Modeling Rational But Inattentive Consumer's Residential Water Demand

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Abstract

We propose a structural water demand model for rational but inattentive consumers under increasing block pricing (IBP). Limited information on IBP caused consumers' inattentiveness, so they respond to "perceived price" instead of marginal price. We apply our model to a water consumption panel dataset in which consumers are tested to be irresponsive to marginal price, so they make decisions based on "perceived price". To test the performance of our model, we use Discrete/Continuous Choice (DCC) Model (assuming consumers are informative and responsive to the IBP) as benchmark. The tests show that our model out-perform DCC for low and high users, while DCC model performs better for mid-level users in our sample.

JEL classification: Q21; Q25; L95; D12;

Keywords: Water Demand; Increasing Block Pricing; Rational but Inattentive Consumers; "Perceived Price"

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1. Introduction

Recent development in behavioral economics suggests that rational consumers may be inattentive in facing complicated choice problem. The inattentiveness is caused by lacking full information due to the high cost to acquire them. Instead, rational consumers tend to apply simplified heuristics for decision making (Madrian, 2014). In the residential water market, consumers normally facing complicated increasing block pricing (IBP). The IBP is a desired pricing strategy since it promotes water conservation among high-users and affordability for low-users. However, IBP's desirability is only achieved if consumers are not only informative but also responsive, otherwise consumers may end up consuming at a suboptimal level, which is higher than optimal level under IBP (see (Ito, 2014) Figure 1 Panel A). The decision-making leads to such suboptimal outcome is that consumers choose to respond to easily acquired "perceived price", instead of marginal price, which is difficult to possess under IBP. Structurally understanding and modeling consumers' decision making in residential water market is important for restoring IBP's desirability and for improving future policy intervention. Literature in this field normally assumes informative and responsive consumers (Discrete/Continuous Choice (DCC) Model, more details in (Hewitt & Hanemann, 1995; Pint, 1999; Olmstead, Hanemann, & Stavins, 2007)), very few studies assumes consumers are inattentive. In this paper, we propose a structural water demand model for rational but inattentive consumers to fill this gap.

The assumption that consumers are informative and responsive under IBP is rather strong, which has been challenged by a stream of recent literature in residential water and electricity market (Shin, 1985; Borenstein, 2009; Nataraj & Hanemann, 2011; Ito, 2013; 2014; Wichman, 2014). Specifically, these studies tests whether consumers respond to the marginal price or other easily acquired "perceived price" such as average price and expected marginal price. Average price is popular since it can be calculated directly from total bill and total usage appeared on monthly bill statement. The expected marginal price is a result of probability weighted marginal prices from different blocks. The probability weights measure the chance that consumers being on different blocks. Shin (1985) uses a specific price perception variable to isolate marginal price and average price to conduct a test. The empirical results support that consumers respond to average price. Borenstein (2009) utilize the change of IBP schedule to estimate the price elasticity using combination of three competing price variables. The results suggest marginal price is the least useful of three measures in gauging consumer response. Ito (2014) exploit price variation of electricity service areas to test consumer's response under IBP. A "bunching" test, i.e. testing if consumers are distributed around the kink points of IBP, and an encompassing test of alternative prices have been conducted. Both results indicate consumers respond to average price instead of marginal price. Similar results can also be found at Ito (2013) in the context of water consumption. Wichman (2014) shows that consumers tend to react to average price in a quasi-experiment when the IBP is introduced. Only in Nataraj and Hanemann (2011), high volume water consumers seem to react to the marginal price.

In this paper, we propose a structural water demand model based on the assumption that consumers are rational but inattentive. In our model, consumers rationally adjust their water consumption towards an optimal level and a comfort zone around it, i.e. consumers' tolerance of deviation from optimal level. However, lacking full information of IBP, consumers rely on "perceived price" for decision making instead of marginal price. The "perceived price" we use is total bill, which is a simplified version of average price without requiring consumers for any calculation. Our model is a two-step decision process involves two time periods (current and future). The first step is a direction decision occurred at the end of current period, when normally the water bill arrives. Consumers decides whether to use more, use same or use less for future period to keep consumption within their comfort zone. Conceptually, the direction decision represents balancing marginal utility and marginal cost. Empirically, it is a trade-off between benefit and cost from consuming water in the random utility framework, we allow household heterogeneity to affect this decision as well. The second step is an adjustment decision started in the future billing cycle. Consumers adjust their future bill based on current bill, conditioning on the direction decision. This process is affected by new conditions in the future period such as weather and household heterogeneity. Our model share similar structure with DCC model, but they differ radically in the nature of information a consumer would need to make water consumption decision. We expect the performance of the two models vary case-by-case based on consumers' information level.

We apply our model to a residential water consumption monthly panel dataset secured from water utility EPCOR. The data includes 5480 households' monthly water consumption from Feb.2005 to Dec.2010 from Sun City, a retirement community located in Phoenix, AZ. The water meters in Sun City are not smart meter, which makes it even more difficult for residents to acquire timely information such as accumulated usage and marginal price. Consequently, consumers are likely to rely only on monthly bill statement for decision making, which makes them inattentive of their water consumption. The IBP rate changed once in Jun.2008. Before estimation, we rigorously test that whether consumers in our sample are inattentive. Specifically, we test if they respond to the marginal price or not from two perspectives. The first test is examining if the distribution of consumers is "bunching" around the block break points of IBP. The "bunching" test originates from literature on progressive tax (Saez, 2010; Chetty, Friedman, Olsen, & Pistaferri, 2011) and it has been applied to residential electricity and water market recently (Borenstein, 2009;

Ito, 2013; 2014). The rationale for "bunching" is that a large number of indifference curves would intersect the kink points of the IBP if consumers respond to marginal price. We can't find strong evidence of "bunching" in our sample. The second test is designed by exploiting the IBP rate change. The change of IBP rate in Jun.2008 leads to heterogeneous marginal price increases for consumers in different usage levels. We first group consumers into different usage levels based on their consistent usage before the rate change, then test if the usage reduction matches the heterogeneous marginal price increases. The result shows that a larger marginal price increase does not necessarily lead to a higher usage reduction. These two tests suggest that consumers in our sample may not respond to marginal price. As a result, demand model based on "perceived price" instead of marginal price may suit our sample consumers better.

We then apply our behavioral model based on "perceived price" to the EPCOR data. The DCC model is also estimated for comparison. Both models are estimated using data before the rate change, the post-rate-change sample is used for performance test. Using estimated parameters, we simulate one-month ahead post-rate-change water consumptions of both models for two performance test. The idea is to test which set of simulated data can better reflect the true data after the IBP rate change. We first calculated monthly mean and quartiles of both simulated data and real data for comparison. The results show that, after one or two months adjustment following the IBP rate change, our behavioral model has closer statistics to the real data than DCC model. Secondly, we again use the IBP rate change to design another test. Grouping consumers into different usage level based on their pre-change consistent usage, we estimate the change of usage caused by rate change with both real and simulated post-change data. The performance of two models is tested by comparing coefficient of simulated data from which model is closer to the real data for various usage levels. The results show that our model predict better for the low and high users, while DCC model is better for the mid-level users. This interesting result indicates that low and high users tend to make decisions based on "perceived price", whereas mid-level users tend to react to marginal price. From the behavioral perspective, the extreme users have less incentive to acquire information to respond to the IBP. For low users, the water consumption is necessity. For high users, most likely with home appliances with high capacity such as swimming pools, consuming less water means forfeiting utility generated from such appliances. Hence, understanding marginal price won't radically change extreme users' consumption, so they save their efforts by responding to "perceived price". On the other hand, mid-level users have the flexibility to adjust their water consumption so that understanding IBP and its marginal price helps them making better decisions.

Our results have significant policy values for restoring IBP's desirability and for improving future policy intervention. IBP's desirability in promoting water conservation for high users and affordability for low users is challenged in facing inattentive consumers. The inattentiveness is caused by consumers' limited information and limited effort to acquire it, therefore "perceived price" is used for decision-making. Providing more information can help in mitigating such problem. Some recent literature using randomized control trial shows that empowering consumers with more information through installing smart devices makes them more responsive to marginal price (Jessoe & Rapson, 2014; Kahn & Wolak, 2013; Attari, Gowrisankaran, Simpson, & Marx, 2014). On the other hand, for improving policy intervention in water or other residential water market, structurally understanding consumers' decision making reveals how to select effective policy instruments. For inattentive consumers, designing policy intervention based on "perceived price" may lead to more direct response than marginal price.

