How Do Consumers Respond to Nonlinear Pricing ? Evidence from Household Water Demand

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Abstract

This paper exploits price variation in residential water pricing in Southern California to examine how consumers respond to nonlinear pricing. Contrary to a prediction from the standard theory of nonlinear budget sets, I find no bunching of consumers around the kink points of nonlinear price schedule. I then explore whether consumers respond to an alternative perception of nonlinear prices. The price schedule of a service area was changed from a linear price schedule to a nonlinear price schedule. This policy change leads an *increase* in marginal price and expected marginal price and a *decrease* in average price for many consumers. Using household-level panel data, I find strong evidence that consumers respond to average price rather than marginal or expected marginal price. Estimates of the short-run price elasticity for the summer and winter months are -.127 and -.097, and estimates of the long-run price elasticity for the summer and winter months are -.203 and -.154.

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1 Introduction

How do consumers respond to nonlinear pricing? Answers to this question play a central role in many areas of economics. For example, taxpayers in many countries make decisions on their labor supply, savings, interest payments, and retirement under nonlinear income tax schedules. Likewise, consumers in many markets including cell phone, electricity, natural gas, and water, choose their consumption under nonlinear price schedules. In each case, the policy implications of nonlinear pricing critically depend on how people respond to nonlinear pricing.

Empirical studies face two major challenges to answer the question. First, a typical research environment in a non-experimental study usually does not provide researchers a counterfactual group that experiences a different price schedule from the group of interest. For example, in non-experimental income tax data, all comparable taxpayers are on the same tax schedule. The lack of clean control groups creates several identification problems as pointed out in recent studies by Heckman (1996), Blundell, Duncan, and Meghir (1998), Goolsbee (2000), and Saez, Slemrod, and Giertz (2009a). Second, economic theory and evidence from laboratory experiments provide different implications about whether consumers respond to marginal price or an alternative perception of nonlinear prices. The standard model of nonlinear budget sets predict that consumers respond to marginal price. However, laboratory experiments often find that people have limited understanding of nonlinear price structures and tend to respond to average price.[1] Liebman and Zeckhauser (2004) provide an alternative theory, "schmeduling", where consumers under a complex price schedule make a sub-optimal choice by responding to average price. Nevertheless, most empirical studies estimate demand based on the assumption that consumers are fully aware of, and therefore respond to, the marginal price of the nonlinear price schedules (e.g. Reiss and White 2005, Olmstead, Hanemann, and Stavins 2007).

This paper exploits price variation in a residential water market in Southern California to investigate whether consumers respond to marginal price or an alternative form of price when faced with nonlinear price schedules. Residential water consumers in Irvine Ranch Water District (IRWD) pay a substantially steep increasing block prices where the marginal price increases by 100% when their consumption exceeds a cutoff level. In addition to this price variation, IRWD's policy change provides a nearly ideal research environment to study the response to nonlinear

[1] Fujii and Hawley (1988) find that many taxpayers do not know their marginal tax rate. de Bartolome (1995) finds that many subjects in his lab experiment use the average tax rate as if it is the marginal rate.

price schedules.

I employ three empirical analyses. First, I follow the methods in Saez (1999), Saez (2009), and Chetty et al. (2010) to explore whether I can find bunching of consumers in the five-tier nonlinear water price schedules. An important implication from the standard theory of nonlinear budget constraints is that a disproportionally large number of indifference curves would intersect the kink points of the nonlinear budget constraint. As a result, if consumers respond to the marginal price of nonlinear prices, the distribution of consumption should show bunching of consumers across the kink points of nonlinear price schedules.

Second, I apply a regression discontinuity design to estimating the price elasticity with respect to marginal price. The change in IRWD's nonlinear price schedule between the winter and summer month produces a discontinuous change in marginal price around the kink points of the nonlinear price schedule. Consumers whose had nearly the same amount of consumption in a month experience a substantially difference change in their marginal price. I use a regression discontinuity design, which is similar to Saez (2003)'s bracket creep study for the elasticity of taxable income, to explore whether consumers respond to marginal price.

Finally, I expolit a policy change in one of IRWD's service area to examine whether consumers respond to marginal price, expected marginal price, or average price when faced with nonlinear price schedules. In 2005, the price schedule in the service area was transformed from a flat marginal price schedule to IRWD's standard five-tier increasing block price schedule. Importantly, this policy change produces an increase in marginal price and a decrease in average price for many consumers in the area. This price variation *between* the marginal price and average price enables me to separately identify the partial effect of each price variable. Furthermore, the surrounding service ares did not have the same price change as the treatment area in the policy change in 2005. I focus on the samples within one mile of the service area border to examine how the consumption in the treatment area changed in response to the policy change relative to the control area.

My empirical analysis relies on a panel data set of household-level monthly water billing records for nearly all households in the area of this study. This confidential data set is directly provided by IRWD. The data set includes detailed information about each customer's monthly bills from 1994 to 2008. I particularly focus on the years around the policy change in 2005 to employ the third empirical analysis. The data in 2006, 2007, and 2008 allow me to examine how the policy change in 2005 affected long-run water consumption behavior.

Results from the three empirical analyses provide strong evidence that consumers respond to average price rather than marginal or expected marginal price when faced with nonlinear price schedules for water. First, I find that the consumption density does not reveal bunching of consumers in any of the kink points in the nonlinear water price schedule. There is no evidence of bunching even in the price schedules that have quite steep discontinuous increases in marginal price. Second, the regression discontinuity estimation provides no evidence of the response to marginal price. The price elasticity estimates with respect to marginal price are close to zero with tight standard errors. Finally, the analysis based on the policy reform in 2005 provides evidence that consumers respond to average price. In particular, when I include both marginal price and average price in the price elasticity estimation, the marginal price has nearly zero effect on consumption, while the average price has a statistically and economically significant effect on consumption. I find the same result with the expected marginal price; when I include both expected marginal price and average price in the price elasticity estimation, the expected marginal price has nearly zero effect on consumption, while the average price has a statistically and economically significant effect on consumption.

Estimates from the price elasticity estimation also provides several notable findings in the magnitude of the price elasticity. First, I find slightly larger price elasticity estimates for the summer months. The short-run price elasticity with respect to average price is -.127 for the summer months and -.097 for the winter months. Second, I also find larger price elasticity estimates for the long-run response to the policy reform in 2005. The estimated long-run price elasticity is -.203 for the summer months and -.154 for the winter months.

All of these estimates have tighter standard errors than previous studies in residential water demand because the price variation in my research design is substantially larger than price variation in most previous studies. In addition to have better precision in estimates, having substantial price variation is particularly important to obtain a reliable estimate when we consider a friction that consumers may face when they respond to a price change. Chetty (2009) shows that when agents have such a friction, bounds on elasticity estimates shrink at a quadratic rate with log price. As a result, pooling several small price changes although useful in improving statistical precision yields less information about the structural elasticity than studying a few large price changes.

Both of my short-run and long-run price elasticity estimates are lower than most estimates in the literature on residential water demand. Espey, Espey, and Shaw (1997) provide a meta analysis of residential water demand and show that the mean price elasticity is 0.51. In recent studies, Hewitt and Hanemann (1995) and Olmstead, Hanemann, and Stavins (2007) use the discrease continuous choice model to estimate the price elasticity. Hewitt and Hanemann (1995) finds an price elasticity estimate of -1.6 and Olmstead, Hanemann, and Stavins (2007) finds an estimate of -.64 for consumers that have increasing block price schedules.

The paper proceeds as follows. Section 2 presents an institutional background and data. Section 3 presents the empirical framework and results. Section 4 concludes and discusses future research avenues.

2 Institutional Background and Data

This section provides institutional backgrounds and data descriptions. The first part describes the background of Irvine Ranch Water District (IRWD). The second part explains the water utility's residential water price schedule and its price variation. Finally, the last part presents data descriptions.

