**Definition**
Billing	Household ID	Household EPCOR ID
	Meter Size	Diameter of water pipe (inches)
	Billing Begin Date	Date billing period begins
	Billing End Date	Date billing period ends
	Total Usage	Total usage in a billing period (kgal)
	Normalized Usage	(Total Usage/Billing Period)*30 days (kgal)
	Marginal Price	Price of last unit water consumed
	Fixed Charge	Monthly fixed fee
	Total Bill	30 days normalized bill ($)
	Average Price	Total Bill/Normalized Usage ($)
	Real Average Price	Adjusted by Phoenix CPI (2001 $)
Property	Real Assessed Home Value	Adjusted by Phoenix CPI (2001 $)
	Lot Size	Size of lot (sq ft)
	Pool Size	Size of pool surface (sq ft)
	Living Area Size	Size of indoor space (sq ft)
	Yard Size	[Lot-(Pool+Living Area)]size (sq ft)
Weather	Normalized AZMET ET	Evapotranspiration (inches/30 days)
	Rain Event FCD	Number of rainy day (events/30 days)

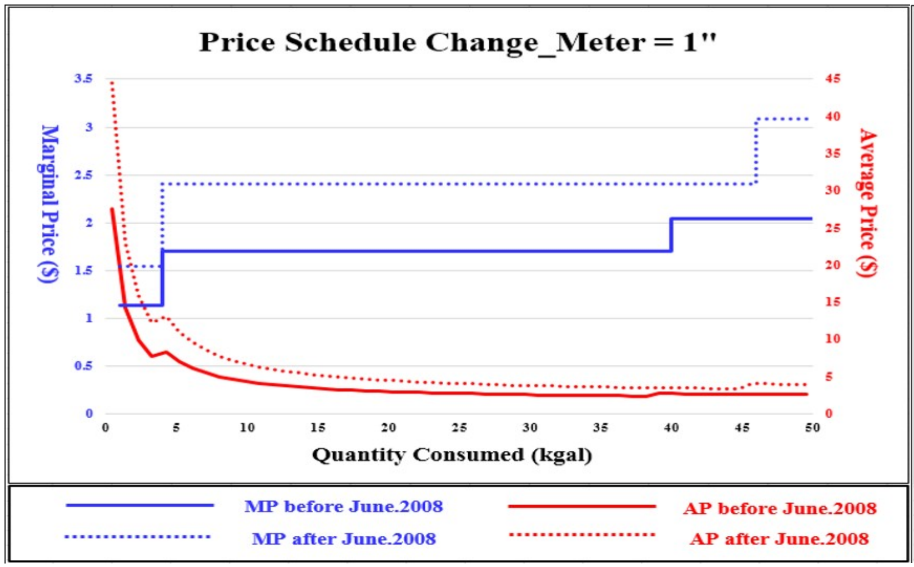


Figure 3.1: Price Schedule (a)

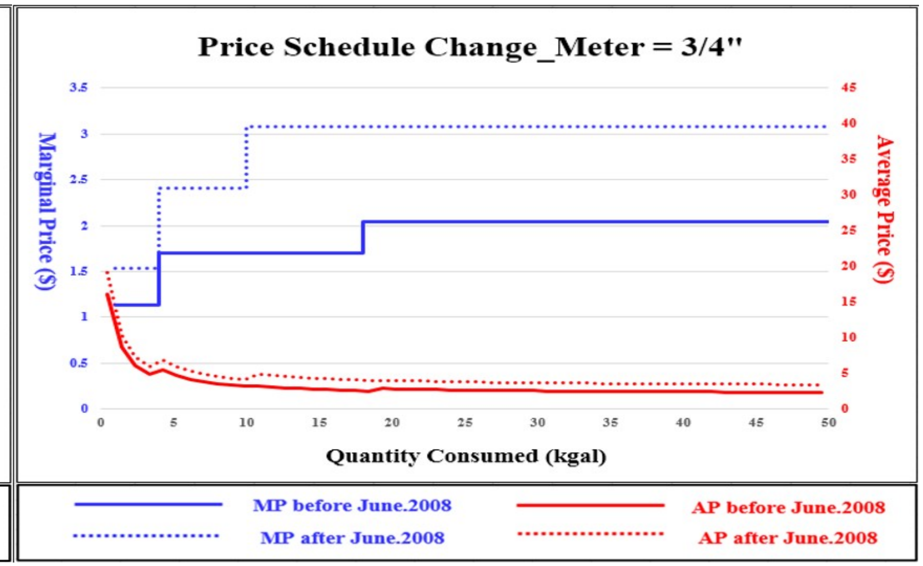


Figure 3.2: Price Schedule (b)

Anthem is a Del Webb planned community opened in 1998. Since then, home construction has continued and the community population grew to $21,700$ at the time of the 2010 Census. Anthem's residential water price schedule was changed in June 2008 for households with both 1" and 3/4" meter sizes, i.e. diameter of water pipe (see Figures 3.1 and 3.2). The marginal price increased from \$1.13 to \$1.54 per kgal, from \$1.7 to \$2.41 per kgal and from \$2.04 to \$3.08 per kgal for tier 1, tier 2, and tier 3, respectively. The break-over between tier 1 and tier 2 remained the same at 4 kgal for all consumers. However, the break-over threshold between tier 2 and tier 3 was changed differently for households with different meter sizes. For households with 1" meter, the break-over threshold was increased from 40 kgal to 46 kgal, while it has been decreased from 18 kgal to 10 kgal for 3/4" meter households. Moreover, the fixed charge increased from \$26.42 to \$42.88 per month for 1" meter household; for their 3/4" counterparts, it increased from \$15 to \$17.53 per month.

The different changes in the break-over threshold by meter size in June 2008 afford an interesting natural experiment. There is a natural break point in the sample data: before the price change and after. And there are two distinct groups of customers – 1" and 3/4" meter – from the same community, Anthem, whose behavior can be measured with different price changes[1]. In order to judge whether customers with different meter sizes differ statistically from one another, median values for water use and household characteristics are compared (see Table 3.2). Sample medians are compared because the median is preferred to the sample mean with skewed data. First, the comparison is made within each meter to examine the impact of the 2008 price change. The result shows for both meters sizes the usage after price change were statistically lower than usage before change, except summer usage for households with 1" meter. Because the break-over between tier 2 and tier 3 had been slightly increased for 1" meter households, the impact of increased price in tier 3 is mitigated. Secondly, the comparison is made across two meter sizes to

[1] The difference in meter size is caused by the fact that Del Webb planned community categorizes lots into big and small sizes. The large lot size is more likely to be equipped with 1" water pipe, while small lot size is more likely to be equipped with 3/4" water pipe.

examine the groupwise differences between households. Households with 1” meter have higher median consumption in all seasons before and after price change than their 3/4” meter counterparts. The results of time-invariant variables are evidence that households with 1” meter size have better economics status, i.e. have higher value homes, larger yards, and a more likely to have a swimming pool.

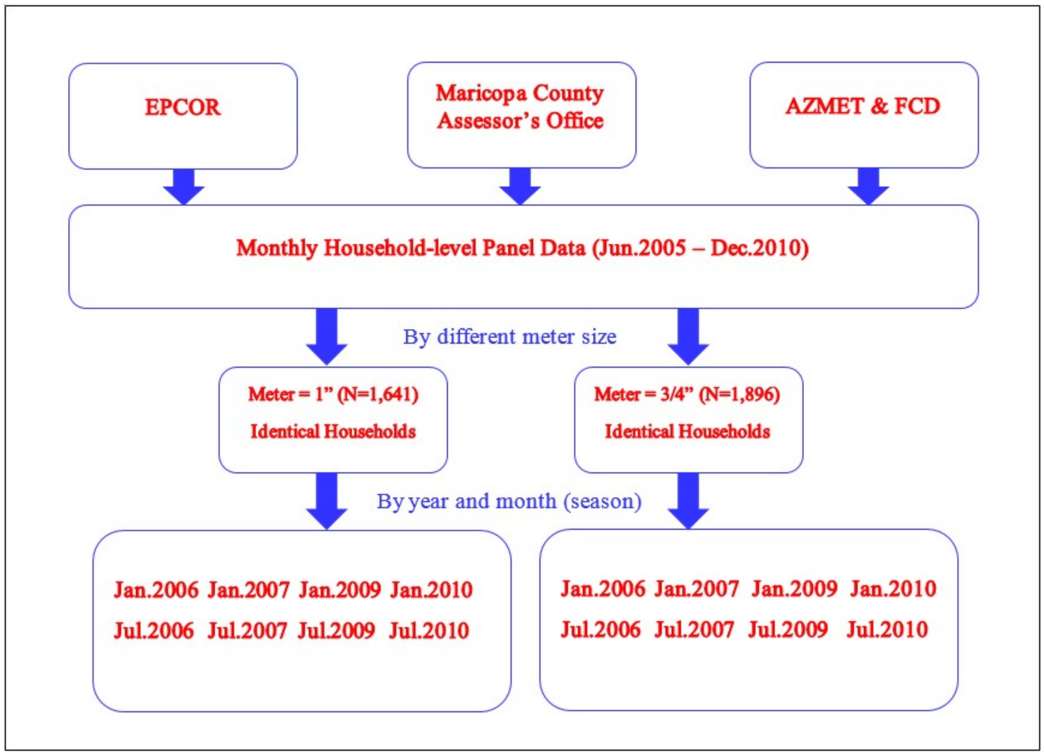
Table 3.2: Descriptive Statistics, Median Values