The rest of paper is organized as follows. In Section 2, we discuss the concept and empirical specification of our model. In Section 3, we describe the data and the tests whether consumers in our sample respond to marginal price or not. In Section 4, we discuss the empirical results and test the performance of our model. In Section 5, we conclude.

2. Model

This section first describes the theoretical concept used to construct our model. Then we describe the detailed empirical representation based on random utility framework.

2.1 Modeling Concept

From the neoclassical economic theory, consumers optimize water consumption (as Figure 1 Panel (a)) through balancing their marginal utility and marginal cost. When marginal utility is equivalent to marginal cost (without loss of generality, assuming the target is to set ratio between marginal utility and marginal cost to 1 to balance the marginal rate of substitution), the optimal water consumption is reached (as Figure 1 Panel (b)). Considering the decision-making process is affected by some random shocks, consumers optimize toward a comfort zone around the optimal level instead. The band of the comfort zone is consumers' tolerance of deviating from optimal. Deviation further away from the comfort zone either below ("underuse") or above ("overuse") are suboptimal. Hence consumers have incentives to adjust their usage back to the comfort zone once they realized they are overusing or underusing water. This process is achieved by balancing marginal utility and marginal cost or equivalently, adjusting the net marginal cost, marginal cost minus marginal utility, towards 0 (as Figure 1 Panel (c)). Adjusting net marginal cost towards 0 has correspondence in adjustment utility towards optimal level (as Figure 1 Panel (d)).

Our model is constructed on the assumption that rational but inattentive consumers are implementing optimization mechanism described above. The rationality refers to the above concept that consumers adjust their consumption towards a comfort zone around the optimal level. The inattentiveness is caused by limited information of marginal price and real time usage, so they rely on "perceived price" for decision making. The "perceived price" we used is (monthly) total bill, which is a simplified version of average price. We assume the (monthly) total usage is available to consumers as well, but not the real-time usage. In our model, the information consumers possess are directly appeared on the monthly bill statement, which requires least effort to acquire. With such information, consumers rely only on monthly bill to understand the situation. Normally, water bill arrives by the end of each billing cycle, so consumer's optimization toward the comfort zone can only affect their behavior in the future billing circle. We construct a two-step model involves two-period (current and future) to capture consumer's behavior in water consumption. The first step is a direction decision happened at the end of current month. The second step is an adjustment decision started in the future billing cycle. The empirical representation is described in the following subsection.

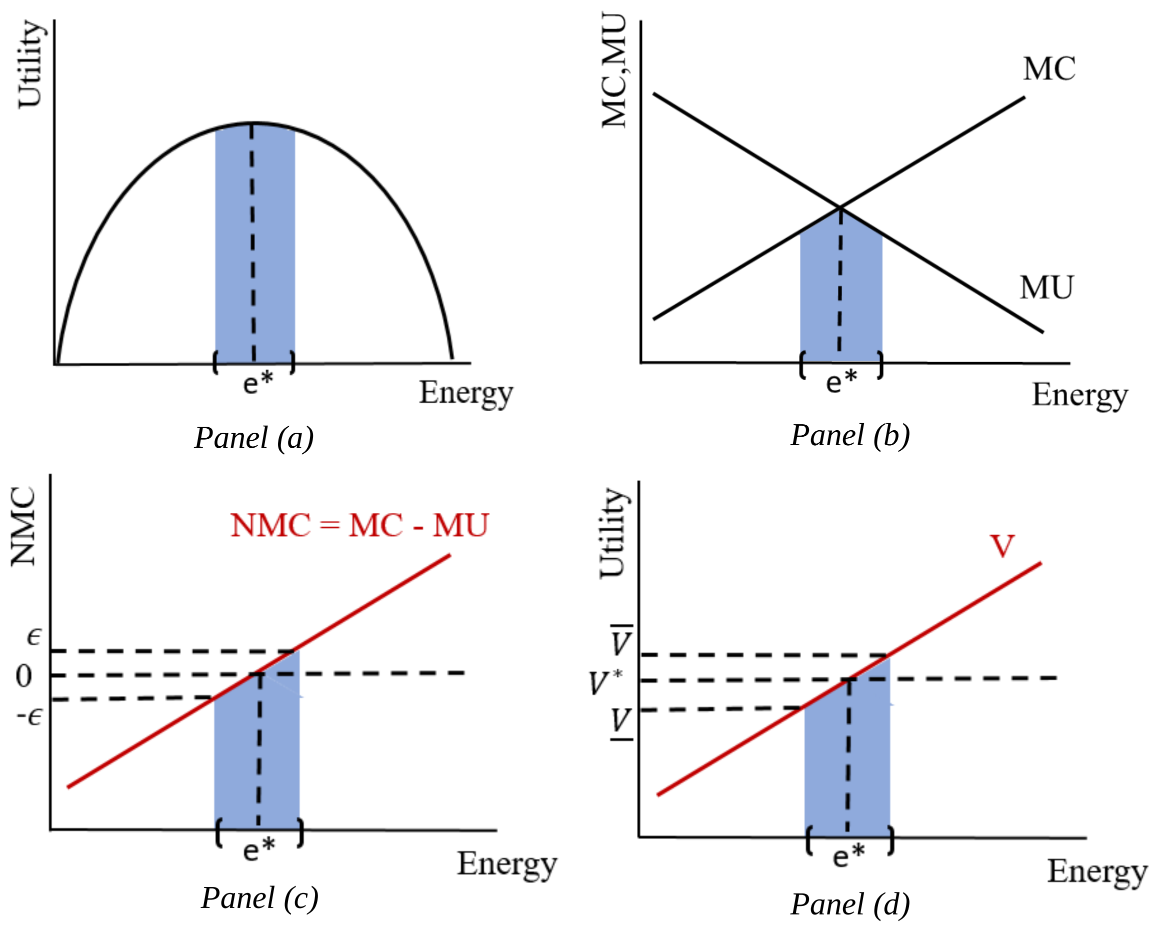


Figure 1. Modeling Concept

2.2 Empirical Specification

We use random utility framework to represent the concept described above. Comparing consumers' future bill to current bill reveals their direction decision and adjustment decision. The direction decision is using more, using same level, or using less. The direction decision is driven by the consumer's understanding whether her current water consumption remain in her comfort zone or not. If not, there is a higher probability that she will adjust reversely to get back to the comfort zone. For example, in the underuse case, consumer has a higher probability to use more in the future billing circle. Conditioning on her direction decision, consumer's adjustment decision is also revealed. The adjustment decision is the percentage change of future bill based on current bill. We model the adjustment percentage change as a fixed step conditioning on the direction decision for two reasons. First, an accurate and flexible adjustment requires an assumption that consumer knows the capacity of her home appliances, which is rather unrealistic. Secondly, adjustment in the water consumption is normally made by adjusting intensity of usage such using certain home appliances from "full load" to "half load", which suits a fixed percentage change better.

The direction decision is modeled based on the indirect utility framework. Consumer i at time t decides her direction for time $t+1$ using following indirect utility:

$$V_t^i = \tilde{V}_t^i + (\beta C_t^i - aB_t^i) + \gamma H_t^i + u_t^i$$

In this indirect utility, $\tilde{V}_t^i$ is a household's optimal indirect utility. B_t^i and C_t^i denotes the benefit and cost of deviating from the optimal level, respectively. Together, $(\beta C_t^i - aB_t^i)$ is our empirical representation of net marginal cost discussed earlier in the modeling concept. H_t^i is household's time-variant heterogeneity. u_t^i is the error term of direction decision. Then for consumer i at time t , the direction decision on future bill is:

$$d_t^i = \begin{cases} 1 \ (\text{"}Use\ More\text{"}) & if \ \ -\infty < V_t^i < \underline{V} \\ 2 \ (\text{"}Remain\ Same\text{"}) & if \ \ \underline{V} < V_t^i < \overline{V} \\ 3 \ (\text{"}Use\ Less\text{"}) & if \ \ \overline{V} < V_t^i < +\infty \end{cases}$$

The direction decision reflects the concept that consumers tend to adjust their water consumption back to a comfort zone. Within the indirect utility, consumer is balancing benefit and cost on the margin. Taking a consumer underuses water for example, her marginal benefit exceeds marginal cost, so she has higher probability to consume more in their future consumption. Consumer's heterogeneity will affect her direction decision. The time invariant part is captured in the $\tilde{V}_t^i$ and the time variant part is captured by the H_t^i. To keep this model identifiable, we following traditions to normalize $\tilde{V}_t^i$ to 0 and assume $u_t^i \sim N(0,1)$. The $\overline{V}$ and $\underline{V}$ are to be estimated, which are the boundary point of the comfort zone.