2.1 Irvine Ranch Water District

Irvine Ranch Water District (IRWD), originally formed in 1961 under the provisions of the state of California Water Code, is an independent special district[2] serving Central Orange County, California. The district provides potable water, wastewater collection and treatment, recycled water programs, and urban runoff treatment to a population of 331,500 in 2011. The districts serves residential, commercial, industrial, public authority, landscape irrigation, and agricultural customers. As an independent public agency, the district is governed by a five-member, publicly elected Broad of Directors.

Figure 1 and 2 present IRWD's service areas, which are approximately 181 square miles from the Pacific coast to the foothills. The District serves the City of Irvine and portions of the Cities

[2]Special districts are one of the forms of local government. Special districts may be dependent (part of a city or county government) or independent (governed by its own publicly elected board of directors). Special districts are further divided into enterprise special districts (fees are billed or assessed, with the amount linked to what each customer uses) and non enterprise special districts (dependent on tax dollars). IRWD is an independent, enterprise special district.

of Costa Mesa, Lake Forest, Newport Beach, Tustin, Santa Ana, Orange and unincorporated Orange County.

One of the important recent historical events in IRWD is its consolidations with other water districts. From 1997 to 2008, IRWD has consolidated with five water districts. In most cases, the objective of consolidations is to reduce reduce overhead and administrative costs and lower rates and charges to customers of the consolidated district. One of the consolidations is closely related to my research design in this study. In 1997, the shareholders of the Santa Ana Heights Water Company elected to merge with IRWD due to rising costs of imported water and lack of potable ground water supplies. As a result, approximately 10,000 residents in the former area of the Santa Ana Heights Water Company have been served by IRWD from 1997. The important fact about this consolidation is that from 1997 to 2004, households in this consolidated area were on the flat marginal price schedule that have been used by the former water provider. In 2004, IRWD announced that the price schedule in Santa Ana Heights serve area was going to be transformed to be the standard block price schedule that were used for most customers in the district.

2.2 Five-Tier Increasing Block Price Schedule in IRWD

Most residential customers in IRWD pay five-tier increasing block prices for their water consumption. The solid line in Figure 3 shows the five-tier increasing block price schedule in August 2002. In every month, IRWD allocates "baseline allocation" to each customer. The baseline allocation depends on seasons (summer and winter months) and customer types. In 2002, for example, the allocation for single-family households in a typical 30 days billing cycle was 18 CCF[3] in the summer months (May to November) and 14 CCF in the winter months (December to April). Condominium customers and apartment customers have different baseline allocations, although this study focuses on single-family customers. In the five-tier increasing block price schedule, consumers pay five different marginal prices for their monthly consumption relative to the baseline allocation. The marginal price equals the first tier rate up to 40% of the baseline, the second tier rate up to 100%, the third tier rate up to 150%, the fourth tier rate up to 200%, and the fifth tier rate over 200% of the baseline. Mean consumption usually falls in the third tier and a fair numbers of consumers fall in the fifth tier.

[3] 1 CCF is 100 cubic feet, which is equal to 748 gallons.

The five-tier increasing block price in IRWD is very steep compared to similar price schedules in other water prices, electricity prices, and tax rates. The third tier rate is set to be twice as large as the second tier rate, the fourth tier rate is twice as large as the third tier rate, and the fifth tier rate is twice as large as the fourth tier rate. Thefore, consumers face a 100% increase in their marginal price when their consumption exceeds the kink points of these tiers. In terms of a percentage increase in marginal rate, this 100% increase is substantially larger than a price increase in other multi-tier nonlinear price schedules. For example, the five-tier increasing block electricity price schedule in California is one of the most steepest nonlinear price schedules in residential electricity pricing, but the price differences between the tiers are usually between 30% and 60%.

Panel A of Figure 4 presents time-series price variation of each of the five tier rates for most consumers in IRWD. From 2000 to 2011, the five tier rates had continuous increases. In 2011, the marginal price for the fifth tier is about $9.48, which is approximately $5 larger than the fourth tier rate. Because of consolidations, consumers in two service areas had different price schedules. Panel B presents the price schedule for Santa Ana Heights customers. After their service area was consolidated in 1997, they have been on the flat marginal price schedule until 2004. Starting in 2005, their price schedule was transformed into the standard five-tier block price that is shows in Panel A. There is other service area that had a different price schedule. Figure 5 presents the price schedules for Lake Forest service area. This area was consolidated in 2001, and had a flat marginal price schedule until 2008. IRWD changed their schedule into a five-tier block price schedule, which is slightly different from the one for other service areas, in 2008.

IRWD changes the price schedules for a couple of reasons. In most of the cases, the reason is related to costs of providing service such as costs of chemicals, energy costs to operate wells, pumping stations and the water reclamation plants. The other reason is related to consolidations. After a consolidation, IRWD usually waits some years to transform the former company's price schedule to IRWD's block price schedule. In one of the sections in this study, I use price variation from the consolidation of Santa Ana Heights service area. Using this price variation may lead to a concern that consumers possibly had a different change at the time of the consolidation in 1997 rather than a price change in water price. IRWD, however, did not change the price schedule immediately. They introduced their block price schedule to these consumers in 2005, which was 8 years after the consolidation. Furthermore, the panel data set of this study allows me to eliminate time-invariant confounding factors. Still, however, there is a concern that Santa Ana Heights area and other areas may have different time-variant unobservables that may confound my analysis. To address the concern, the final empirical analysis section focuses only on households within one mile of the service area border between Santa Ana Heights service area and Irvine service area.

2.3 Data

The primary data set of this study consists of panel data of household-level monthly water billing records from January 1994 to 2008.[4] I obtained the data set directly from IRWD with a confidentiality agreement. The records include all residential customers served by IRWD. Each monthly record includes a customer's address, billing start date and end date, monthly consumption, service area code, and residential types (single-family, condominium, or apartment). The records also include the square footage of a customer's unit for some customers. The billing data do not include price information. I collect historical price schedules from documents published by IRWD. To ensure the preciseness of the price information, I verify the information with staffs at IRWD.

For the first and second parts of the following empirical analyses, I use all of the single-family households that are on IRWD's standard five-tier increasing block price schedule. The total number of observation is 64,601 single-family households. The last part of the analysis uses single-family households that are within one mile of the service area border between Santa Ana Heights service area and Irvine service area. The total observations of this border sample is 5,985 households.

Table 1 summarizes descriptive statistics. The first column shows the statistics for all samples. Mean consumption is particularly high in June, July, August, and September, and low in January, February, and March. Columns 3 and 4 present the statistics for the border sample. Mean square footage is higher than all samples around the border of Santa Ana Heights service area. Mean consumption is also slightly larger in this area. However, both of mean square footage and monthly water consumption are quite similar between the two groups within one mile of the border. The final column presents t-statistics for the difference in the means. The

[4]I thank Amy McNulty and Fiona Sanchez for their help and support for providing the data set for this study.

differences of these statistics are not statistically different from zero.

3 Empirical Analysis

This section provide three empirical analyses to examine how consumers respond to nonlinear water price schedules. The first method uses price variation across the kink points of a nonlinear price schedule to estimate the response to marginal price. If consumers respond to their marginal price of water, the nonlinearity of price schedules would create bunching of consumers around the kink points. The second identification strategy uses a regression discontinuity design that exploits a discontinuous change in marginal price. I use that fact that consumers with nearly the same consumption level experienced substantially different changes in marginal price between November and December, and between April and May. Results from these two analyses provide evidence that consumers do not respond to marginal price. The final section, therefore, explores whether consumers respond to alternative perceptions of price by using price variation across service areas.