Time-invariant Variables								
Variable/Median	Meter=1”			Meter=3/4”			P-value*	
Home Value (1,000 $)	205.9			127			<.0001	
Yard Size (Sq ft)	10,232			6,495			<.0001	
% with Pool	46%			30%			<.0001	
Pool Size (Sq ft)****	458			450			<.0001	
Time-varying Variables								
Variable/Median	Meter=1”			Meter=3/4”			P-value*	
Time	Before 2008	After 2008	P-value**	Before 2008	After 2008	P-value**	Before vs. Before***	After vs. After***
Usage (Kgal)	8.43	7.94	<.0001	8.27	7.24	<.0001	<.0001	<.0001
Usage_Jan (Kgal)	7.50	6.77	<.0001	7.24	6.20	<.0001	<.0001	<.0001
Usage_Jul (Kgal)	10.34	10.14	0.21	10.00	9.09	<.0001	<.0001	<.0001

* – % with Pool is tested by the proportion test; all other entries are tests for differences in medians using the Wilcoxon-Mann-Whitney test.
** – test for difference in median with same meter size.
*** – test for difference in median across two meter size with same time period.
**** – households without pool are excluded.

The above two differences make the natural experiments available so that comparisons can be made across customers with different meter sizes. Specifically, it is possible to detect the impacts of different price changes and to examine the influences of varied groupwise water usage level and economic status. In order to achieve these goals, the original panel data have been divided into several cross-sectional subsamples based on three criteria: year, month and meter size (see Figure 3.3). For the same meter size, all subsamples contains identical households, meaning comparison across seasons and years are for the same customers.

Figure 3.3: Data Generating Process



The original panel data have observations between June 2005 and December 2010. Given the price structure changed at June 2008, the original data are divided into two groups, namely before change and after change. Before change refers to years 2006 and 2007, while after the change refers to year 2009 and 2010. For identical households within the same meter size, the impact of price changes can be measured by comparing before change to after change. Data for 2005 were excluded due to the low quality. Data for 2008 were also excluded because the price change was probably not anticipated by most customers prior to receiving their first bill following the rate schedule change.

Another criterion for dividing the sample is month so that the impact of seasonality can be studied. Seasonality is studied because winter usage reflects more non-discretionary indoor usage whereas summer reflects more discretionary outdoor usage. Previous literature in residential water demand shows both demand and price elasticity will be affected by seasonality. January and July are chosen for winter and summer respectively because of their extreme monthly water usage level and monthly evaportranspiration level. The impact of seasonality on demand is expected to be captured by comparing January price response to July in same year and same meter size.

The different meter sizes provide two more perspectives of cross-meter comparisons. First, price structure change varies across households with different meter size. Given the fact that all households in Anthem are comparable, their varied responses are the measure of impact caused by the way that the price schedule changed. Second, meter size is also an indicator for groupwise water usage level and economic status. Thus, the influences of price structure change, groupwise water usage level, and economic status on demand and price elasticity can be captured by comparison across the two meter sizes controlling for year and month.

The comparisons mentioned above can be summarized in the following four types. First, compare identical customers with the same meter size to show the impact of price schedule change in 2008. Second, compare identical customers with the same meter size to show the influence of seasonality. Third, compare across the two meter sizes to show the difference between two different price changes. Fourth, compare across the two meters sizes comparison in same time period to show how groupwise water usage level and economic status matter.

CHAPTER 4

Model, Hypotheses and Results

4.1 Model

QR model is introduced to estimate 16 cross-sectional samples identified in the previous chapter as

$$Q_i(\tau) = \beta_0(\tau) + \beta_1(\tau)LagAP_i + \beta_2(\tau)HomeVal_i + \beta_3(\tau)YardET_i + \beta_4(\tau)PoolET_i$$

$$+\beta_5(\tau)YardRain_i + \epsilon_i(\tau),$$

where τ denotes a particular quantile.

Table 4.1: Model Specification

Notation	**Definition**	**Measured by**
Q	Household water consumption	Normalized usage
LagAP	Real lagged average price	Last period real average price
HomeVal	Real home value	Assessed home value
YardET	Yard Evapotranspiration	Yard Size * Normalized ET
PoolET	Pool Evapotranspiratoin	Pool Size * Normalized ET
YardRain	Yard Rain Event	Yard Size * Rain Event

Real lagged average price is chosen because average price can be used without assuming consumers have full information. A Shin's test has been performed in all 16 subsamples by QR. Most calculated k values are not equal to 0, which implies that the full price information assumption about marginal price is not appropriate for consumers in EPCOR data. Lagged average price can mitigate the simultaneity between current quantity and average price. Real assessed home value is introduced as a proxy for income, which also controls for the size of household to some extent. Yard evapotranspiration and pool evapotranspiration are introduced to account for variations caused by both weather and property characteristics. Rain event is interacted with yard size to capture the effect of precipitation events rather than precipitation amount.

In the above model, τ refers to the percentile chosen for QR. The 9 deciles from 0.10 to 0.90 as well as the 5th percentile and 95th percentile are estimated to generate the conditional distribution of dependent variable. The model is estimated by minimizing the weighted sum of the absolute deviation of the errors as

$$\min[\sum_{y_i \geq x_i b_\tau} \tau |y_i - x_i b_\tau| + \sum_{y_i < x_i b_\tau} (1-\tau)|y_i - x_i b_\tau|\,],$$

where $\hat{\beta}_\tau$ is the estimate of β_τ [23, 24]. This model has been estimated using the PROC QUANTREG procedure in SAS.

4.2 Hypotheses

The hypotheses can be categorized in terms of methodology and price elasticity comparison. For methodology, the QR results are compared with LS result to examine any differences. The hypotheses are as follows:

- **Hypothesis 1**: "U-shaped" quantile price coefficients: $\beta_{Low(\tau)} \neq \beta_{LS}$ and $\beta_{High(\tau)} \neq \beta_{LS}$.
- **Hypothesis 2**: "U-shaped" quantile price elasticities: $Elas_{Bottom(\tau)} \neq Elas_{Low(\tau)}$ and $Elas_{Bottom(\tau)} \neq Elas_{High(\tau)}$, where $Elas_{bottom(\tau)}$ refers to the most price elastic quantile.

The "U-shaped" QR price coefficient is expected because low quantile households' water demand is non-discretionary, which is less responsive to water price. High quantile households consume water to maintain pools and landscaping, which is less responsive to water price as well. Besides, considering high quantile households' knowledge of water price from their previous water bill, relatively low average price does not provide much incentive for reducing water usage. The "U-shaped" price coefficient causes "U-shaped" price elasticity. Because of the high usage and low average price for high quantile households, their price elasticity is expected to become quite inelastic.

For price elasticity comparison, the QR price elasticity is compared according to natural experiments as discussed in Chapter 3. The hypotheses concerning the effect of price changes, the effect of seasonality, and the effect of groupwise water usage level and economic status are as follows.

- **Hypothesis 3**: The price increase in 2008 makes consumers more price elastic: $|Elas_{Before}| < |Elas_{After}|$.

- **Hypothesis 4**: For households with 3/4" meter, lowering break-over between tier 2 and tier 3 makes affected households j more price elastic: $|Elas_{j,Before}| < |Elas_{j,After}|$. However, there is less pressure to make 1" meter households affected by price change more price elastic because of the increased break-over.