For the second-step adjustment decision, consumer's future bill is an percentage adjustment from current bill conditioning on the direction choice, the specification is:

$$bill_{t+1}^i = \left(\theta^k + \eta^k Z_{i,t+1}\right) \cdot bill_t^i + \epsilon_{it}^k$$

where $k = \{1,2,3\}$ for $d_{i,t} = \{1,2,3\}$, respectively. θ^k refers to an average fixed adjustment for kth direction. $Z_{i,t+1}$ includes weather and household heterogeneity, which is used to control the new situation during period $t + 1$. No constant is involved so that the future bill is now adjusted from the current bill instead of its conditional mean. The ϵ^k is adjustment error for different directions. We assume that each ϵ^k is distributed normally as $\epsilon^k \sim N(0, \sigma_k)$ and there is no correlation between adjustment errors for different directions. The 0 expectation means that consumer's monthly adjustment errors for direction k converge to 0 over a long period time, conditioning on the direction decision.

The two-step decision is connected by assuming direction error u and adjustment error ϵ are jointly distributed as:

$$\begin{bmatrix} u \\ \epsilon^1 \\ \epsilon^2 \\ \epsilon^3 \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_1\sigma_1 & \rho_2\sigma_2 & \rho_3\sigma_3 \\ \cdots & \sigma_1^2 & 0 & 0 \\ \cdots & \cdots & \sigma_2^2 & 0 \\ \cdots & \cdots & 0 & \sigma_3^2 \end{bmatrix} \right)$$

where ρ_k is the correlation between direction error and adjustment error at kth direction. Since we normalized direction error to 1, the adjustment error σ_k are automatically normalized based on direction error. Above error assumption is a simplified version, more general assumption of error structure can be implemented as well in this framework. The estimation of this model can be jointly done by maximum-likelihood technique. The log-likelihood for individual i at time t with direction decision k can be written as:

$$LL_{i,t+1} = \sum_{k=1}^{3} I_{\{d_{i,t+1}=k\}} \log \tilde{L}_{i,t+1}^{k}$$

$$\tilde{L}_{i,t+1}^{k} = \frac{1}{\sqrt{2\pi}} * \frac{\exp(-\frac{(s_k)^2}{2})}{\sigma_k} * [\Phi(r_k) - \Phi(n_k)]$$

where $I_{\{.\}}$ is indicator function and

$$\mathrm{s_k} = \frac{bill_{i,t+1}^{k} - \left(\theta^k + \eta^k Z_{i,t+1}\right) \cdot bill_{i,t}}{\sigma_k}, r_j = \frac{B^k - \rho_k\, s_k}{\sqrt{1-\rho_k^2}}, n_j = \frac{A^k - \rho_k s_k}{\sqrt{1-\rho_k^2}}$$

and

$$\begin{cases} A^1 = -\infty, B^1 = \underline{V} - V_t^i \ \ (\text{"}Use\ More\text{"}) \\ A^2 = \underline{V} - V_t^i, B^2 = \overline{V} - V_t^i \ \ (\text{"}Remain\ Same\text{"}) \\ A^3 = \overline{V} - V_t^i, B^3 = +\infty \ \ (\text{"}Use\ Less\text{"}) \end{cases}$$

2.3 Comparison Between Our Model to DCC Model

DCC Model originates from literature associated with non-linear budget set (Burtless & Hausman, 1978; Hausman, 1985; Moffitt, 1986; 1990) and discrete/continuous demand estimation (Hanemann, 1984; Dubin & McFadden, 1984). Here we compare our model to the very recent Olmstead et al (2007) and Olmstead (2009) version. The construction of two models both follows a two-step procedure. In our model, consumers first choose direction of future bill by the end of current billing cycle, then adjust future bill from current bill when the future billing cycle started. In DCC model, consumers first choose which block of IBP to locate, then choose optimal usage level within different block. Although sharing similar modeling structure, the amount of information consumers possessed are radically different. In our model, the decision variables are the modest information appeared on monthly bill statement. In the DCC model, the decision variables are the detailed information of IBP such as the marginal price and block thresholds level. We expect the performance of two models to vary case-by-case. Consumers' information level and context of different studies determine the performance. DCC model fits informative, responsive and rational consumers, while our model fits rational but inattentive consumers.

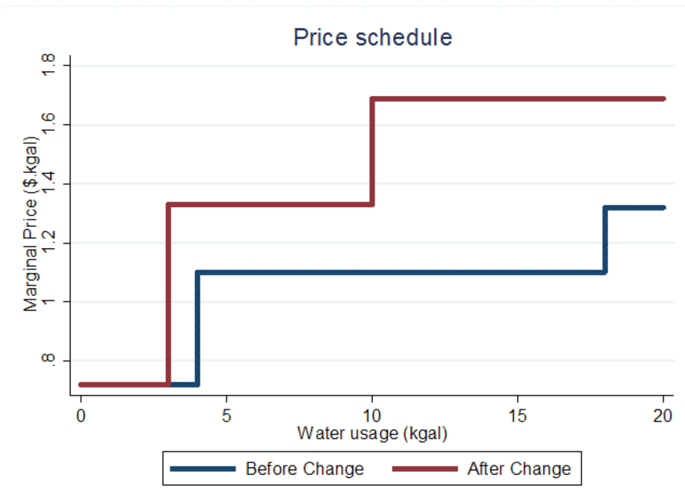
3. Data

This section describes the data and the price schedule. Before estimating our model, we first formally examine if the consumers in our sample are inattentive, i.e. irresponsive to marginal price. We test consumer's response through two different perspectives. Our first test is "bunching test" based on usage distribution of consumers in the whole community, i.e. testing if consumers are distributed around the block thresholds. Secondly, the change of IBP rate in Sun City is exploited to design another test. The IBP rate change in our data leads to heterogeneous increase in marginal price for consumers with various usage levels. Consumers are grouped into different usage levels based on their pre-rate-change consistent usage. We test if the usage reduction across different groups matches the heterogeneous increase in marginal price. Results from both tests suggest that consumers in our sample tend to respond to "perceived price" instead of marginal price.

3.1 Background, Summary Statistics and Rate Schedule

Our primary data is a monthly balanced panel of residential water bill under IBP provided by "EPCOR Utility" from Feb.2005 to Dec.2010. There are 5480 households in our sample from a retirement community Sun City located in Phoenix, AZ. In Sun City, the monthly water usage is not measured by smart meters. Instead, the EPCOR agents use tradition measurement to record usage by the end of each month. Consequently, residents are less likely to have a clear track of their real-time usage within each month. Understanding the marginal price of IBP decided by the accumulated usage is also difficult. Therefore, residents in our sample tend to rely on information appeared on monthly statement come by the end of each month for decision making instead of marginal price, which makes them inattentive.

During our studying periods, the IBP rate in Sun City changed once on Jun.1st 2008 as Figure 2. Before the change, Sun City has three blocks with two thresholds at 4 kgal and 18 kgal. The marginal prices per kgal are \$0.72, \$1.10 and \$1.33 from block 1 (the lowest) to block 3 (the highest). The monthly fixed charge is \$6.33. After the change, the new thresholds are reallocated to 3 kgal and 10 kgal. The new marginal prices are \$0.72, \$1.32 and \$1.69 from block 1 to block 3, respectively. The monthly fixed charge increases to \$7.99. The change in marginal price and reallocating of thresholds together lead to larger raise of marginal price between 3 to 4 kgal and 10 to 18 kgal.



Price Schedule	Before Change (Feb.2005 - May.2008) Marginal Price	Tier Break	Fix Charge	After Change (Jun.2008 - Dec.2010) Marginal Price	Tier Break	Fix Charge
Tier 1	\$ 0.72	4 kgal	\$6.33	\$ 0.72	3 kgal	\$7.99
Tier 2	\$ 1.10	18 kgal		\$ 1.33	10 kgal	
Tier 3	\$ 1.32			\$ 1.69		

Figure 2. IBP Rate Schedule in Sun City

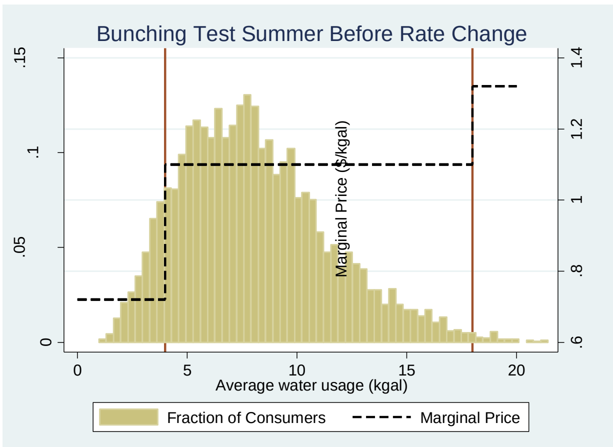
According to the 2010 census, Sun City has population 37,499. The Median household income is \$36,464. The percentage of senior population (over 65 years old) is 74.9%. Using the billing address, we match the bill data with Maricopa County Assessors' Office data to get real estate information. The information includes assessed home value, indoor area (living area) size and outdoor area (yard area) size. We calculated the discounted assessed home value as income measure for these senior citizens. Also, our weather data is acquired from the Arizona Meteorological Network (AZMET). Following water demand literature, the weather index we use is evapotranspiration, which is determined by solar radiation, wind speed, humidity and temperature to measure the amount of water getting out of ground (Brown, 2014). The summary statistics of key variables are summarized in Table 1. The average monthly bill rises after the IBP rate change from $13.15 to $15.79. Consequently, the average monthly usage drops from 7.37 kgal to 6.95 kgal.