3.1 Bunching Around Kink Points

3.1.1 A Standard Model of Nonlinear Budget Sets and Bunching of Consumers

The standard model of nonlinear budget sets provides an important implication about demand under nonlinear price schedules. Consider a consumer who has a two-tier nonlinear water price schedule for water consumption x. The marginal price equals p_1 for up to k units of consumption and p_2 for any additional consumption. Suppose that the consumer has wealth W and quasilinear utility:

$$u(x, y) = W + V(x). \tag{1}$$

In the standard model of nonlinear budget sets, the consumer solves the following utility maximization problem:

$$\max_x u(x) = W - (p_1 \cdot x_1 + p_2 \cdot x_2) + V(x), \tag{2}$$

where x_1 and x_2 are consumption in the first and second tier. The demand under the standard model can be described as:

$$
x^*_{MP} \quad = \quad \begin{cases} x^*(p_1) & \text{if } x^*(p_1)) \leq k \\ k & \text{if } x^*(p_2)) \leq k \leq x^*(p_1)) \\ x^*(p_2) & \text{if } x^*(p_2)) \geq k, \end{cases} \tag{3}
$$

where $x^*(p_1)$ and $x^*(p_2)$ are the demand when the consumer faces a linear price schedule of p_1 or p_2.

Figure 6 illustrates demand curves derived in equation (3). An important implication from this equation is that if consumer preferences are convex and smoothly distributed across the kink point k, many demand curves intersect the vertical part of the price schedule as illustrated in the figure. In other words, a disproportionally large number of indifference curves would intersect the kink of the nonlinear budget constraint. As a result, the distribution of consumption should show bunching of consumers across the kink points (**?**). Saez (2009) shows how elasticities can be estimated by examining bunching around kinks under the assumption that individuals respond to nonlinear price schedules as the standard model predicts.

In the income tax literature, several studies including Saez (1999), Saez (2009), and Chetty et al. (2010) use this method to estimate the elasticity of taxable income with respect to nonlinear income tax rates. Most studies that use the US income tax records do not find bunching of taxpayers except for self-employed workers. For example, Saez (2009) finds no bunching across wage earners in income tax schedules in tax return data in the US. Chetty et al. (2010) find small but significant bunching for wage earners in their Danish tax recode data, although institutional factors in Denmark are likely to affect the bunching in addition to labor supply responses. In residential electricity data, Borenstein (2009) and Ito (2010) also find no evidence of bunching of consumers in five-tier increasing block price schedules in California.

3.1.2 Results

Using a large household-level consumption data, I explore evidence of bunching of consumers in the nonlinear price schedule in IRWD. Figure 4 shows the histogram of household-level monthly water consumption for the Irvine service area in Irvine Ranch Water District in 1994 (Panel A) and 2008 (Panel B). The horizontal axis shows consumption relative to customers' baseline allocations. The figures also show the marginal price ($) of water per CCF (100 cubic feet = 748 gallons). The solid lines display the locations of the kink points in the five-tier increasing block rates.

The histograms show no evidence of bunching around the kink points in both years. In 1994, the consumption distribution is smooth and does not have visible bunching of customers around any kink points. In particular, it is striking to find no bunching around the second, third, and fourth kink points, because consumers face a 100% increase in marginal price when their consumption exceeds these kink points. In terms of a percentage increase in marginal rate, this 100% increase is substantially larger than a price increase in other multi-tier nonlinear price schedules. For example, the five-tier increasing block electricity price schedule in California is one of the most steepest nonlinear price schedules in residential electricity pricing, but the price differences between the tiers are usually between 30% and 60%. In contrast, water consumers in IRWD faces a 100% increase when they cross each of the second, third, and fourth kink points. No bunching of consumers suggest evidence that consumers may not respond to their marginal price of water. The next section examines how consumers change their consumption when some of them experience a large increase in marginal price but others do not have the price change.

3.2 A RD Design to Estimate the Response to Marginal Price

This section presents the second way to estimate the price elasticity with respect to marginal price. My empirical strategy is similar to a regression discontinuity design used by Saez (2002). Saez uses a bracket creep that is created by inflation to estimate the elasticity of taxable income with respect to marginal income tax rates. From 1979 to 1981, the US income tax schedule was fixed in nominal terms while inflation was high (around 10%). This high inflation produced a real change in tax rate schedules. As a result, taxpayers near the top-end of a tax bracket were more likely to creep to a higher bracket and thus experience a rise in marginal rates the following year than the other taxpayers.

An important point about the price variation in Saez's study is that the price variation does not come from changes in marginal income tax rates. In this period, the income tax schedule itself did not change. However, the bracket creep moves taxpayers near the top-end of a bracket to the next bracket, while a similar taxpayer near the middle of the bracket is likely to remain in the same bracket. This quasi-experiment provides him treatment and control groups for changes in marginal income tax rate.

3.2.1 A RD Design Using a Discontinuous Change in Marginal Water Rates

I introduce a similar regression discontinuity design for the five-tier nonlinear price schedule in IRWD. A key component of the price schedule is a consumer's baseline allocation. For example, consumers pay the first tier rate up to 40% of their baseline allocation and the second tier rate between 40% and 100% of their baseline allocation. I use that fact that the baseline allocation is different between the summer months (May to November) and winter months (December to April) so that the whole price schedule makes a substantial horizontal shift between May and June, and between November and December.

Figure 8 illustrates the horizontal shift of a price schedule between November and December. Because the baseline allocation is 18 CCF for the summer months and 14 CCF for the winter months, the price schedule shifts left from November to December. As a result, consumers near the top-end of a tier in November are likely to experience an increase in their marginal price, while consumers near the bottom-end of a tier in November are unlikely to experience a change in their marginal price. For example, consider consumers that are in the fourth tier in November. A consumer that is in S_4 in November is likely to be in the next tier and experience a marginal price increase in December, while a consumer in the bottom part of the fourth tier is likely to remain in the fourth tier and thefore face the same marginal price.

3.2.2 Identification Strategy

Let x_{it} denote consumer i's average daily water consumption during billing month t and $mp_t(x_{it})$ be the marginal price of water. Suppose that the consumer has a quasi-linear utility function and responds to a water price with a constant elasticity β. Then, the demand function can be described as:

$$\ln x_{it} = \alpha_i + \beta \ln mp_t(x_{it}) + \eta_{it}, \tag{4}$$

with an individual fixed effect α_i and an error term η_{it}. Let me note some assumptions behind the model. First, the assumption of a quasi-linear utility function eliminates income effects from a price change. Second, this estimation assumes that the response to price is immediate and does not have lagged effects. Third, the elasticity is constant over time and over households.

Ordinary Least Squares (OLS) produce an inconsistent estimate of β because $mp_t(x_{it})$ is a function of x_{it}. Under increasing block price schedules, η_{it} is positively correlated with $mp_t(x_{it})$.[5] This simultaneity bias is exactly the same problem as the identification problem in the income tax literature that usually involve estimation under a progressive income tax schedule.

To address the simultaneity bias, I consider the following two-stage least squares (2SLS) estimation. Suppose that between billing month t_0 and t, a water utility, IRWD changes the baseline allocation as illustrated in Figure... Let $\triangle \ln x_{it} = \ln x_{it} - \ln x_{it_0}$ denote the log change in consumer i's consumption between billing month t_0 and billing month t, and $\triangle \ln mp_t(x_{it}) = \ln mp_t(x_{it}) - \ln mp_{t_0}(x_{it_0})$ the log change in the price. Finally, for the endogenous price variable $\triangle \ln mp_t(x_{it})$, I define a set of instrumental variables:

$$\begin{aligned} S_{it}^{j} &= 1 \text{ if } x_{it_0} \in \text{treatment in tiear } j\text{=1, ..., 4 at } t_0 \\ &\quad 0 \text{ otherwise.} \end{aligned} \tag{5}$$

That is,$S_{it}^{j} = 1$ if consumer i is the top-end of tier j in t_0. For example, consider a consumer that is in the top-end of the forth tier. For this consumer, $S_{it}^{4} = 1$ and $S_{it}^{1} = S_{it}^{2} = S_{it}^{3} = 0$. Intuitively, the dummy variable S_{it}^{j} works as an instrumental variable because it is a good predictor of a price change that is produced by the change in the baseline allocation between the two billing months.