Controlling for meter size and season, the 2008 price increase is expected to make consumers in Anthem overall more price elastic. The different price changes by reallocating break-over differently is expected to have opposing effects. For households with 3/4" meter, lowering the break-over creates extra burden for affected consumers which makes them more price elastic after the price change. For households with 1" meter, increasing break-over means a lower price for affected consumers, so they have less pressure to be more price elastic.

- **Hypothesis 5**: Households are more price elastic in winter than summer: $|Elas_{winter}| > |Elas_{summer}|$.

Controlling for meter size and year, consumers are expected to be less price elastic in summer than winter. Previous studies have found consumers are less price elastic in winter, because the winter usage are indoor non-discretionary usage. In summer, households tend to be more price elastic because their outdoor usage is discretionary. However, discretionary usage is not necessarily more price elastic, especially for the short-run. For example, the water consumption for gardening is derived by the landscape, but this consumption may not be price elastic, because consumers have to use water to keep plants alive; otherwise, the dead plants will make the landscape looked bad. Also, swimming pools require constant water use in summer. If pools are not properly filled and maintained, they fill with algae and look ugly.

- **Hypothesis 6**: Households with 3/4" meter are more price elastic because of their lower usage level and lower economic status: $|Elas_{Meter=3/4"}| > |Elas_{Meter=1"}|$.

Controlling for year and season, households with 3/4" meter is expected to be more price elastic than their 1" meter counterparts. The difference can be explained by groupwise water usage level and economic status. First, households with 3/4" meter in general have lower usage, which perhaps implies that they are more water conservative, so they may pay more attention to price change. Second, consumers with 1" meter are generally more comfortable economically, so they may already possess or have the means to maintain fancy landscaping and pools that consume water intensively. Hence, discretionary usage for maintaining landscape and pools is expected to make consumers with 1" meter less price elastic.

4.3 Empirical Results

The 16 cross-sectional subsamples of the same households are used to estimate QR and LS. Confidence intervals for each estimated QR coefficient are obtained by bootstrapping. In what follows, all the non-price variables will be referred to as control variables. Most QR coefficients for control variables are statistically significant except for some real assessed home value and the interaction term between rain event and yard size (see Table 4.2). These insignificant coefficients may be caused by the fact that the real estate price and rain events recorded are to some extent homogeneous within Anthem. The signs of all statistically significant variables are as expected.

Table 4.2: Statistical Significance of Control Variables

Control Variable - % of 11 Quantile Estimates Statistically Different from 0*								
Year	2006				2007			
Month	January		July		January		July	
Meter	1”	3/4”	1”	3/4”	1”	3/4”	1”	3/4”
HomeVal	46	82	46	10	19	100	55	19
YardET	81	73	100	100	100	55	64	91
PoolET	81	64	82	82	100	73	100	82
YardRain	N/A**	N/A	55	100	100	0	19	28
Year	2009				2010			
Month	January		July		January		July	
Meter	1”	3/4”	1”	3/4”	1”	3/4”	1”	3/4”
HomeVal	37	100	73	37	19	100	55	100
YardET	82	74	100	100	82	55	100	91
PoolET	73	91	100	100	100	100	100	100
YardRain	19	64	19	28	28	19	19	0

* - 0%: lowest significance level; 100%: highest significant level.
** - No Rainfall at this time period.
Note: All significant coefficient estimates have expected signs.

Besides these control variables, the QR results on real lagged average price are as expected. The 95 percent confidence interval for QR price coefficient are calculated by bootstrapping. Using the estimated price coefficients, price elasticities for QR are calculated by the following procedures: 1) for each household, choose the best-fit quantile (τ^*) by

$$\tau^* = \min\{|y_i - \hat{y}_i(\tau)| \,|\, \hat{y}_i(\tau) = X_i'\hat{\beta}(\tau), \tau \in \{.05, .1, \ldots, .95\}\};$$

2) calculate ith households' price elasticity on the best-fit quantile by

$$Elasticity_i = \frac{RLAP_i}{Q_i} \cdot \hat{\beta}_{\tau^*}, \text{where } \hat{\beta}_{\tau^*} \text{ is the estimated value of } \beta_{\tau^*};$$

3) for each level of best-fit quantile, take median price elasticity of all households on this level as price elasticity to represent this quantile. The reason for using median instead of mean is that it gives a more robust result in the presence of extreme monthly usage. The confidence intervals for the elasticities are calculated in the same manner by replacing $\hat{\beta}_{\tau^*}$ by its bootstrap confidence interval.

4.3.1 Methodological Results

The difference between quantile and conditional mean regression can be summarized as follows. First, price coefficients estimated by QR are statistically different from the one estimated by LS in some quantiles as expected in **Hypothesis 1**. These robust differences occur primarily on low quantiles such as 5th and 10th percentiles and high quantiles such as 80th and 90th percentile (see Figure 4.1 and 4.2; shaded areas indicate statistical difference between QR and LS coefficients). This result implies that LS constant price coefficient does not capture the conditional distribution of water usage for extreme consumers. LS overestimates of the magnitude of price marginal effect for households with low and high water usage.

The difference in price coefficients between QR and LS (Q-LS coefficient difference) is affected by price change, seasonality, groupwise usage level and economic status. The price increase in June 2008 enlarges the Q-LS coefficient difference, because the price change enlarges the difference in water consumption behaviors between medium quantiles and extreme quantiles. Seasonality affects Q-LS coefficient difference differently on varied quantiles. For low quantile households, Q-LS coefficient difference shrinks in summer, perhaps because hot weather in summer mitigates the gap of non-discretionary usage between low and medium quantiles. However, for high quantile households, the Q-LS coefficient difference expands in summer because outdoor discretionary usage increases more for high quantile households than their medium quantile counterparts. From the perspective of groupwise usage level and economic status, the Q-LS coefficient difference is smaller for households with 3/4" meter than their 1" counterparts. This can be attributed to the fact that households with 3/4" have a smaller range of water usage than their 1" counterparts, so the behavioral difference is smaller for households with 3/4".