Variable	Description	Units	Nobs.	Mean	Std. dev.	Min.	Max.
Usage	Monthly usage	1,000 gallon	389,080	7.19	3.70	0.86	25.86
Usage_before	Monthly usage before rate change	1,000 gallon	219,200	7.37	3.73	0.86	25.86
Usage_after	Monthly usage after rate change	1,000 gallon	169,880	6.95	3.64	0.86	25.86
Bill	Monthly bill	$	389,080	14.30	4.91	6.30	51.89
Bill_before	Monthly bill before rate change	$	219,200	13.15	4.17	6.30	39.38
Bill_after	Monthly bill after rate change	$	169,880	15.79	5.37	8.72	51.89
Weather	Evapotranspiration	mm	389,080	6.58	2.54	1.79	10.92
Living area	Livging area size	100 ft^2	389,080	15.30	3.56	7.88	43.82
Yard area	Yard area size	100 ft^2	389,080	9.15	3.08	0.32	91.79
Income	Assessed home value discounted by CPI	$1,000	389,080	90.93	27.29	21.56	558.19

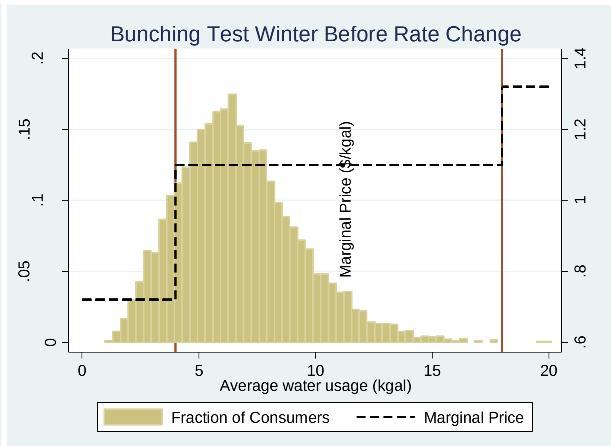
Table 1. Descriptive Statistics

3.2 Test of Response to Marginal Price – "Bunching" Test

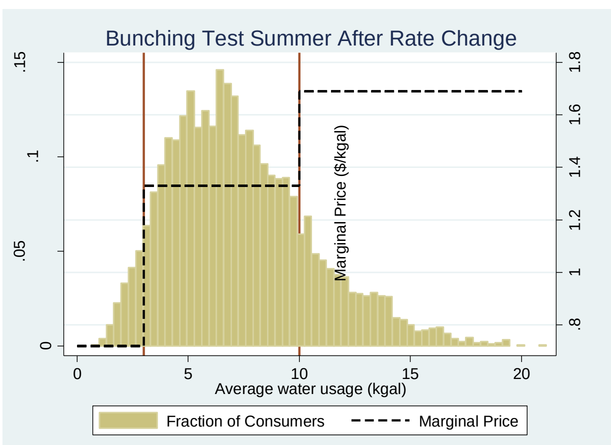
Suggested by recent literature in residential water (Ito, 2013), electricity (Borenstein, 2009; Ito, 2014) and progressive tax (Saez, 2010; Chetty, Friedman, Olsen, & Pistaferri, 2011), we should be able to observe "bunching" around the IBP thresholds if consumers react to marginal price. The intuition is that a large number of indifference curves would intersect the thresholds, which leads to a sudden increase of consumer percentage (Figure 2 of (Borenstein, 2009)). Also, since the price rate changes in Jun.2008, the "bunching" should adjust accordingly if consumers react to new marginal price timely. We calculate each consumer's average usage before and after the rate change and plot the histogram in Figure 3 to examine if there is "bunching". The summer (June, July and August) and winter (December, January and February) usage are distinguished since water consumption is strongly affected by seasonality. If consumers respond to IBP, we should be able to observe (1) histogram increase dramatically at the IBP thresholds, and (2) histogram increase at the new thresholds after the rate change.



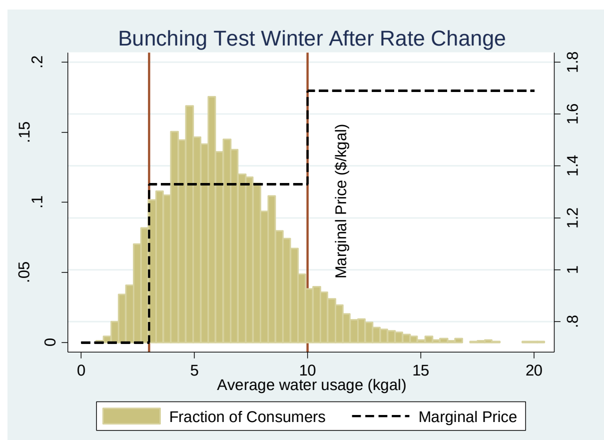
Panel (a)



Panel (b)



Panel (c)



Panel (d)

Note: The histograms are consumers' average water consumption before and after the rate change. Summer and winter has been distinguished. The rate structures are depicted with the black dash lines. The red vertical lines are the block break points.

Figure 3. "Bunching" Test

Based on Figure 3, we don't have strong evidence to support "bunching". Before the rate change in Jun.2008, Panel (a) and Panel (b) shows that there are relatively larger increases of consumer percentage occurred before and after the 4 kgal threshold. The 18 kgal cannot be verified clearly due to a lack of observations. After the rate change, Panel (c) and Panel (d) shows that the fraction of consumers increases most in the middle of two thresholds 3 kgal and 10 kgal, instead of at them. In summary, there is no clear "bunching" at the thresholds. The absence of "bunching" suggests consumers either respond to marginal price with nearly zero elasticity or respond to "perceived price" other than marginal price. The former conjecture may not be true in our sample since the average usage drops after the rate change. Since the "bunching" test relies only on the distribution, we haven't utilized household fixed effect contained in the panel data. To further validate the second conjecture, we conduct another test designed on IBP rate change while controlling household fixed effect.

3.3 Test of Response to Marginal Price Using Change of Rate

Using the IBP rate change, we design a second test based on consumers' individual water consumption data. The Jun.2008 rate change leads to disproportionate marginal price increase for consumers with different usage levels. The marginal price remains same for consumers with very low usage (1-3 kgal). For the rest consumers, the marginal price increases heterogeneously. For consumers use 3-4 kgal, 4-10 kgal, 10-18 kgal, and beyond 18 kgal, the marginal price increases 84.7%, 20.9%, 53.6% and 28%, respectively. If consumers respond to the marginal price, the extent of usage reduction should agree with the heterogeneous marginal price increase. We would expect that consumers use 3-4 kgal and 10-18 kgal reduce their consumption most in the percentage.

To test if the usage reduction matches to the heterogeneous marginal price increase, we first group consumers into different usage levels. Using usage data before the IBP rate change, we calculate consumers' average usage level. Then we assign each consumer to the integer usage level closest to her average usage for grouping. Again, the summer (June, July and August) and winter (December, January, February) has been studied separately due to strong seasonality. We then estimate following equation for each usage group j to evaluate the usage reduction in a "pre-change vs. post-change" version:

$$\ln(c_{it}) = After \cdot \lambda + x_{it}\xi + \mu_i + \epsilon_{it}, \qquad if\ i \in j \qquad (1)$$

where $\ln(c_{it})$ is the natural logarithm of consumer i's usage at time t. The $After$ is the dummy variable with value 1 if it is after rate change. The parameter λ measures the percentage usage change after the rate change. The x_{it} is control variables includes weather and household's real estate information. The μ_i is household fixed-effect. Equation (1) is different from "Difference-in-Difference" estimator, since there is no control group. Without a control group, variables should be included to control the exogenous trends which might affect water consumption. In our case, the weather and household's real estate information (income measure) in x_{it} are introduced for this purpose. The detailed estimation results are included in the Appendix 2. Here, we plot the coefficient of λ with its 95% confidence interval in Figure 4 with the percentage change of marginal price for our test. The histogram (the right axis) indicates the percentage of household within each usage group. We expect that the higher confidence bound for consumers between 3-4 kgal and 10-18 kgal should be lower than the lower confidence bound of their neighbors.