Obviously, the instruments S_{it}^{j} are a function of x_{it_0}. Saez, Slemrod, and Giertz (2009b) and Ito (2010) point out that when $\triangle \ln x_{it} = \ln x_{it} - \ln x_{it_0}$ is used as a left hand side variable, the error term and x_{it_0} are likely to be highly correlated because of the mean reversion in consumption. Suppose that a consumer experiences a positive transitory shock at t_0. This positive transitory shock makes the consumer's consumption at t_0 larger than the consumption at t_1, aside from any behavioral response to a price change. That is, in panel analyses, the mean reversion produces a negative correlation between the error term and x_{it_0}.

An advantage of these instruments, S_{it}^{j}, is that the bias from the mean reversion can be controlled by including $f(x_{it_0})$, a flexible smooth control function of x_{it_0} in a regression. In the same way as a typical regression discontinuity design, including a flexible smooth function $f(x_{it_0})$ does not distroy identification because of the discontinuous nature of S_{it}^{j}.

[5] For example, if a household has a positive shock in η_{it} (e.g. a friend's visit) that is not observable to researchers, the household will locate in the higher tier of its nonlinear rate schedule.

I estimate the following 2SLS equation:

$$\triangle \ln x_{it} = \gamma_t + \beta \triangle \ln mp_t(x_{it}) + f(x_{it_0}) + \varepsilon_{it}, \tag{6}$$

instrumenting for $\triangle \ln mp_t(x_{it})$ with a set of the four indicator variables S^j_{it} where j = 1, ..., 4. As a flexible smooth function $f(x_{it_0})$, I include the first, second, and third order of polynomials of x_{it_0}.

3.2.3 Results

Figure 8 illustrates the instrumental variables that I use in the 2SLS estimation. The solid line shows the five-tier increasing block price schedule in November. The dashed line shows the price schedule in December. From November to December, the baseline allocation changes from 18 CCF to 14 CCF. As a result of this change, households whose November consumption is near the top-end of a tier are more likely to experience an increase in marginal price in December compared to households whose November consumption is near the bottom part of a tier.

How does this change in the price schedule affect a consumer's marginal price from November to December? I use consumption data in November and December in 1996 as an example to show how a consumer's marginal price was affected by the change in the price schedule. Panel A of Figure 9 plots the mean percent change in marginal price and predicted marginal price over November consumption levels. First, for each level of November consumption, I calculate the mean of the percentage change in "predicted" marginal price, $[mp_t(x_{it_0}) - mp_{t_0}(x_{it_0})]/m_{t_0}(x_{it_0})$ to show where the price variation comes from. This predicted marginal price tells how much price change a consumer would experience if the consumer does not change consumption from November to December. The change in predicted marginal price corresponds to Figure 8 that shows that consumers near the top-end of a tier experiences a price increase. For example, consumers in the top-end of the second, third, or fourth tier would have a 100% increase in marginal price. This is because the tier rate in the next tier is exactly double. Second, I calculate the mean of the percentage change in "actual" marginal price, $[mp_t(x_{it_0}) - mp_{t_0}(x_{it_0})]/m_{t_0}(x_{it_0})$. Consumers in the top-end of each tier experienced large increases in marginal price, wheres consumers whose November consumption was slightly above the kink points had very small changes.

Another interpretation of Panel A of Figure 9 is that the figure shows the first stage relationship between the actual price change and the instruments. The four instrumental variables, S_{it}^{j} where j = 1, ..., 4, strongly predict the change in marginal price. I can also use the predicted change in marginal price $[mp_t(x_{it_0}) - mp_{t_0}(x_{it_0})]/m_{t_0}(x_{it_0})$ as an instrument. Conceptually, these two different instruments exploit essentially the same exogenous price variation. In fact, the following estimation results do not change by using either of the two types of instruments.

Because consumers on the right and left sides of the kink points experience substantially different price changes shown in Panel A, there should be a discontinuous difference in their changes in consumption if they actually respond to marginal price. Panel B shows that there is no evidence of such behavior found in the data. I calculate the mean percent changes in consumption as $(x_{it} - x_{it_0})/x_{it_0}$. The change in consumption shows strong mean reversion; consumers that consume less in November are likely to increase their consumption in December whereas consumers that consumer a lot in November are likely to decrease their consumption in December. However, the change in consumption is smooth across the discontinuities of the price change, which suggests that consumers do not respond to the change in marginal price.

Figure 9 essentially illustrates what the 2SLS in equation (6) estimates. In the 2SLS estimation, I regress the change in consumption on the change in marginal price by using the instruments S_{it}^{j} . I also include the control function $f(x_{it_0})$ to deal with the mean reversion in x_{it_0}. The identification assumption is that the instruments S_{it}^{j} are uncorrelated with the error term in the second stage regression ε_{it} given the control function for the mean reversion in consumption.

Table 2 presents regression discontinuity estimates of the price elasticity with respect to marginal price. I use data from 1996 for this table. Results do not change when I use other years. Essentially, the price elasticity estimates are nearly zero with tight standard errors. The first two columns use November and December consumption data. I first include the full sample. To control for the mean reversion in consumption, I include the first, second, and third order of polynomials of x_{it_0}. Adding higher orders of polynomials does not change the estimate of the price elasticity. The estimation may have bias if the polynominal function of x_{it_0} does not sufficiently control for the mean reversion. For a robustness check, I follow Angrist and Lavy (1999) and estimate the same equation using the samples close to the kink (discontinuity) points. The second column shows that the price elasticity estimate does not change. Finally, the last two columns include the same regression using the price change from April to May, in which the allocation baseline changes from 14 CCF to 18 CCF. The price elasticity estimates are close to zero, which suggests evidence that consumers do not respond to the marginal price of water.

3.3 Using Price Variation Across Service Areas to Estimate Demand

The results from the previous two sections suggest evidence that consumers do not respond to the marginal price of water. Does it imply that nonlinear pricing provides no effect on household water consumption? The results can be explained by two possible reasons. The first possible reason is that the demand for residential water consumption has truly zero price elasticity. If the demand is fully inelastic, then the demand curves become vertical in Figure 6 and will produce no bunching of consumers around the kink points. Therefore, zero price elasticity will be consistent with the finding of no bunching.

Another possibility is that consumers may make their decision with respect to an alternative perception of price rather than marginal price. For example, suppose that consumers respond to the average price or expected marginal price of nonlinear water prices. Then, the histogram of consumption will show no bunching even if the demand has a significant price elasticity. This is because the average price and expected marginal price of a nonlinear price schedule do not have discontinuous kink points, in contrast to the discontinuous shape of its marginal price curve. For the same reason, the response to the average or expected marginal will be still consistent with the findings in the RD estimation in the previous section. The RD design exploits the discontinuous shape of the marginal price schedule, but at the same time, the RD design essentially eliminates the price variation of the average and expected marginal prices so that I can not estimate the price elasticity with respect to these two alternative perceptions of price.

3.3.1 Price Variation Across Service Areas

This section uses a similar empirical strategy to Ito (2010) to examine whether consumers have nearly zero price elasticity for water or they respond to an alternative perception of price rather than marginal price. Ito (2010). Ito (2010) estimates residential electricity demand by exploiting price variation across a spatial discontinuity in electric utility service areas. The territory border of two electric utilities lies within several city boundaries in southern California. As a result, nearly identical households experience substantially different nonlinear electricity price schedules.

In this study, I exploit price variation across different service areas in IRWD. Figure 10 shows two different price schedules in 2002. Most consumers in IRWD paid the five-tier increasing block prices. Consumers in Santa Ana Heights service area, however, paid a flat marginal price schedule that does not change with consumption levels. The figure shows that the marginal price is higher in the flat price schedule than the block price schedule up to 100% of the baseline allocation. However, the marginal price is the same in the third tier (100% to 150% of the baseline allocation) and lower in the flat price schedule above 150% of the baseline allocation.