Figure 4.1: Price Coefficient for January

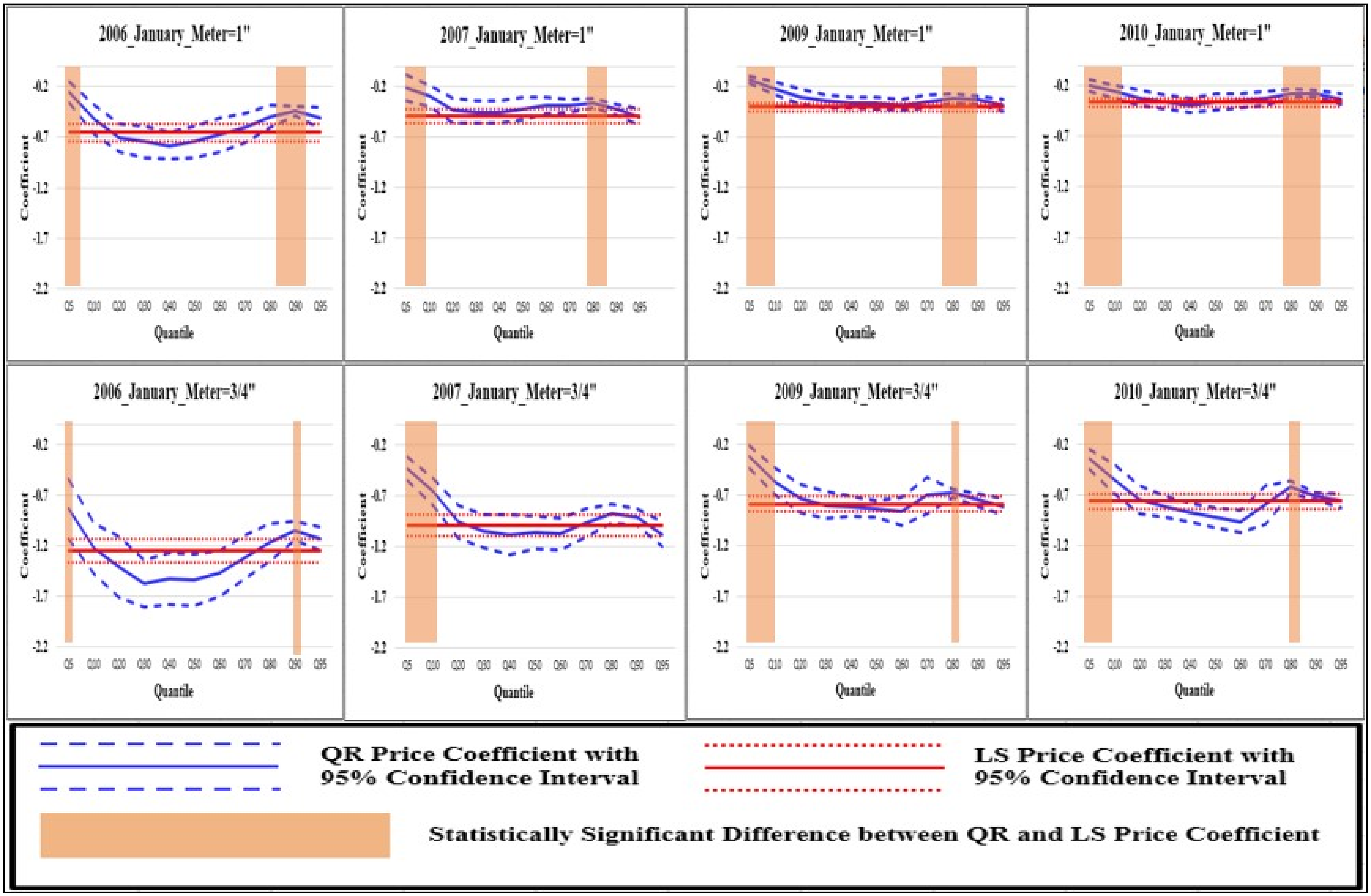
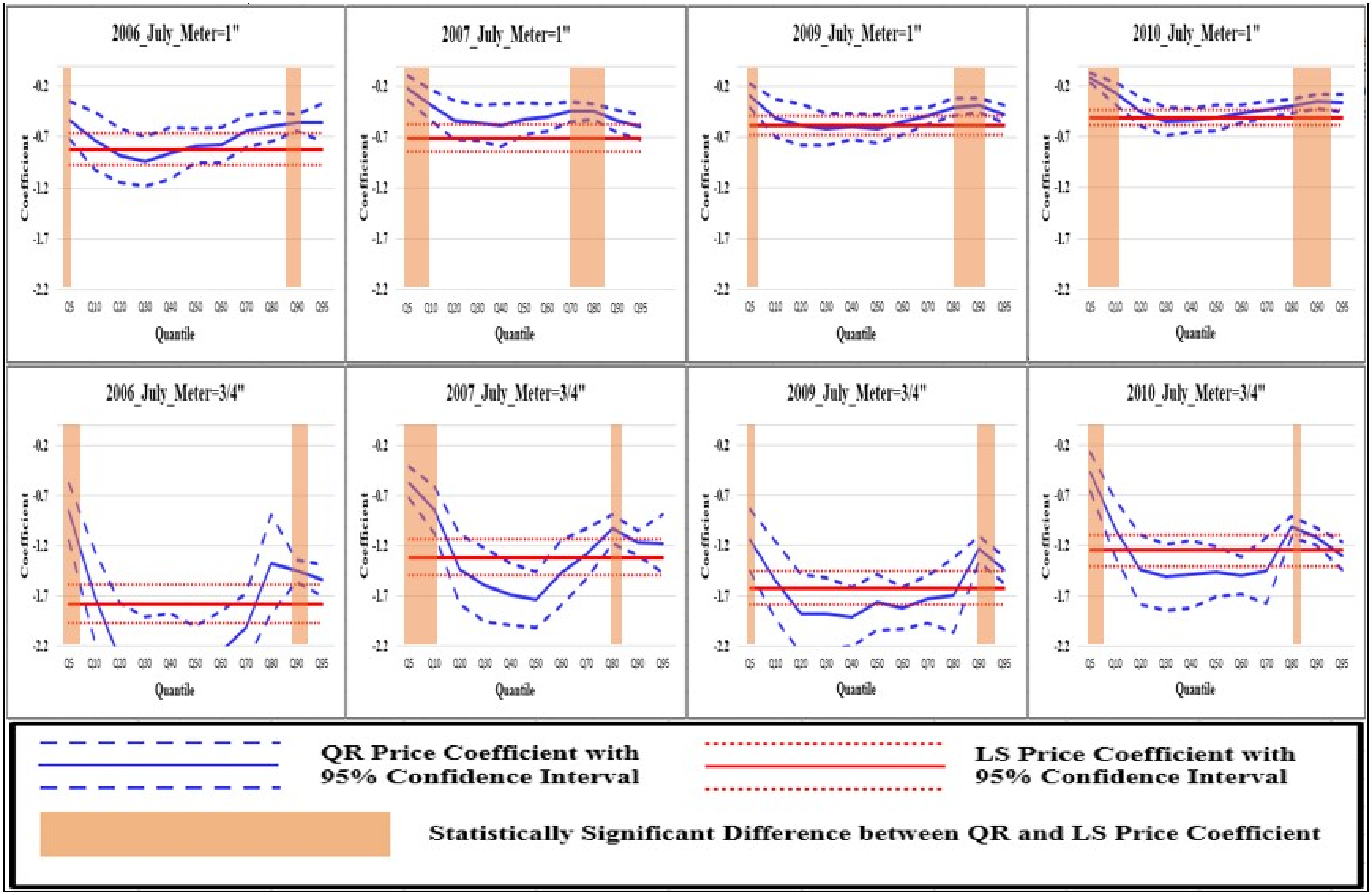


Figure 4.2: Price Coefficient for July



Second, QR results provide new insights into the understanding of price elasticity. Monotonically increasing price elasticities curve with different magnitudes are found across different quantiles in majority subsamples. The monotonically increasing price elasticity curves converges to 0 because Q_i keeps increasing while $RLAP_i$ and $\hat{\beta}_\tau$ are bounded values. The statistical significance of **Hypothesis 2**, i.e. a "U-shape" price elasticity, can only be partially validated by comparing price elasticity on each quantile with the 20th quantile, which is the most price elastic percentile (See Figure 4.3 and 4.4; shaded areas indicate statistical difference in price elasticity between highlighted quantile and 20th percentile). Consumers at the median or higher quantiles are statistically less price elastic than the consumers at 20th percentile. However, there are no statistical differences between low quantiles and 20th percentile in any subsamples.

The statistically different price elasticities between highlighted quantiles and 20th quantile imply that households with high water usage are statistically less price elastic than the most elastic households. Households with extremely high water usage are expected to have landscaping and pools requiring high water demand. In order to maintain the utility gained from landscaping and pools, customers have to bear the extra water cost, which is relatively cheap given their knowledge of a low average water price. Hence, high quantile households are less sensitive to price change.

The difference in price elasticity between highlighted quantile consumers and the 20th percentile households (τ-20th elasticity difference) is affected by price change, seasonality, groupwise usage level and economic status. The price increase in June 2008 enlarges τ-20th elasticity difference. The high quantile households are less price elastic than the 20th percentile, so the increased price has less effect on high quantile households, which enlarges the gap in elasticities for the 20th and high quantiles. The τ-20th elasticity difference is larger in summer than in winter because the difference of outdoor discretionary usage peaks in summer. Moreover, households with 3/4" meter have larger τ-20th elasticity difference than their counterparts with 1" meter.