According to Figure 4, there is no clear evidence that consumer on average use 3-4 kgal, 10-18 kgal has relative higher usage reduction compared to their neighboring counterparts. From panel (a), the summer reduction for consumers at 3-4 kgal is not statistically different from 0. For 10-18 kgal consumers, their coefficients are not well below their neighbors. From panel (b), the winter usage reduction for 4 kgal is again not statistically different from 0. Compared to 4-10 kgal users, the 10-18 kgal users reduce slightly more as expected. Since there are no enough observations in the high usage group because of a lower winter usage, we can't compare 10-18 kgal users to higher users. In summary, the higher increase in marginal price does not necessarily leads to more usage reduction. We again verify the conjecture that consumers do respond to the other "perceived price" instead of marginal price.

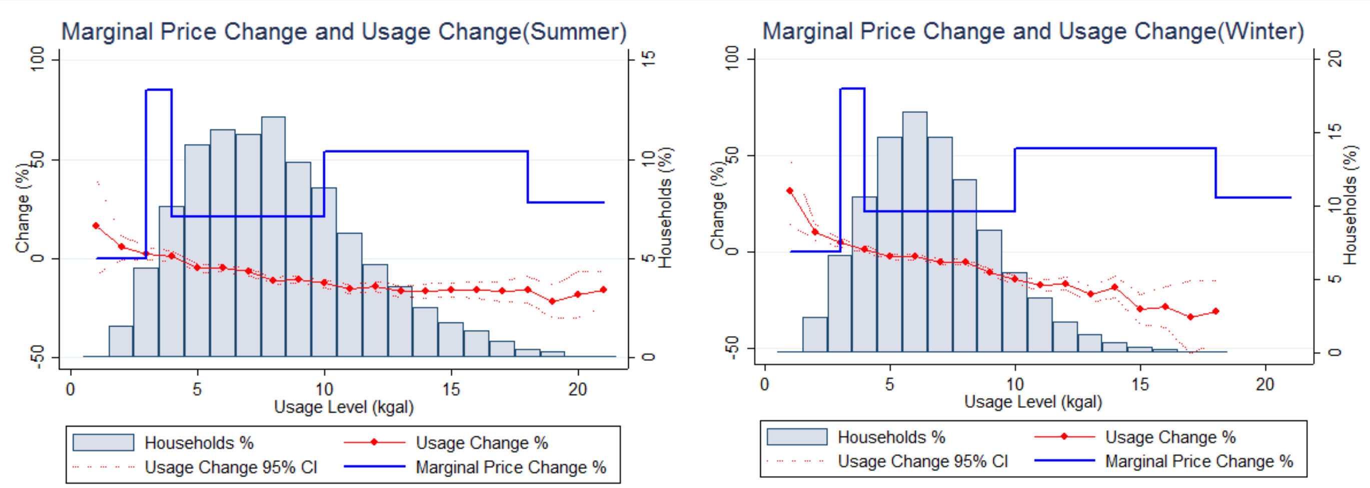


Figure 4. Test of Response to Marginal Price Using IBP Rate Change

4. Empirical Results

In this section, we present the empirical results of estimating our model using Sun City data. To test the performance of our model, we estimate DCC model as benchmark. Based on our earlier test that consumers in Sun City tend to be inattentive, so we expect that our model fit Sun City sample better. Our estimation is conducted using subsample before IBP rate change in Sun City. Using estimates of both model from pre-rate-change periods, we simulate post-rate-change usage. Comparing the simulated usage to real data, we evaluate the model performance through two approaches. First, we calculated the main statistics (mean and quartiles) of simulated usage and real usage to compare them on a monthly basis. The results suggest that our model is closer to the real usage, after one or two months adjustment. Secondly, we design another test based on the change of IBP rate. We test which set of simulated usage data better reflects consumers' response to the rate change. The result is interesting: our behavioral model performs better than DCC for consumers with low and high usage, while DCC is better for the rest consumers with mid-level usage.

4.1 Estimation Results

The variables we used in direction decision are lagged bill difference $(bill_t^i - bill_{t-1}^i)$ for cost C_t^i and lagged usage difference $(usage_t^i - usage_{t-1}^i)$ for benefit B_t^i. These two variables measure the very recent trade-off consumers made on the margin of their water consumption. We add consumer's CPI discounted assessed home value to be the time-variant households' heterogeneity H_t^i. For the adjustment decision, Z_{t+1}^i includes weather condition in the $t+1$ period, measured by evapotranspiration, and households' real estate variables such as indoor living area and outdoor yard area size. The result of our model using pre-rate-change subsample is included in Table 2. The parameters for direction decision and adjustment decision are jointly estimated.

Variable	Estimates	Std. error
Direction Regression		
Lagged bill difference	0.0629 ***	(0.0026)
Lagged usage difference	0.0187 ***	(0.0021)
Income	-0.0012 ***	(0.0001)
Cutoff 1 ($\underline{V}$)	-0.1577 ***	(0.0068)
Cutoff 2 ($\overline{V}$)	0.2868 ***	(0.0067)
Main Regression (Bill goes up)		
Weather * Lagged bill	0.0089 ***	(0.0002)
Living area * Lagged bill	0.0037 ***	(0.0001)
Yard area * Lagged bill	0.0004 ***	(0.0001)
Lagged bill	1.0789 ***	(0.0052)
Main Regression (Bill stays)		
Weather * Lagged bill	0.0000 ***	(0.0000)
Living area * Lagged bill	0.0000 ***	(0.0000)
Yard area * Lagged bill	0.0000 ***	(0.0000)
Lagged bill	0.9999 ***	(0.0000)
Main Regression (Bill goes down)		
Weather * Lagged bill	0.0020 ***	(0.0001)
Living area * Lagged bill	0.0020 ***	(0.0001)
Yard area * Lagged bill	0.0013 ***	(0.0001)
Lagged bill	0.7185 ***	(0.0018)
Others		
σ_1	2.4217 ***	(0.0019)
σ_2	0.0015 ***	(0.0000)
σ_3	1.9347 ***	(0.0024)
ρ_1	0.0247	(0.0256)
ρ_2	0.9674 ***	(0.0005)
ρ_3	0.4467 ***	(0.0065)

Note: *** $p < 0.001$.

Table 2. Estimates of Our Model

The results in Table 2 are as expected. For direction decision, consumers balance between marginal cost and marginal utility of water consumption. A higher marginal cost lower the probability of using more in future bill cycle, while a higher marginal utility increase of probability. A higher income also increases the probability for using more. The cutoff points are located around 0 due to the way we normalize the constant, it shows that consumers always try to adjust water consumption to a comfort zone around the optimal level (normalized at 0).

For adjustment decisions, the variable of interest is the current bill. For consumers decide to "use more", "stay same" and "use less", their future bills are approximately 107%, 99% and 71% of current bill. Interestingly, consumers make larger adjustments when they decide to cut water consumption. For other control variables, a drier weather (a higher evapotranspiration) leads to a larger adjustment for "use more" case and a smaller adjustment for "use less" case. Other variables such as indoor and outdoor area size are mainly used as control variables, we don't have find clear interpretation for them. The reason is that these two variables only measure only the size without containing detailed information such as if the outdoor area include a swimming or not. Other estimates like standard error and correlation are within reasonable range.

We also conduct two robustness checks to further verify our model. The first robustness check is designed based on the hypothesis that consumers with different income level may have radically different behavior due to the budget constraint. We separate the whole sample into three segments (lower 25%, medium 50%, and higher 25%) based on households' assessed home values to estimate our model separately for each segment. Secondly, consumers' water consumptions are induced by their home appliances, so the capacity of home appliance may lead to different behavior. We calculate consumers average usage level of all sampling period to measure their home appliance capacity. We again separate the whole sample into three segments (lower 25%, medium 50%, and higher 25%) based on average usage level to estimate our model separately for each segment. The results for both robustness checks are reported in Appendix 3. Our major results remain for all three segments in first test. The major results also remain for medium 50% and higher 25% segments in the second test, but partial results not significant in lower 25% segment.