This substantial difference in marginal price creates notable price variation in marginal price and average price. Figure 10 includes the average price curve for the block price schedule. The average price is higher for the flat price schedule up to 200% of the baseline allocation than the block price schedule but lower for the consumption above 200% of the baseline allocation.

Consumers in Santa Ana Heights paid the flat price until 2004. Their price schedule, however, was changed into the block price schedule in 2005. As a result, the first and second tier had decreases in both marginal and average prices. The third tier had no change in marginal price but a decrease in average price. The fourth tier had an increase in marginal price but a decrease in average price. Finally, the fifth tier had increases in both marginal and average prices.

This policy change in 2005 provides several advantages for my price elasticity estimation. First, the policy change created nearly ideal price variation *between* the change in marginal price and the change in average price. Consumers experienced substantially different changes in their marginal and average prices. In particular, consumers in the third tier experienced no change in marginal price but a decrease in average price. Consumers in the fourth tier experienced an increase in marginal price and a decrease in average price. Having different price variation *between* marginal price and average price is key to examine whether consumers respond to marginal or average price.

Second, this policy change provided a group that can be potentially used as a control group for the policy change. The policy change only affected consumers in Santa Ana Heights service area. Therefore, consumers in the surrounding areas, which already had the block price schedule since 1990's, can be potentially used as a control group. To use the surrounding areas as a control group, I need the parallel trend assumption between the water consumption between the treatment and control group; in the absence of a price change, the water consumption in the treatment and control groups would have the same change before and after the policy change.

My analysis focuses on households within one mile of the service area border. I examine the validity of this parallel trend assumption in the border samples.

Third, this policy change provides a useful research environment to explore the long-run price elasticity of water demand. In general, a rate change in water prices, electricity prices, or tax rates, occurs successively over time. When a rate change occurs frequently, it is difficult to see the long-run effects of a rate change. In the research environment in this paper, the substantial rate change happened in 2005 to Santa Ana Heights consumers compared to the surrounding areas, and these two groups of consumers had the exactly the same price schedule after 2005. That is, the *relative* price between the two groups had a substantial change in 2005, but no change after 2005. I exploit this environment to explore the long run effects of a rate change on water consumption.

3.3.2 Identification Strategy

Between the two groups in the one-mile border samples, I estimate the price elasticity for water demand using the following identification strategy that is used in Ito (2010). Let x_{it} denote household i's average daily water consumption during billing month t and $p_t(x_{it})$ be the price of water, which is either the marginal, expected marginal, or average price of x_{it}. Suppose that the household has a quasi-linear utility function and responds to electricity prices with a constant elasticity β. Then, the demand function can be described as:

$$\ln x_{it} = \alpha_i + \beta \ln p_t(x_{it}) + \eta_{it}. \tag{7}$$

Ordinary Least Squares (OLS) produce an inconsistent estimate of β because $p_t(x_{it})$ is a function of x_{it}. Under increasing block price schedules, η_{it} is positively correlated with $p_t(x_{it})$. Most previous studies of nonlinear price schedules use consumer *i's* previous consumption levels (e.g. the last year's consumption) to constract instruments. However, recent studies (e.g. Saez 2004, Saez, Slemrod, and Giertz 2009a) point out the identification problems of these instruments and suggest using repeated-cross section analysis. My identification strategy also uses repeated-cross section analysis that examine how the *distribution* of consumption changes in response to the change in price.

In the consumption data in each time period and in each of the treatment and control groups, I first divide the data into deciles of consumption. Denote G_1 as a dummy variable for the first decile group of the consumption distribution, G_2 for the second decile group, ..., and G_{10} for the top decile group of the consumption distribution. That is, the ten dummy variables G_g are simply group dummy variables for ten deciles. I include the data from January 2002 to December 2008. Therefore, the data set includes 84 year-month time periods. I run the 2SLS

$$\text{ln}x_{it} = \beta \text{ln}p_{ut}(x_{it}) + \gamma_{ut} + \lambda_{gt} + \theta_{gu} + Z_{it}'\delta + \varepsilon_{it}, \tag{8}$$

using the three-way interactions of time dummy variables, decile group variables, and utility dummy variable $Time_t \cdot G_g \cdot SA_i$ as instruments. SA_i is a dummy variable for Santa Ana Heights households. As in the standard DDD estimation (e.g.. Gruber (1994) and Gruber and Poterba (1994)), this model provides full nonparametric control for service-area-specific time effects that are common across decile (γ_{ut}), time-varying decile effects (λ_{gt}), and service-area-specific deciles effects (θ_{gu}). The identification assumption is that $Cov(Time_t \cdot G_g \cdot SA_i, \varepsilon_{it}) = 0$ for each t and g. Thus, the required assumption is that there is no contemporaneous shock that affects the *relative* outcomes of decile groups in the same service area for the same time period.

To test whether consumers respond to marginal price or average price, I also include both prices in the model. In this case, the estimating equation is

$$\text{ln}x_{it} = \beta_1 \text{ln}mp_{ut}(x_{it}) + \beta_2 \text{ln}ap_{ut}(x_{it}) + \gamma_{ut} + \lambda_{gt} + \theta_{gu} + Z_{it}'\delta + \varepsilon_{it}. \tag{9}$$

I also run the model that includes both expected marginal price and average price.

$$\text{ln}x_{it} = \beta_1 \text{ln}emp_{ut}(x_{it}) + \beta_2 \text{ln}ap_{ut}(x_{it}) + \gamma_{ut} + \lambda_{gt} + \theta_{gu} + Z_{it}'\delta + \varepsilon_{it}. \tag{10}$$

The nonparametric control variables γ_{ut}, λ_{gt}, and θ_{gu} flexibly control for unobservable economic and weather shocks to household water consumption. Consumers have different billing cycles, therefore, weather conditions can be different among different billing cycles given a billing month. To control for different shocks to each billing cycle, I also include time-varying billing cycle level fixed effects $Cycle_t$.

3.3.3 Results

As illustrated in Figure 10, consumers in Santa Ana Heights experienced different changes in marginal and average prices depending on their consumption levels. The marginal price had a decrease in the first and second tier, no change in the third tier, and an increase in the fourth and fifth tiers. The average price had a decrease in the first, second, third, and fourth tiers, and an increase in the fifth tier. Therefore, if consumers respond to their marginal price, I should observe the following distributional changes in consumption: 1) the consumption in the bottom of the consumption distribution should *fall* relative to the control group, 2) the consumption between 100% and 150% of the baseline allocation should have *no change* relative to the control group, and 3) the consumption above 150% of the baseline allocation should *rise* relative to the control group.

Figure 11 shows five percentiles (percentile 10, 25, 50, 75, and 90) of consumption for the treatment group (SA) and control group (IR). The vertical axis is the monthly consumption relative to the baseline allocation (%) so that I can relate this graph with the relative price change that happened to the two groups. First, I examine the validity of the control group by looking whether the parallel trend assumption holds before the policy change in 2004. In this border sample, the figure shows evidence that each percentile of the two groups moves in a parallel way before 2004.

Second, I explore the effect of the policy reform in 2005 on the consumption distribution. Relative to the control group, the treatment group's consumption increases in percentile 10, 25, 50, and 75. In contrast, the treatment group's consumption in percentile 90 falls relative to the control group. These findings contradict the prediction for the response to marginal price. Rather, these findings are more consistent with the response to average price. From 2004 to 2005, most parts of the consumption distribution experienced a decrease in average price relative to the control group. Only consumers whose consumption level is larger than 200% of the baseline allocation experienced an increase in average price. Therefore, the relative rise in consumption in percentile 10, 25, 50, and 75 are consistent with the response to average price. Furthermore, from 2004 to 2005, the treatment group's consumption in percentile 90 has a decrease relative to the control group. This finding is also consistent with the average price response because consumption levels above 200% of the baseline allocation experienced an increase in average price.