Figure 4.3: Price Elasticity for January

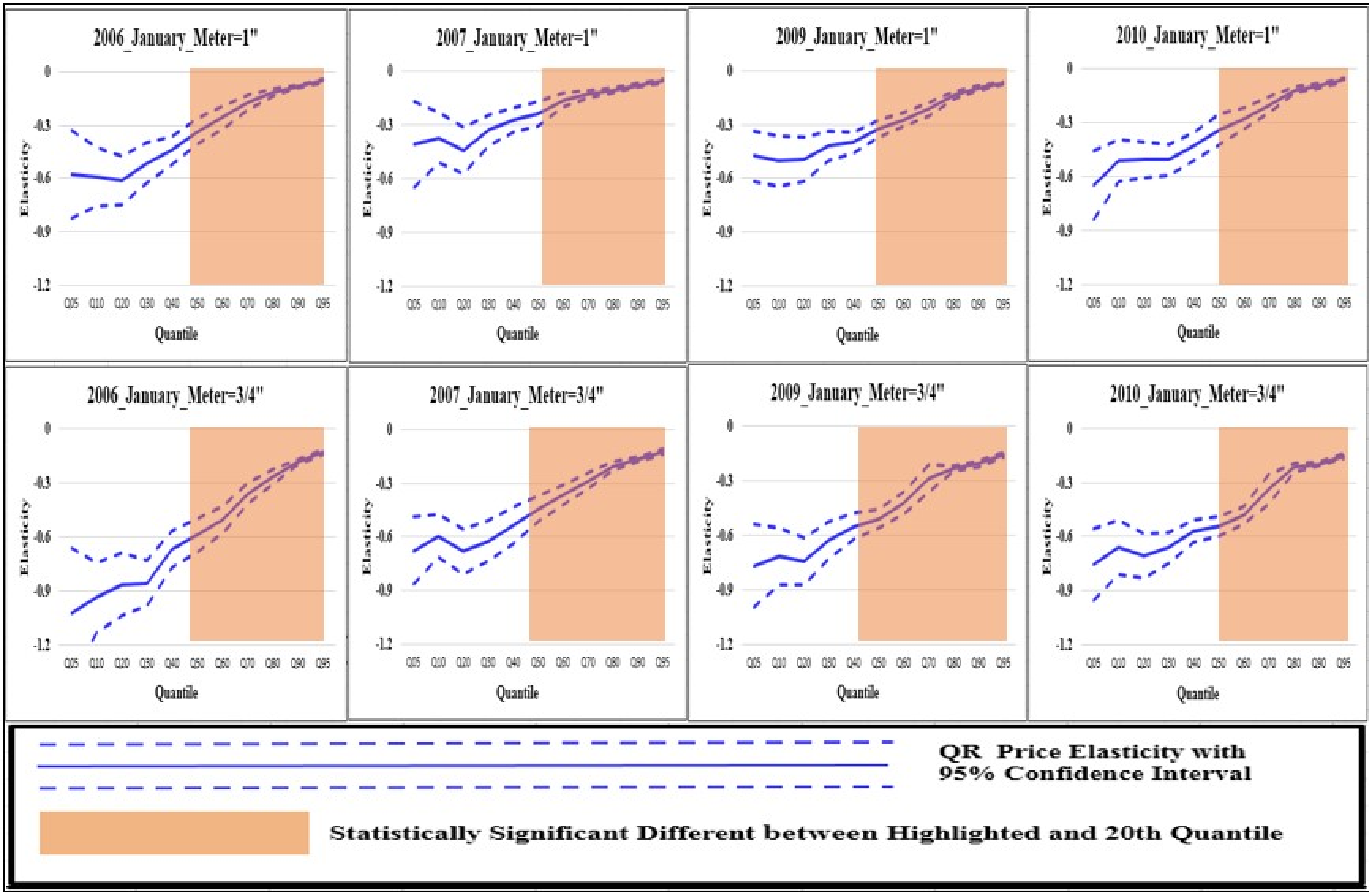
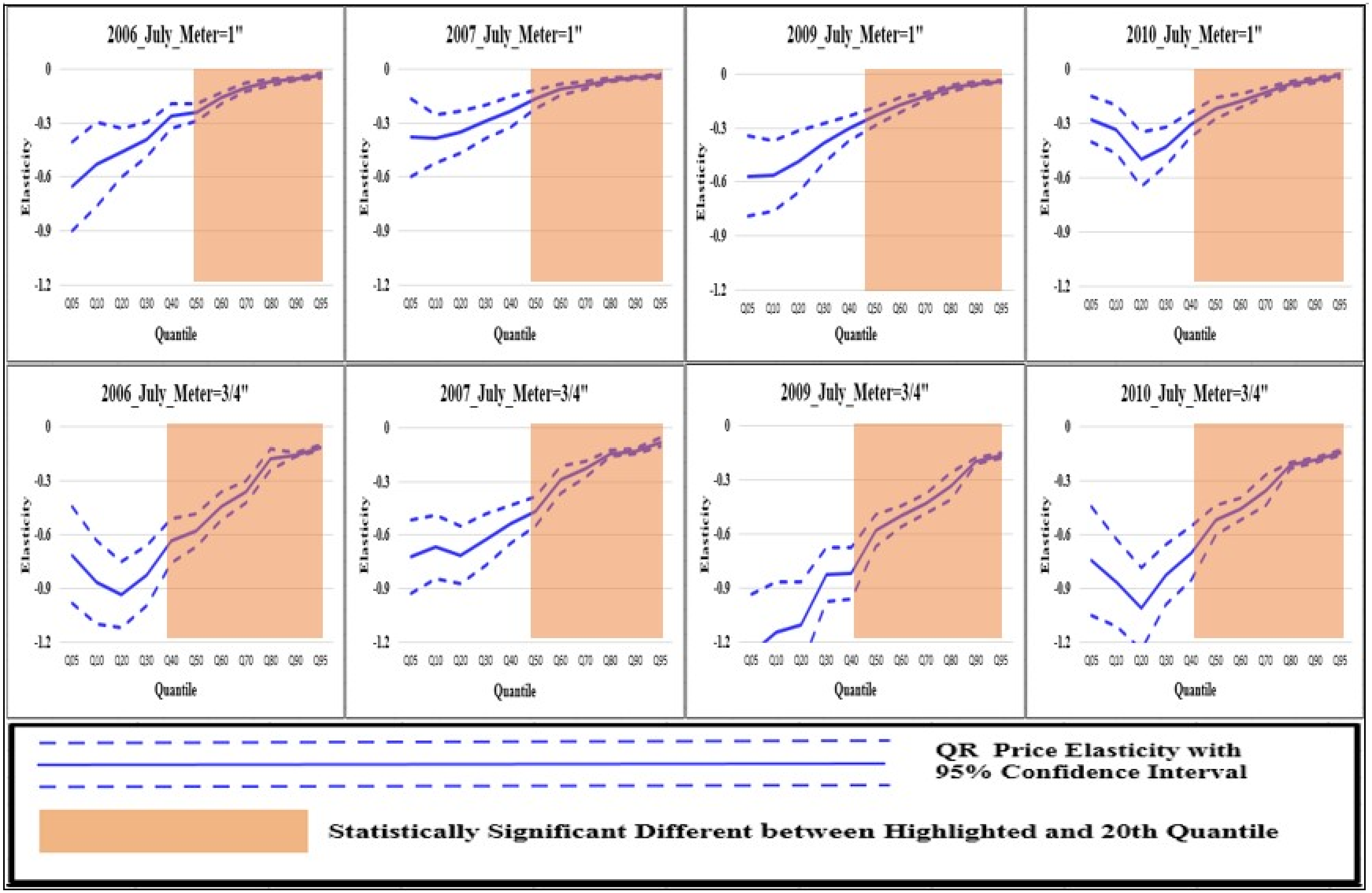


Figure 4.4: Price Elasticity for July



4.3.2 Price Elasticity Comparisons

Besides methodology, comparisons of price elasticity are made based upon the natural experiment discussed in Chapter 3 to capture the specific impact of different price changes, seasonality, groupwise water usage level and economic status as follows. The year 2007 and 2010 are chosen for comparison to control the abnormal precipitation in January 2006 and July 2009.

Before vs. After Price Change

First, most price elasticities after the price increase in June 2008 are not statistically lower than before (see Figure 4.5 to 4.8). This result rejects **Hypothesis 3**, which stated price change in 2008 should make consumers statistically more price elastic. **Hypothesis 4** is at least partially corroborated. Households at higher quantiles, which would have been affected by lowering the break-over between tiers 2 and 3, display statistically more price response in 2010. By contrast, customers with 1" meter size at high quantiles do not show statistically different price response, a pattern consistent with the break-over being increased.