We then estimate DCC model following exact procedures on Olmstead et al (2007) and Olmstead (2009). The elasticity is simulated using non-parametric approach suggested by Olmstead (2009). Results are summarized in Table 3. Following these two papers, the economic explanation is focused on the simulated price and income elasticities. The negative price elasticity and positive income elasticity are as expected. In other DCC applications, the standard deviation of consumer heterogeneity error (σ_η) is higher than the optimization error (σ_ϵ). However, the standard deviation of consumer heterogeneity is very small in our sample. We found similar results in Dale et al. (2009). The small magnitude may be caused by the fact that our sample included a single community, whereas most other applications included multiple communities located in different cities.

DCC Model Estimates		
Variable	Coefficient	Std. error
ln (price)	-1.522***	(0.080)
ln (virtual income)	1.521***	(0.050)
Weather	0.028***	(0.001)
Living area	-0.065***	(0.002)
Yard area	-0.017***	(0.001)
Constant	-3.911***	(0.160)
σ_η	0.014***	(0.004)
σ_ϵ	0.605***	(0.002)

Simulated Elasticity		
Variable	Elasticity estimates	Std. error.
Price	-0.22***	(0.02)
Income	0.11***	(0.01)

Note: *** *P <0.001*

Table 3. DCC Model Estimates

4.2 Performance Test Based on Statistics

Using pre-change estimates of both models, we simulated one-month-ahead usage for the post-change periods. The simulator of our behavioral model is discussed in the Appendix 1. For DCC model, we use the simulator listed on Olmstead (2009) (Appendix). We then calculate the statistics (mean and quartiles) of simulated usage on a monthly basis to compare to the real usage for all periods after the rate change. The results for different statistics are plotted in Figure 5.

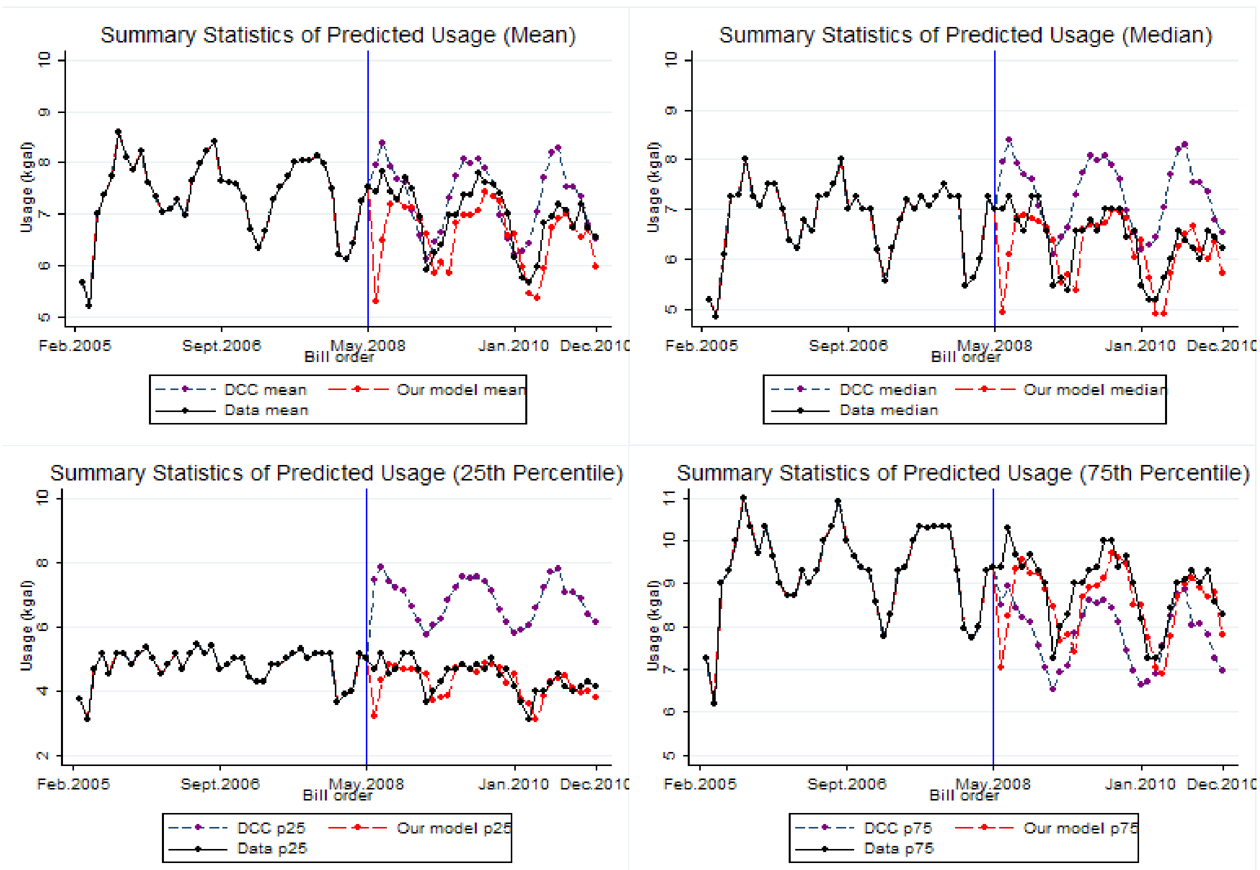


Figure 5. Results of Performance Test Using Statistics

The results from Figure 5 are as we expected. Generally, after one or two month adjustment following the rate change, our behavioral model start to perform better than DCC in the rest periods. The results are consistent for different statistical measures. It agrees with our earlier conjecture that consumers in our sample are inattentive in water consumption. Our model predicts a sudden decrease in the one or two month following the rate change. The reason is that the monthly bills are overall increased in Sun City after the rate change due to higher monthly fixed charge and marginal price. A higher monthly bill compared to previous monthly will increase the probability of using less water in our model. After the bill information updated later, the predicted from our model back to normal. The comparison based on statistics is direct, but it does not utilize the household fixed effect contained in the panel data. To further examine the model performance, we use the change of IBP rate to test while controlling household fixed effect. We test which set of simulated data better reflect consumers' response to the rate change.

4.3 Performance Test Using Change of Rate

Our second test of model performance is again based on the IBP rate change. We test which set of simulated post-rate-change usage data better reflect the reality. We estimate the "pre-change" vs. "post-change" fixed-effect model specified in equation (1) with real data first, then replace the post-rate-change usage by two sets of simulated data to test which model predicts consumers' response better. Similar to the approach we took in Section 3.3, we estimate consumers in different usage groups separately since the rate change has heterogeneous impact for consumers with various usage levels. Summer and winter are distinguished to control the seasonality. The coefficient λ, measured the percentage usage change after rate change, using post-change real data and simulated data are plotted in Figure 6 with their 95% confidence interval to test the performance of our model. Again, the histogram (the right axis) indicates percentage of households within each usage group. The detailed estimation results are included in the Appendix 2.

Figure 6 shows very interesting results. Our behavioral model fits real usage better for the low and high users, while the DCC result fits the users in the middle better (approximately 25% and

15% households in the summer and winter, respectively). It implies that consumers with low and high usage tend to make decision based on "perceived price" while middle usage consumers tend to respond to marginal price. Extreme users have less incentives to acquire more information to react to the marginal price. Low users consume water as necessity, understanding marginal price will not dramatically affect their consumption. For high users, most likely own home appliances with extreme large capacity, consuming less water leads to forfeiting utility generated from these home appliances, which is not quite bargain for them. Since spending time and effort to acquire marginal price may still not change their consumption, they have less incentive to do so and their decision relies on the "perceived price" required modest time and effort. On the other hand, consumers with mid-level usage has flexibility to adjust their water consumption. As a result, acquiring marginal price and being responsive to the IBP is rewarding to them because they will not only make better decisions but also execute them.