Finally, the path of the change in consumption suggests evidence of the long-run response to the price change. The relative price between the treatment and control groups had a large change in 2004, but no change after that. The relative consumption, however, seems to have a gradual change over time. I estimate the short-run and long-run elasticity in the following section. A concern about the gradual change in consumption is a potential time trend that is different between the treatment and control groups. The figure provides some evidence that this is unlikely to be a concern in this case. In 2002, 2003, and 2004, there is no clear evidence of different time trends between the two groups in each percentile. Moreover, the relative consumption starts to change at the exactly the same timing of the policy change.

To statistically estimate the price elasticity of demand, I run equation (8) for each of the three price definitions: marginal price, expected marginal price, and average price. I calculate expected marginal price by assuming that consumers have errors with a standard deviation of 20% of their consumption. I also estimate equation (9) and equation (10) to test whether consumers respond to marginal price, expected marginal price, or average price. First, I estimate these equations using contemporaneous price variables to obtain short-run price elasticity estimates. Second, for each price variable, I calculate the average of the twelve-month lag prices and use these price variables to estimate long-run price elasticity estimates. The intuition behind this estimation is that the twelve-month average would capture the price response to lagged prices.

Table 3 shows estimates for the short-run price elasticity in the summer months (May to November). The price elasticity estimate is -.094 for the marginal price, -.081 for the expected marginal price, and -.127 for the average price. In Column 4, I include both marginal and average price. Suppose that consumers respond to the nonlinear price schedule as the standard economic model predicts. Then, once the marginal price is included in the regression, adding the average price should not change the estimated coefficients. Column 4 shows opposite evidence. Once the average price is included, adding the marginal price does not statistically change the effect of the average price. Moreover, the effect of marginal price becomes economically small and statistically insignificant. Table 4 provides estimates for the short-run elasticity for the winter month (December to April). The magnitude of the elasticity estimates is slightly smaller than the summer months. The regressions including both marginal and average prices or expected marginal and average prices show the same evidence as the results from the summer months.

Table 5 and 6 present the long-run price elasticity estimates for the summer and winter months. Each price variable is the twelve-month average of the variable instead of the contemporaneous price. The price elasticity estimates are significantly larger than the short-run estimates. For example, in the summer months, the price elasticity estimates are -.171 for the marginal price, -.152 for the expected marginal price, and -.203 for the average price. The regressions including both marginal and average prices or expected marginal and average prices show the same evidence as the results from the short-run price elasticity estimation. Therefore, the results provide evidence that consumers respond to average price rather than marginal or expected marginal price both in the short-run and long-run.

4 Conclusion and Future Work

This paper explores whether consumers respond to marginal price or an alternative form of price when faced with nonlinear price schedules. The standard model of nonlinear budget sets predict that consumers optimize their consumption with respect to marginal price, or expected marginal price when they account for uncertainty about their consumption. An alternative prediction is that consumers may make a sub-optimal choice by responding to average price. Theoretically, consumers make this sub-optimal choice when the cognitive costs of responding to marginal price are higher than the utility gain from re-optimizing with respect to marginal price. To empirically test the three predictions, I exploit price variation in a residential water market in Southern California and conduct three empirical analyses using a panel data set of household-level monthly water billing records.

Results from the three empirical analyses provide strong evidence that consumers respond to average price rather than marginal or expected marginal price when faced with nonlinear price schedules for water. First, I find that the consumption density does not reveal bunching of consumers in any of the kink points in the nonlinear water price schedule. There is no evidence of bunching even in the price schedules that have quite steep discontinuous increases in marginal price. Second, the regression discontinuity estimation provides no evidence of the response to marginal price. The price elasticity estimates with respect to marginal price are close to zero with tight standard errors. Finally, the analysis based on the policy reform in 2005 provides evidence that consumers respond to average price. In particular, when I include both marginal price and average price in the price elasticity estimation, the marginal price has nearly zero effect on consumption, while the average price has a statistically and economically significant effect on consumption. I find the same result with the expected marginal price; when I include both expected marginal price and average price in the price elasticity estimation, the expected marginal price has nearly zero effect on consumption, while the average price has a statistically and economically significant effect on consumption.

Estimates from the price elasticity estimation also provides several notable findings in the magnitude of the price elasticity. First, I find slightly larger price elasticity estimates for the summer months. The short-run price elasticity with respect to average price is -.127 for the summer months and -.097 for the winter months. Second, I also find larger price elasticity estimates for the long-run response to the policy reform in 2005. The estimated long-run price elasticity is -.203 for the summer months and -.154 for the winter months.

This paper leaves three additional questions for my future work. First, this study focuses on water consumption of single-family households, but the water billing data set also includes condominium households and apartment residents. It would be valuable to examine how consumers in a condominium or apartment respond to a price change because their outside water use is presumably lower than single-family households. Second, Lake Forest service area, one of other service areas in IRWD, also had a large price increase in 2008. A potential advantage of this price change is that Lake Forest service area include a large number of households so that it may be possible to examine more details about how different types of consumers respond to a price change differently. Finally, tax assesor's data can be also useful to explore potential heterogeneous responses to a price change. Because the billing data set includes a consumer's address information, it is possible to match the water consumption data with detail housing data such as swimming pools, number of bedrooms, and square footage of indoor and outdoor areas of each housing unit, when tax assesor's data are available to this study.

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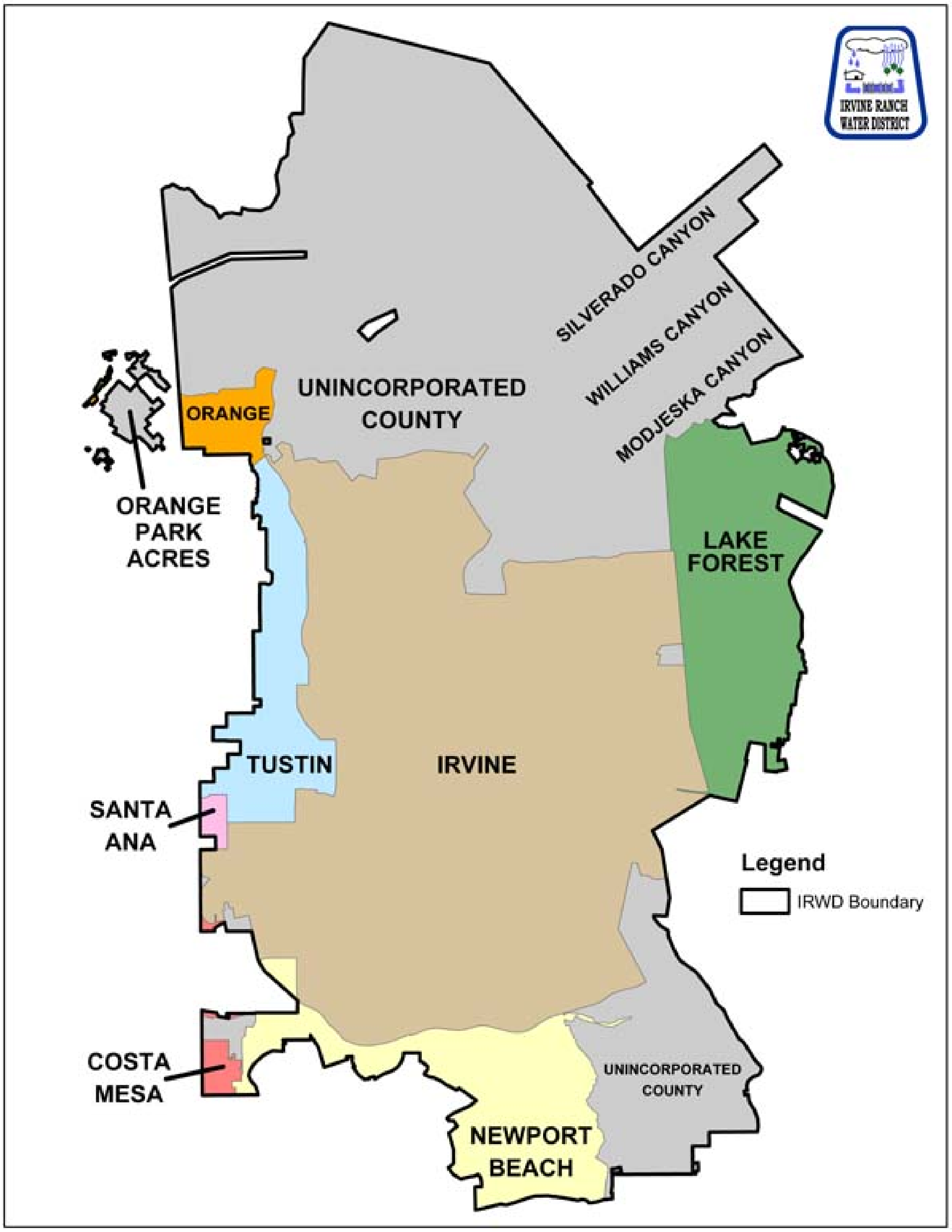
Figure 1: Orange County and Irvine Ranch Water District (IRWD)