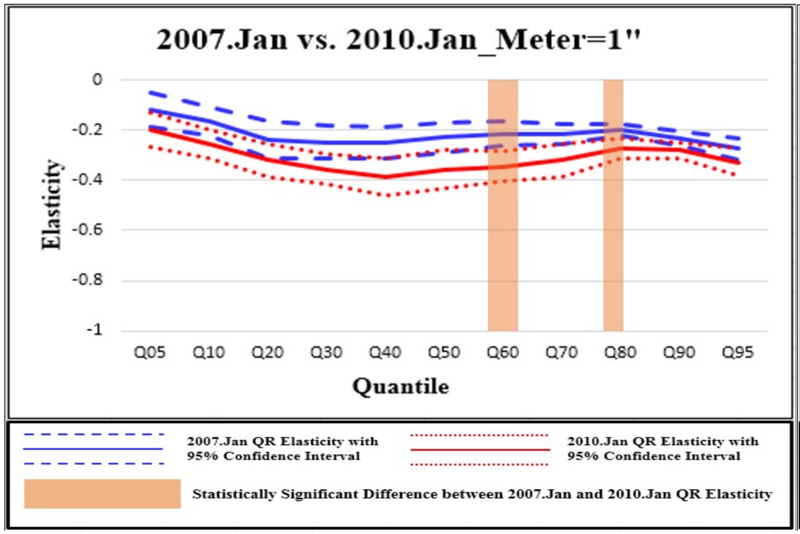


Figure 4.5: Price Change (a)

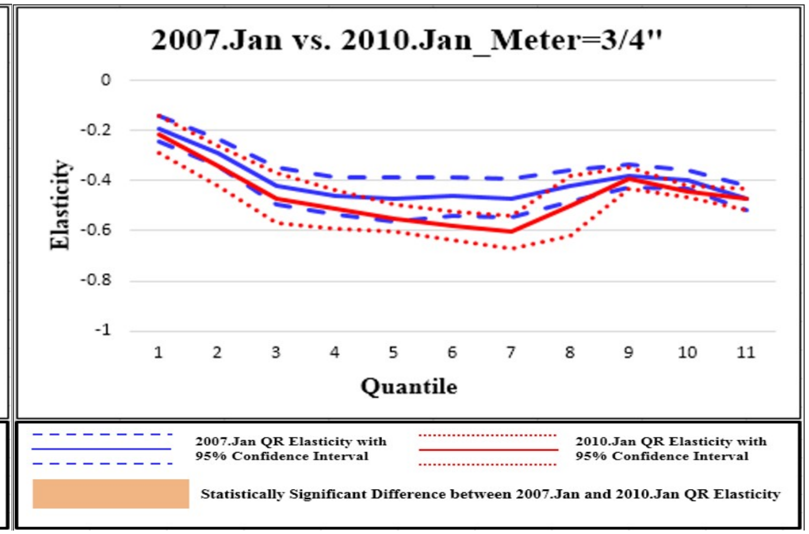


Figure 4.6: Price Change (b)

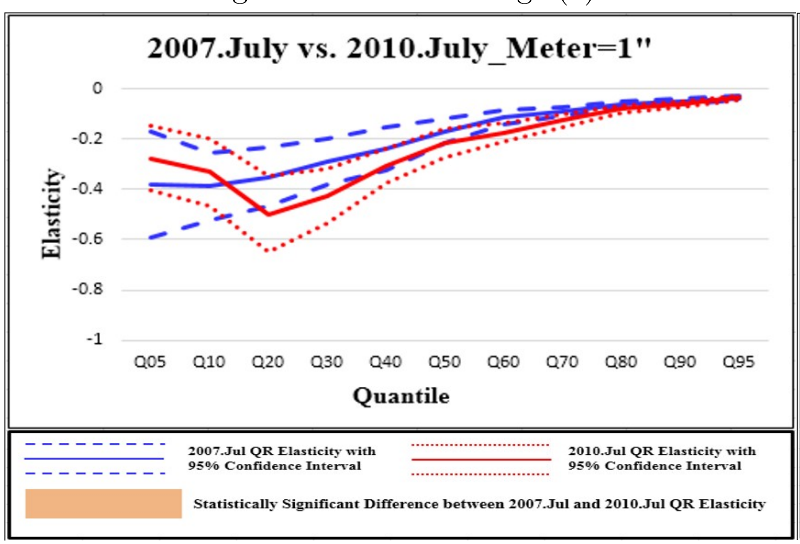


Figure 4.7: Price Change (c)

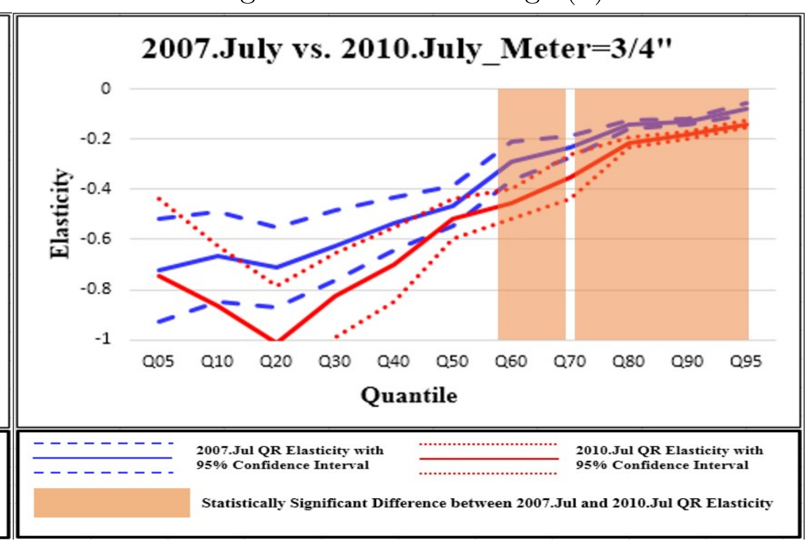


Figure 4.8: Price Change (d)

Summer vs. Winter

Second, summer price elasticities are significantly lower than winter price elasticities only for high quantiles (see Figure 4.9 to 4.12). **Hypothesis 5** is partially corroborated. More interestingly, the results imply that the effect of seasonality occurs only for high quantiles consumers. For high water users, a large proportion of their water usage is outdoor discretionary usage, which can vary dramatically across seasons. However, for low quantile water consumers, indoor discretionary usage is their main water consumption, which varies less seasonally. Hence, the difference of price elasticities caused by seasonality will affect high quantile water consumers more than the low quantile consumers.

The difference in price elasticity caused by seasonality is affected by price change, groupwise usage level and economic status. The increased price in June 2008 expands the difference of price elasticity for 1" meter households, while mitigating the difference for 3/4" meter households. The different impact may relate to how the price schedule changed, since the break-over for 1" meter and 3/4" meter are reallocated differently. For 1" meter households, the increased break-over partially lowers the cost for affected households, so these households have less pressure to be more price elastic, which expands the statistical difference in price elasticity. For 3/4" meter households, lowering the break-over costs affected households more in water consumption, so they become more price elastic, which lessens the statistical difference in price elasticities caused by seasonality. From the perspective of groupwise usage level and economic status, the difference in price elasticity caused by seasonality is larger for households with 3/4" than their 1" counterparts. A potential reason is households with 1" meter have more outdoor discretionary usage derived from their landscapes and pools, which leads to more significant difference in price elasticity caused by seasonality.

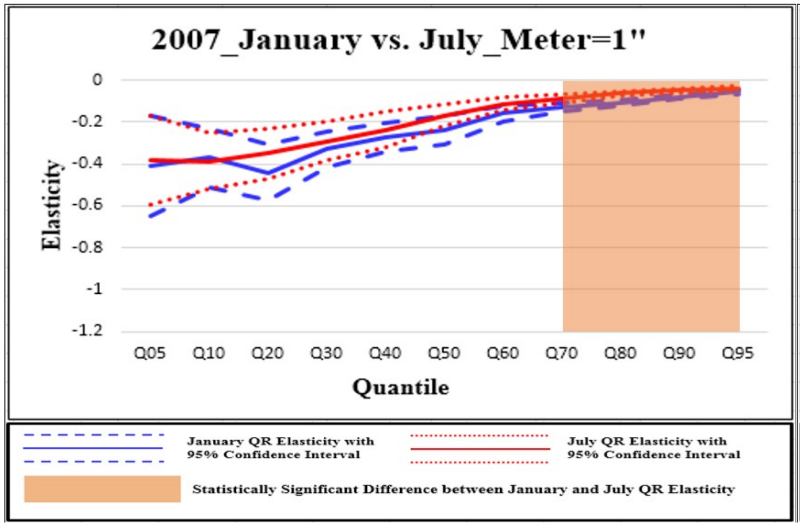


Figure 4.9: Seasonality (a)