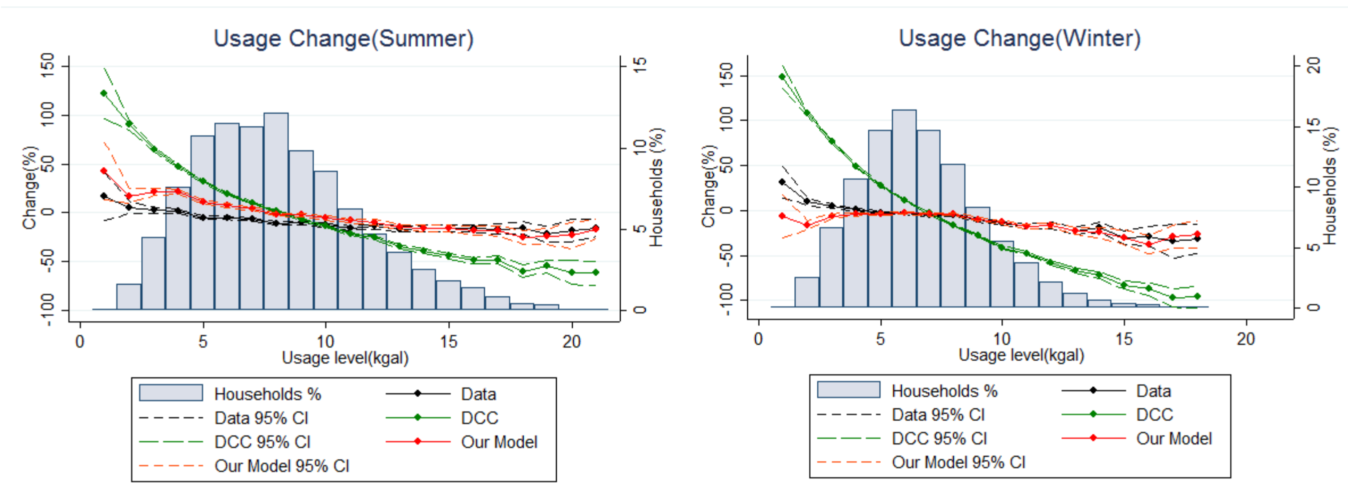


Figure 6. Results of Performance Test Using Change of Rate

5. Conclusion

In this paper, we propose a structural water demand model for rational but inattentive consumers. We start by testing whether consumers in Sun City, AZ respond to marginal price or "perceived price" in water consumption. The test results suggest that "perceived price" should be decision variable for our sample consumers. Then we estimate our model with DCC model as benchmark to test the model performance. The performance of two models suggest that consumers with low and high usage more likely to respond to "perceived price", while mid-level users tend to respond to marginal price. Our approach can be easily generalized from water demand to other residential energy demand. We understand that this paper is limited by the fact that there is only a single community under studied. Also, the data we have does not included detailed real estate information other than the indoor and outdoor size. These limitations are to be tested and corrected by future research.

This paper helps in exploring the decision making process of rational but inattentive consumers in the residential water market. The results can be used in restoring the desirability of IBP and in improving the effectiveness of future policy intervention. IBP's desirability is maximized if consumers are informative and responsive to the marginal price. Both requirements are barely met by inattentive consumers. To solve this problem, more information and incentives should be provided to inattentive consumers. Recent literature using randomized control trial shows that empowering consumers through smart devices with more information makes them more responsive to marginal price (Jessoe & Rapson, 2014; Kahn & Wolak, 2013; Attari, Gowrisankaran, Simpson, & Marx, 2014). For improving the effectiveness of future policy intervention, our model suggests that for inattentive consumers, policy instrument may be more effective if it is constructed based on "perceived price" such as total bill instead of marginal price.

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Appendix

Appendix 1. Simulator of Expected Usage

This section describes our one-month-ahead simulator of expected usage. Since the our model is constructed using bill, we simulate the expected bill then convert it back to the usage. All the parameter estimates are denoted with hat. The expected bill is:

$$E\left(bill_{i,t+1} | B_t^i, C_t^i, H_t^i, Z_{t+1}^i, bill_t^i\right) = \sum_{k=1}^{3} bill_{t+1}^i(k) \cdot \Pr(d_t^i = k)$$

where

$$bill_{t+1}^i = \left(\hat{\theta}^k + \hat{\eta}^k Z_{t+1}^i\right) \cdot bill_t^i + \hat{\rho}_k \hat{\sigma}_k \cdot \frac{\phi\left(\hat{A}^k\right) - \phi\left(\hat{B}^k\right)}{\Phi\left(\hat{B}^k\right) - \Phi\left(\hat{A}^k\right)}$$

and

$$\Pr\left(d_t^i = k\right) = \Phi\left(\hat{B}^k\right) - \Phi\left(\hat{A}^k\right)$$

and

$$\begin{cases} \hat{A}^1 = -\infty, \hat{B}^1 = \underline{\hat{V}} - \left\{\left(\hat{\beta} C_t^i - \hat{\alpha} B_t^i\right) + \hat{\gamma} H_t^i\right\} \quad (\text{"}Use\ More\text{"}) \\ \hat{A}^2 = \underline{\hat{V}} - \left\{\left(\hat{\beta} C_t^i - \hat{\alpha} B_t^i\right) + \hat{\gamma} H_t^i\right\}, \hat{B}^2 = \hat{\overline{\overline{V}}} - \left\{\left(\hat{\beta} C_t^i - \hat{\alpha} B_t^i\right) + \hat{\gamma} H_t^i\right\} \quad (\text{"}Remain\ Same\text{"}) \\ \hat{A}^3 = \hat{\overline{\overline{V}}} - \left\{\left(\hat{\beta} C_t^i - \hat{\alpha} B_t^i\right) + \hat{\gamma} H_t^i\right\}, \hat{B}^3 = +\infty \quad (\text{"}Use\ Less\text{"}) \end{cases}$$

After simulated the bills, we convert the results into the usage for further analysis.

Appendix 2. Estimates of Equation (1)

This section summarizes the estimates of equation (1). There are 3 versions of results, the difference is using either true data or simulated data of our model and DCC model for the post-change periods. Here we report the parameters of interests λ, which measures the percentage change of usage after the IBP rate change.

Estimation Results for Usage Change: Summer

Usage group		*Real data*		*DCC model*		*Our model*	
	# Obs.	Estimates	Std. error	Estimates	Std. error	Estimates	Std. error
1	90	0.1650***	(0.1239)	1.2238***	(0.1302)	0.4285	(0.1486)
2	1584	0.0569***	(0.0313)	0.9029***	(0.0262)	0.1750***	(0.0364)
3	4464	0.0241***	(0.0165)	0.6523***	(0.0130)	0.2146***	(0.0187)
4	7506	0.0142***	(0.0123)	0.4770***	(0.0093)	0.2179***	(0.0137)
5	10602	-0.0491***	(0.0098)	0.3168***	(0.0069)	0.1102***	(0.0107)
6	11322	-0.0486***	(0.0093)	0.1943***	(0.0065)	0.0751***	(0.0096)
7	11142	-0.0669***	(0.0088)	0.1046***	(0.0061)	0.0445***	(0.0091)
8	11952	-0.1104***	(0.0087)	0.0125***	(0.0059)	-0.0168***	(0.0088)
9	9720	-0.1035***	(0.0091)	-0.0674***	(0.0063)	-0.0222***	(0.0093)
10	8478	-0.1256***	(0.0100)	-0.1351***	(0.0069)	-0.0538***	(0.0101)
11	6192	-0.1548***	(0.0112)	-0.2182***	(0.0076)	-0.0806***	(0.0113)
12	4644	-0.1403***	(0.0133)	-0.2524***	(0.0093)	-0.0949***	(0.0136)
13	3546	-0.1654***	(0.0144)	-0.3469***	(0.0107)	-0.1464***	(0.0146)
14	2484	-0.1620***	(0.0176)	-0.3946***	(0.0130)	-0.1557***	(0.0183)
15	1782	-0.1554***	(0.0180)	-0.4403***	(0.0151)	-0.1615***	(0.0183)
16	1368	-0.1592***	(0.0201)	-0.4899***	(0.0166)	-0.1818***	(0.0209)
17	846	-0.1655***	(0.0259)	-0.4812***	(0.0202)	-0.1864***	(0.0260)
18	414	-0.1556***	(0.0336)	-0.5976***	(0.0309)	-0.2483***	(0.0370)
19	324	-0.2181***	(0.0421)	-0.5487***	(0.0324)	-0.2429***	(0.0413)
20	90	-0.1812***	(0.0580)	-0.6117***	(0.0625)	-0.2298***	(0.0677)
21	90	-0.1552***	(0.0449)	-0.6196	(0.0606)	-0.1647***	(0.0501)

Note 1)*** $p < 0.001$.
2)In our model 1,099 observation was dropped.