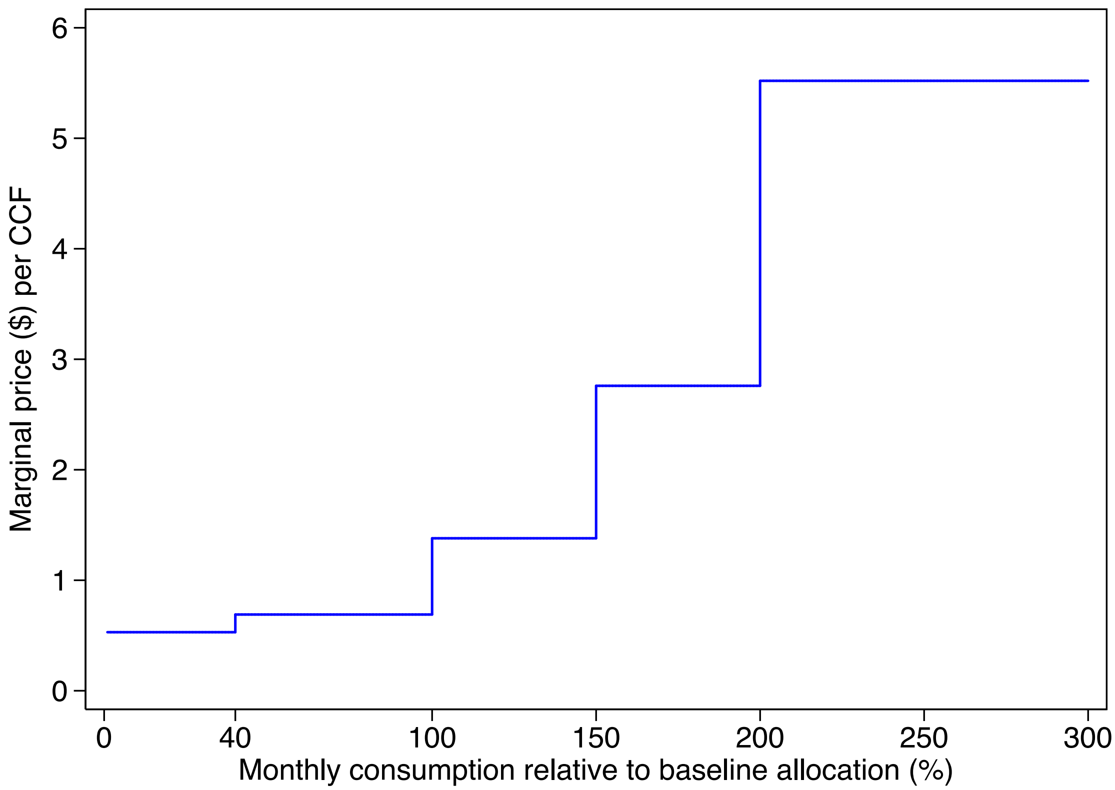
Notes: This figure shows a service territory map of Irvine Ranch Water District (IRWD). The service area approximately 181 square miles from the Pacific coast to the foothills in Orange County, California. The original map is provided by IRWD.

Figure 2: Service Areas of Irvine Ranch Water District (IRWD)



Notes: This figure shows service ares in Irvine Ranch Water District (IRWD). The District serves the City of Irvine and portions of the Cities of Costa Mesa, Lake Forest, Newport Beach, Tustin, Santa Ana, Orange and unincorporated Orange County. Santa Ana Heights service area was consolidated in 1997 and Lake Forest service are was consolidated in 2001. The original map is provided by IRWD.

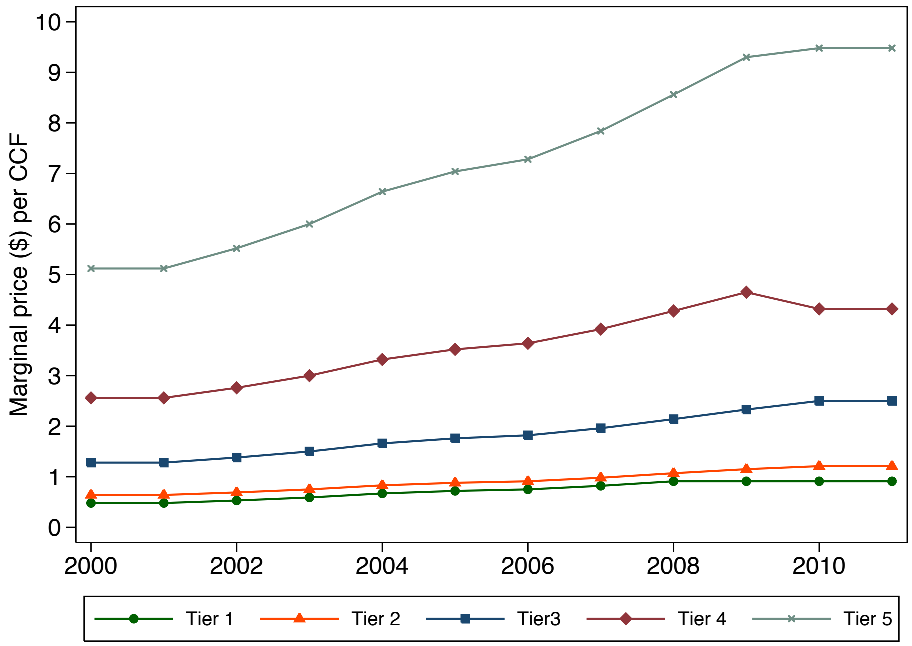
Figure 3: Five-Tier Increasing Block Price Schedule in IRWD in August 2002



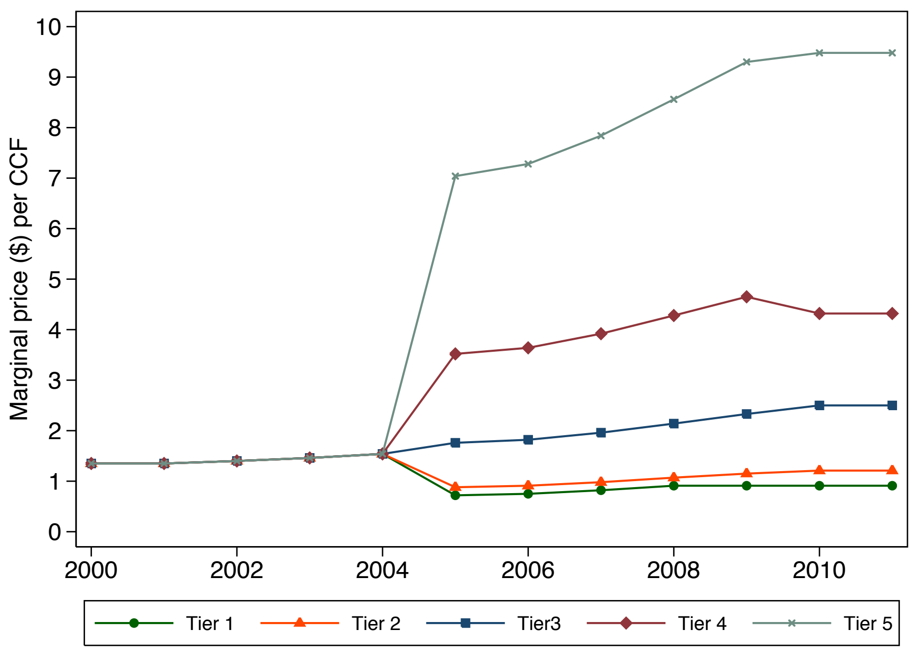
Notes: This figure shows the five-tier increasing block price schedule in IRWD in August 2002. IRWD allocates "baseline allocation" to a customer, and the customer's marginal price depends on consumption relative to the baseline allocation. The marginal price equals the first tier rate up to 40% of the baseline, the second tier rate up to 100%, the third tier rate up to 150%, the fourth tier rate up to 200%, and the fifth tier rate over 200% of the baseline.