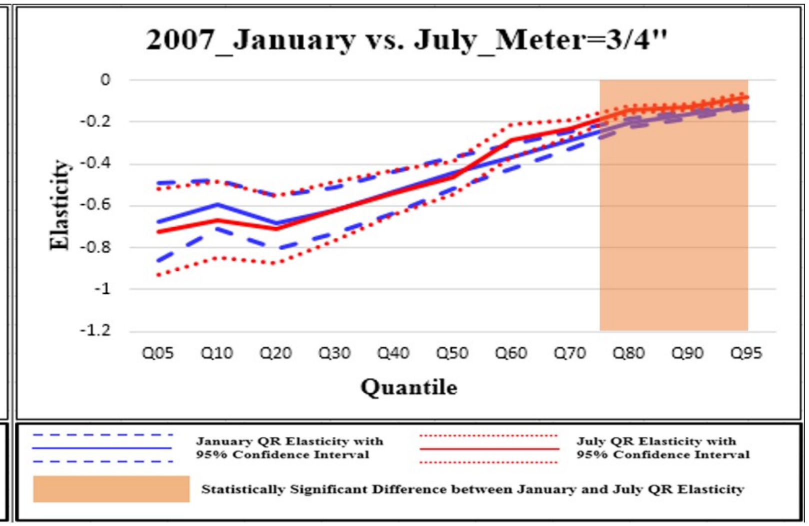


Figure 4.10: Seasonality (b)

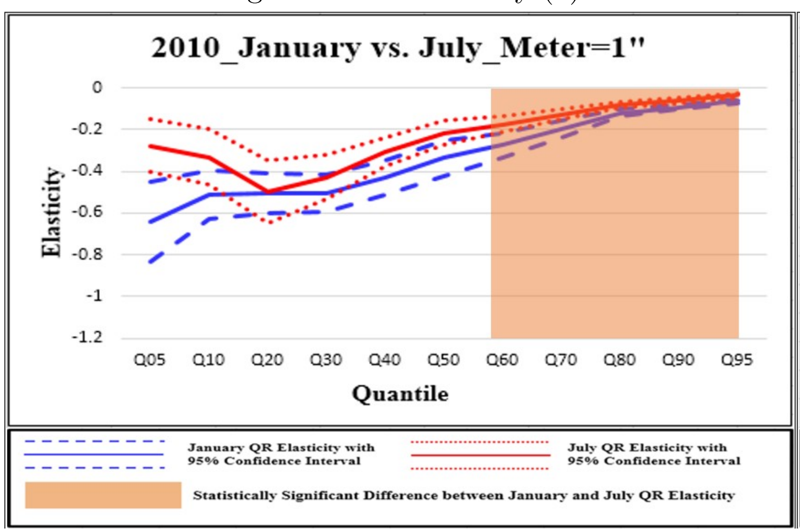


Figure 4.11: Seasonality (c)

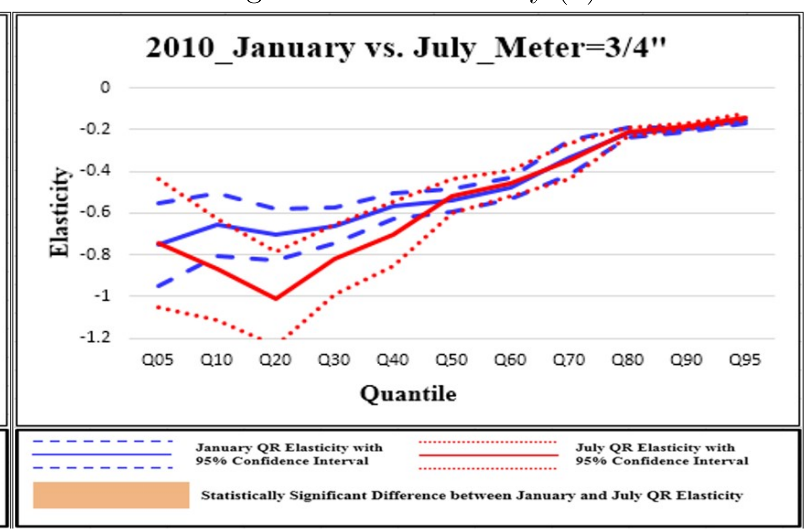


Figure 4.12: Seasonality (d)

Meter Size = 1" vs. 3/4"

Last, households with 3/4" meter are more price elastic than their 1" counterparts due to groupwise usage level and economic status (see Figure 4.13 to 4.16). **Hypothesis 6** is verified in the majority of quantiles, except several low quantiles. Households with 3/4" meter have lower usage level, so perhaps they are more water-conservative than their 1" meter counterparts, which suggests 3/4" meter households may pay more attention to price changes. Also, more economically comfortable consumers tend to be less sensitive to price change, because they are more likely to invest in landscaping, pools and fountains that consume water intensively. These equipments create discretionary water cost that consumers have no choice but to bear, which makes them less sensitive to price. Interestingly, no statistical difference of price elasticity in low quantiles between 3/4" and 1" customers has been found. The likely reason is that extreme low water consumers with different meters have similar usage level and economic status.

The difference in price elasticity caused by groupwise water usage level and economic status are affected by price change and seasonality. The specific impact of price change in June 2008 is undetermined. From the perspective of seasonality, the difference in price elasticity is larger in summer than winter. Summer outdoor usage expands the difference in price elasticity caused by groupwise usage level and economic status because households with 1" meter have to bear water cost to keep their outdoor equipment functional, making them less price sensitive in summer.

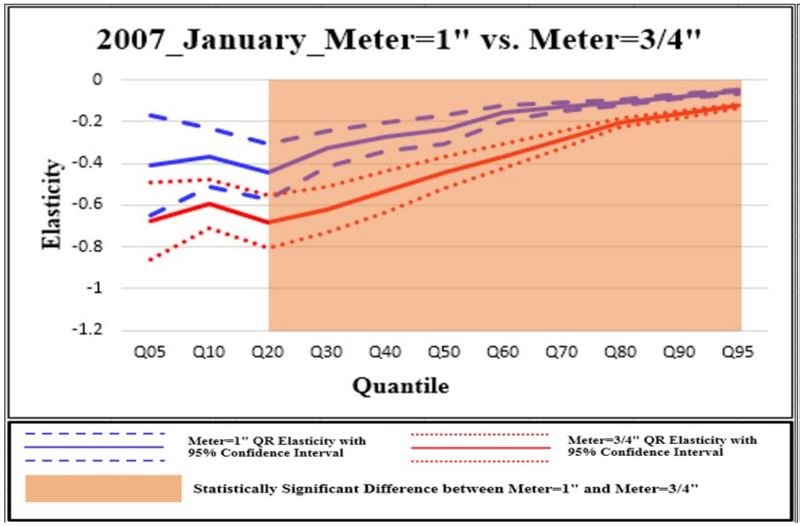


Figure 4.13: Meter Size (a)

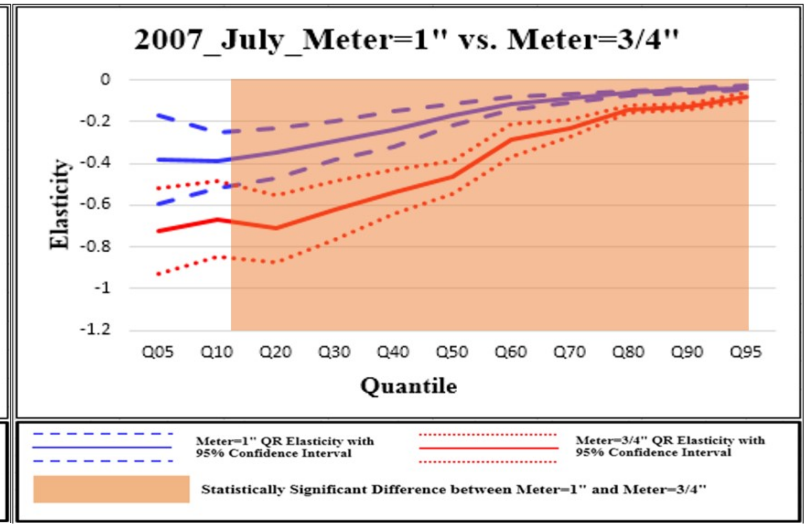


Figure 4.14: Meter Size (b)