Estimation Results for Usage Change: Winter

Usage group		*Real data*		*DCC model*		*Our model*	
	# Obs.	Estimates	Std. error	Estimates	Std. error	Estimates	Std. error
1	102	0.3163***	(0.0885)	1.4794***	(0.0640)	-0.0618	(0.1189)
2	2311	0.1020***	(0.0202)	1.0842***	(0.0150)	-0.1597***	(0.0253)
3	6217	0.0471***	(0.0117)	0.7669***	(0.0086)	-0.0587***	(0.0137)
4	9920	0.0150***	(0.0089)	0.4963***	(0.0067)	-0.0383***	(0.0097)
5	13675	-0.0243***	(0.0073)	0.2800***	(0.0055)	-0.0353***	(0.0079)
6	15257	-0.0266***	(0.0065)	0.1173***	(0.0049)	-0.0254***	(0.0069)
7	13623	-0.0514***	(0.0072)	-0.0310***	(0.0054)	-0.0436***	(0.0074)
8	10997	-0.0529***	(0.0075)	-0.1627***	(0.0056)	-0.0353***	(0.0076)
9	7749	-0.1058***	(0.0090)	-0.2826***	(0.0067)	-0.0953***	(0.0092)
10	5068	-0.1436***	(0.0108)	-0.4095***	(0.0082)	-0.1317***	(0.0110)
11	3468	-0.1756***	(0.0139)	-0.4748***	(0.0102)	-0.1810***	(0.0140)
12	1980	-0.1638***	(0.0164)	-0.5775***	(0.0117)	-0.1621***	(0.0157)
13	1154	-0.2215***	(0.0205)	-0.6615***	(0.0142)	-0.2237***	(0.0201)
14	616	-0.1830***	(0.0282)	-0.7191***	(0.0191)	-0.2439***	(0.0296)
15	346	-0.2997***	(0.0403)	-0.8287***	(0.0233)	-0.2978***	(0.0416)
16	201	-0.2868***	(0.0530)	-0.8729***	(0.0337)	-0.3790***	(0.0512)
17	34	-0.3383***	(0.0921)	-0.9700***	(0.0507)	-0.2882***	(0.0634)
18	50	-0.3102***	(0.0810)	-0.9621***	(0.0596)	-0.2689***	(0.0753)

Note:1) *** $p < 0.001$.

2) In our model 358 observation was dropped.

Appendix 3. Results of Robustness Checks

This section summarizes the results of our robustness checks. The major results hold for all expect they are only partially hold for the lower 25% segment of robustness test 2.

Robustness Check: By Income Group

Variable	*Lower Income Group* Avg. Income: $61,860		*Middle Income Group* Avg. Income: $89,640		*High Income Group* Avg.Income:$122,820	
	Estimates	Std. error	Estimates	Std. error	Estimates	Std. error
Direction Regression						
Lagged bill difference	0.2647 ***	(0.0027)	0.3103 ***	(0.0042)	0.1340 ***	(0.0061)
Lagged usage difference	0.1654 ***	(0.0027)	0.2299 ***	(0.0047)	0.0873 ***	(0.0078)
Income	-0.0011 ***	(0.0003)	-0.0027 ***	(0.0003)	-0.0010 ***	(0.0002)
Cutoff 1 ($\underline{V}$)	-0.3296 ***	(0.0215)	-0.5026 ***	(0.0301)	-0.3627 ***	(0.0267)
Cutoff 2 ($\overline{V}$)	0.2958 ***	(0.0218)	0.0921 ***	(0.0300)	0.1509 ***	(0.0252)
Main Regression (Bill goes up)						
Weather * Lagged bill	0.0082 ***	(0.0003)	0.0069 ***	(0.0002)	-0.0032 ***	(0.0003)
Living area * Lagged bill	0.0006	(0.0004)	-0.0018 ***	(0.0003)	-0.0003	(0.0003)
Yard area * Lagged bill	-0.0018 ***	(0.0004)	0.0002	(0.0002)	0.0001	(0.0001)
Lagged bill	1.1618 ***	(0.0072)	1.1588 ***	(0.0048)	1.0316 ***	(0.0066)
Main Regression (Bill stays)						
Weather * Lagged bill	0.0000 ***	(0.0000)	0.0000 ***	(0.0000)	0.0000 ***	(0.0000)
Living area * Lagged bill	0.0000 ***	(0.0000)	0.0000 ***	(0.0000)	0.0000	(0.0000)
Yard area * Lagged bill	0.0000 ***	(0.0000)	0.0000 ***	(0.0000)	0.0000 ***	(0.0000)
Lagged bill	1.0000 ***	(0.0000)	1.0000 ***	(0.0000)	1.0000 ***	(0.0000)
Main Regression (Bill goes down)						
Weather * Lagged bill	0.0028 ***	(0.0002)	0.0021 ***	(0.0002)	0.0020 ***	(0.0002)
Living area * Lagged bill	-0.0007 ***	(0.0003)	-0.0040 ***	(0.0003)	0.0040 ***	(0.0003)
Yard area * Lagged bill	0.0005 *	(0.0003)	-0.0010 ***	(0.0002)	-0.0019 ***	(0.0001)
Lagged bill	0.7115 ***	(0.0035)	0.8030 ***	(0.0051)	0.6764 ***	(0.0058)
σ_1	2.3377 ***	(0.0039)	2.2720 ***	(0.0022)	2.8630 ***	(0.0046)
σ_2	0.0000 ***	(0.0000)	0.0000 ***	(0.0000)	0.0000 ***	(0.0000)
σ_3	1.8792 ***	(0.0030)	2.0942 ***	(0.0037)	2.2649 ***	(0.0040)
ρ_1	0.0944 ***	(0.0071)	-0.0183 ***	(0.0035)	-0.9830 ***	(0.0028)
ρ_2	-0.1368 ***	(0.0036)	0.4777 ***	(0.0017)	0.5488 ***	(0.0101)
ρ_3	0.7153 ***	(0.0140)	0.6422 ***	(0.0100)	0.5725 ***	(0.0096)

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Robustness Check: By Usage Group

Variable	*Lower User Group* Avg. usage: 4.09 kgal		*Middle User Group* Avg. usage: 6.97 kgal		*High User Group* Avg.usage:10.71kgal	
	Estimates	Std. error	Estimates	Std. error	Estimates	Std. error
Direction Regression						
Lagged bill difference	0.2957***	(0.0813)	0.1709***	(0.0051)	0.0345***	(0.0027)
Lagged usage difference	0.0458***	(0.3397)	0.0690***	(0.0091)	0.0375***	(0.0033)
Income	-0.0028***	(0.0095)	-0.0032***	(0.0003)	-0.0012***	(0.0001)
Cutoff 1 ($\underline{\mathrm{V}}$)	-0.4973***	(0.4316)	-0.5320***	(0.0150)	-0.3247***	(0.0127)
Cutoff 2 ($\overline{\mathrm{V}}$)	0.4006***	(0.2542)	0.0310***	(0.0133)	0.0657***	(0.0129)
Main Regression (Bill goes up)						
Weather * Lagged bill	0.0061***	(0.0107)	-0.0013***	(0.0007)	-0.0009***	(0.0002)
Living area * Lagged bill	0.0022	(0.0159)	0.0006***	(0.0007)	-0.0007	(0.0002)
Yard area * Lagged bill	0.0009***	(0.0316)	-0.0003	(0.0003)	-0.0017	(0.0002)
Lagged bill	1.0716***	(0.1741)	1.1809***	(0.0317)	1.0417***	(0.0037)
Main Regression (Bill stays)						
Weather * Lagged bill	0.0000***	(0.0000)	0.0000***	(0.0000)	0.0000***	(0.0000)
Living area * Lagged bill	0.0000***	(0.0000)	0.0000***	(0.0000)	0.0000	(0.0000)
Yard area * Lagged bill	0.0000***	(0.0001)	0.0000***	(0.0000)	0.0000***	(0.0000)
Lagged bill	0.9998***	(0.0018)	0.9999***	(0.0000)	1.0000***	(0.0000)
Main Regression (Bill goes down)						
Weather * Lagged bill	-0.0034***	(0.0460)	-0.0027***	(0.0004)	0.0040***	(0.0002)
Living area * Lagged bill	-0.0035***	(0.0111)	0.0018***	(0.0001)	0.0014***	(0.0001)
Yard area * Lagged bill	0.0035*	(0.0416)	0.0005***	(0.0002)	-0.0016***	(0.0001)
Lagged bill	0.8183***	(0.0212)	0.7795***	(0.0035)	0.7358***	(0.0034)
σ_1	1.6004***	(0.1769)	2.4487***	(0.0033)	3.7393***	(0.0046)
σ_2	0.0010***	(0.0018)	0.0008***	(0.0001)	0.0000***	(0.0000)
σ_3	1.3829***	(0.4842)	1.5550***	(0.0054)	2.6724***	(0.0053)
ρ_1	-0.2368***	(1.0430)	-0.0027***	(0.1572)	-0.9939***	(0.0002)
ρ_2	0.4093***	(0.8788)	-0.6439***	(0.0055)	-0.0688***	(0.0091)
ρ_3	0.4600***	(0.3061)	0.2104***	(0.0554)	0.4623***	(0.0040)

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.