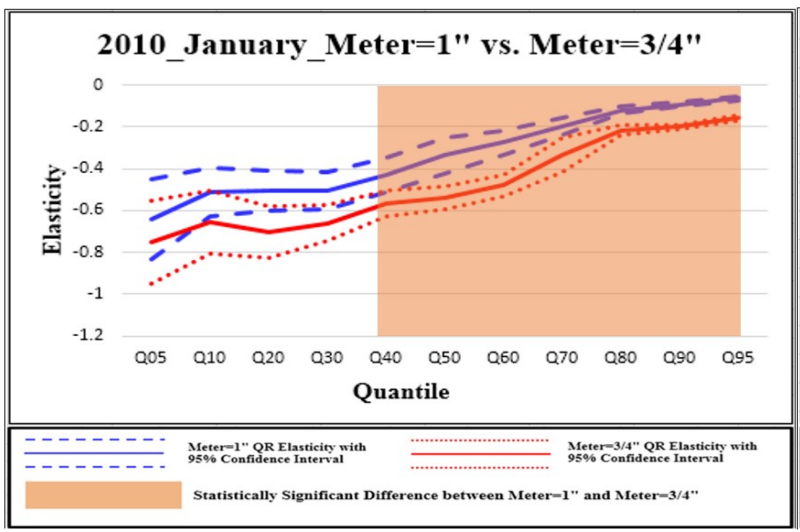


Figure 4.15: Meter Size (c)

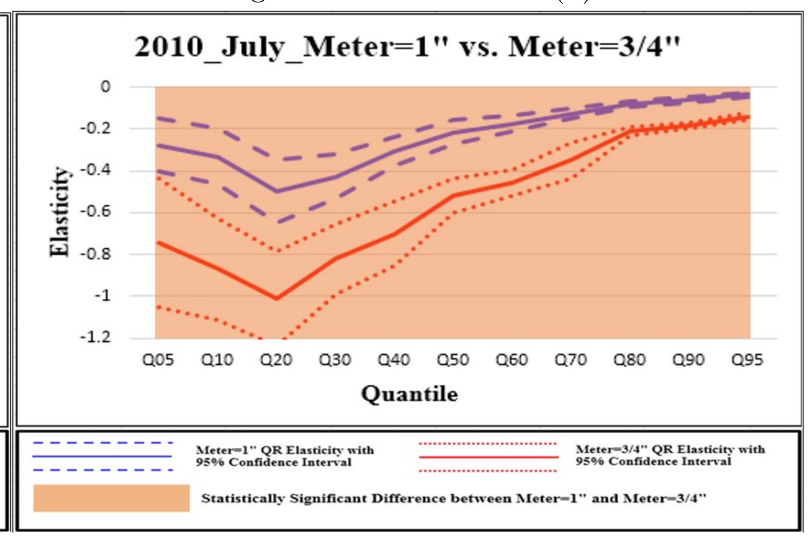


Figure 4.16: Meter Size (d)

4.3.3 Summary

QR has been introduced to estimate residential water demand. Both QR and LS are estimated in 16 cross-sectional samples. QR results on price coefficients are found statistically different from LS coefficients for extreme quantiles, indicating LS may have overestimated the marginal effect of price for low and high consumption households. QR price coefficients have been used to calculated price elasticity. "U-shaped" price elasticities are expected to be founded, but its statistical significance is only verified partially.

The marginal effects of price change and seasonality have been studied in the residential water demand literature. The price elasticity estimated by QR are compared to examine the specific impact of price change and seasonality by this paper. The EPCOR data provides a natural experiment to compare the influence of reallocating break-over. The differences in descriptive statistics within each meter size and across meter sizes suggest studying the effect of the natural experiment by meter size is legitimate.

The empirical results of price elasticity comparison can be summarized as follows. First, price increases in June 2008 have not made households more price elastic overall. Second, lowering the break-over makes affected households more price elastic. Third, households are found to be more price elastic in winter than in summer. More interestingly, seasonality only matters for high quantile households. Last, households with lower usage level and lower economic status tend to be more price elastic.

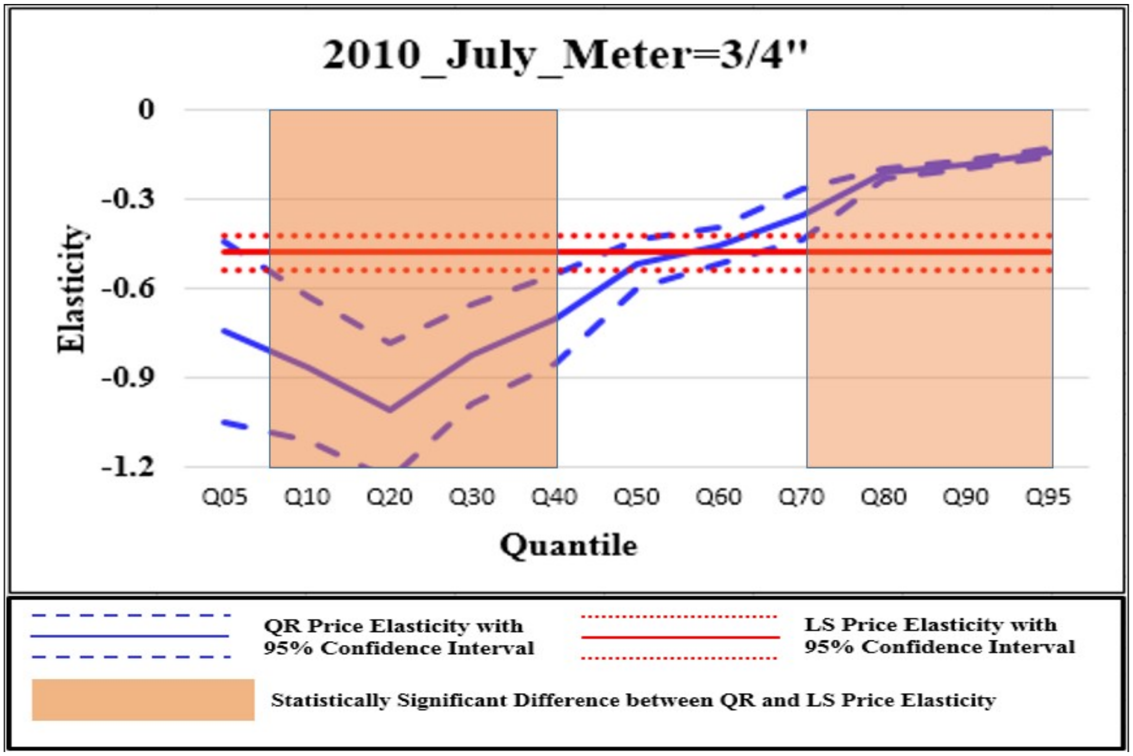
CHAPTER 5

Policy Implications

The empirical results suggest several ideas for further study, for public policy makers, and for water supply companies. First, from the perspective of estimation approach, QR is more desirable for situations where there is heteroskedasticity, outliers, and a skewed distribution of water use, because QR characterizes the conditional distribution of the dependent variable. Figure 5.1 is an example about different price elasticity caused by different approaches from the 16 subsamples estimated. For the situation in Figure 5.1, LS price elasticity is less desirable because it either underestimates or overestimates the price elasticity in 8 of 11 of all estimated quantiles. Secondly, instead of minimizing sum of squared errors, QR minimizes sum of absolute errors. This method assigns less weight to the extreme observations, which allows policy maker to understand problems from a different angle. Last, LS only estimates the average elasticity across all water customers. However, price elasticities can potentially vary by quantity of water usage, so QR results provide more comprehensive information. For industries such as electricity and wireless service with block rate structure, similar results are expected in applying QR.

From the perspective of price schedule designing, the empirical results imply high quantile households are less price elastic. For a water company like EPCOR, interested in earning more profit, charging higher price for high quantile households while maintaining current price for low and medium quantile households would be attractive. Organizations like Arizona Corporation Commission may wish to maintain or even lower slightly the price for low and medium quantile households to protect low-usage consumers. Another implication of the empirical results is that seasonality only affects high quantile consumers. For both EPCOR and the Arizona Corporation Commission, a price schedule adjusted seasonally may serve both of their interests. Based on current price schedule, the summer price for low

Figure 5.1: Example: QR vs. LS Price Elasticity



users can be lowered slightly, while for high quantile users it can be increased so that EPCOR could charge more while the Arizona Corporation Commission could protect welfares of low quantile consumers.

From the perspective of water conservation in desert cities like Phoenix, the empirical results imply that economic policy should put less weight on high quantile consumers. The price elasticity for high water consumers is lower than for the medium quantiles, which implies that the effectiveness of price-related policies on high water consumers is limited. Although the difference in price elasticity between low quantile and medium quantile has not yet been statistically established, similar result seems likely. More efficient policy aimed at low and high quantile consumers might involve non-price factors on monthly maximum usage.

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