Figure 4: Tier Rates from 2000 to 2011

Panel A. IRWD's standard five-tier block price schedule

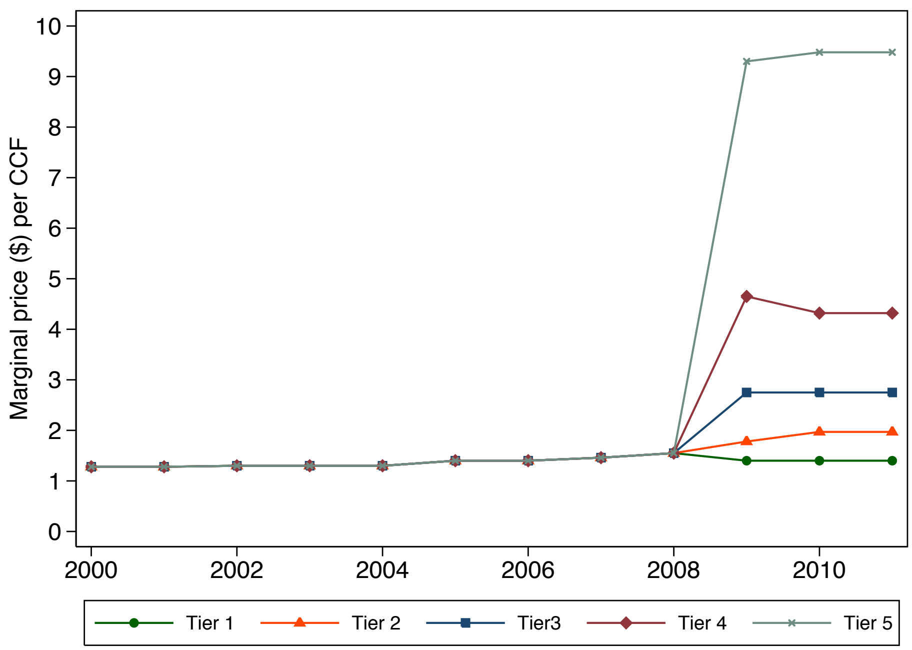


Panel B. Price Schedule in Santa Ana Heights Service Area



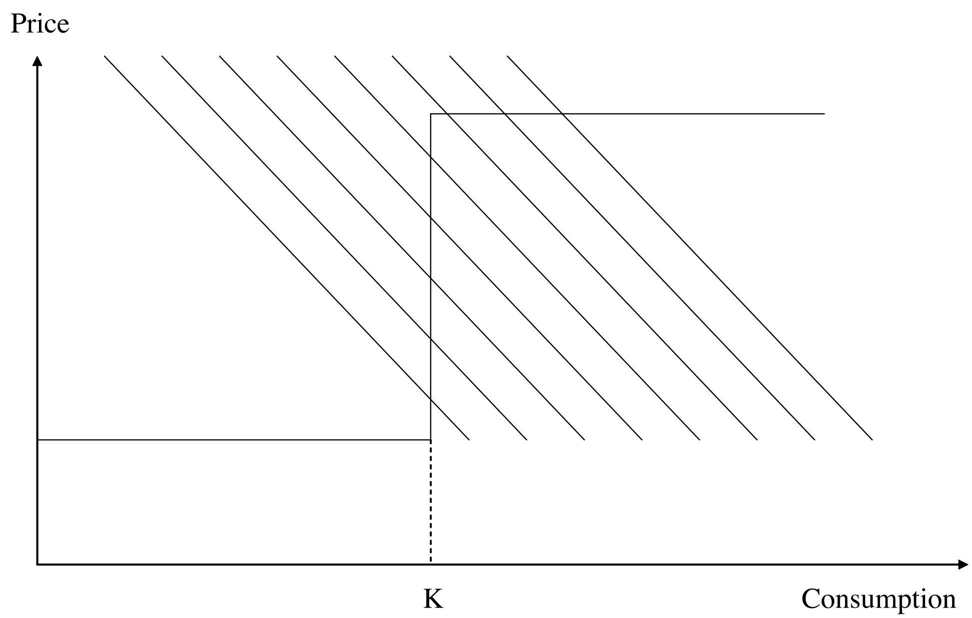
Notes: Panel A shows the time-series price variation of each of the five tier rates in IRWD's standard price schedule. Panel B shows the time-series price variation of the price schedule in Santa Ana Heights service area, which had a flat marginal price schedule until 2004 and was transformed into IRWD's standard rate in 2005.

Figure 5: Tier Rates from 2000 to 2011 (Lake Forest Service Area)



Notes: This figure shows the time-series price variation of the price schedule in Lake Forest service area, which had a flat marginal price schedule until 2008 and was transformed into a five-tier increasing block price schedule in 2009.

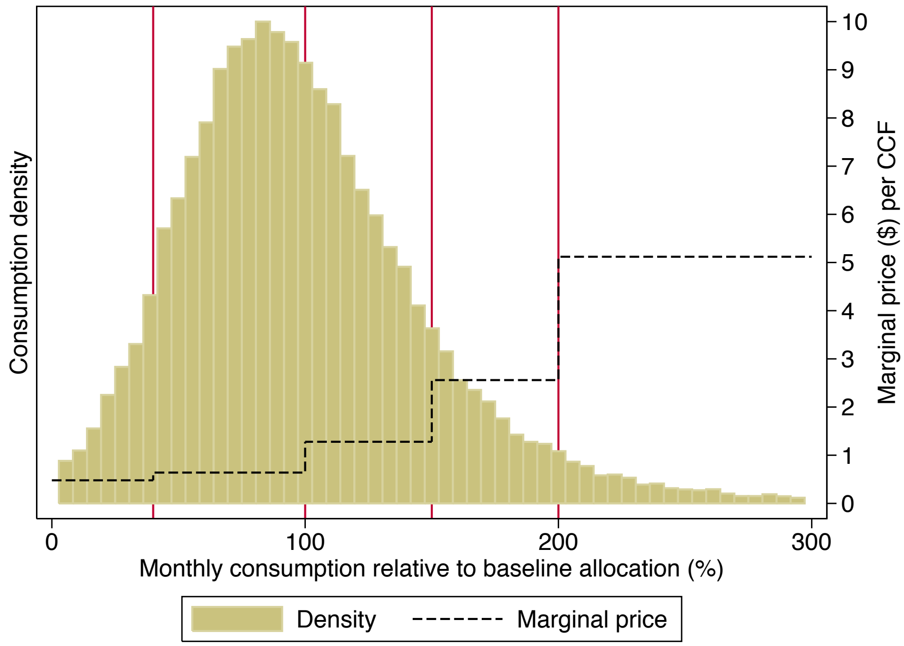
Figure 6: A nonlinear Price Schedule and Demand Curves



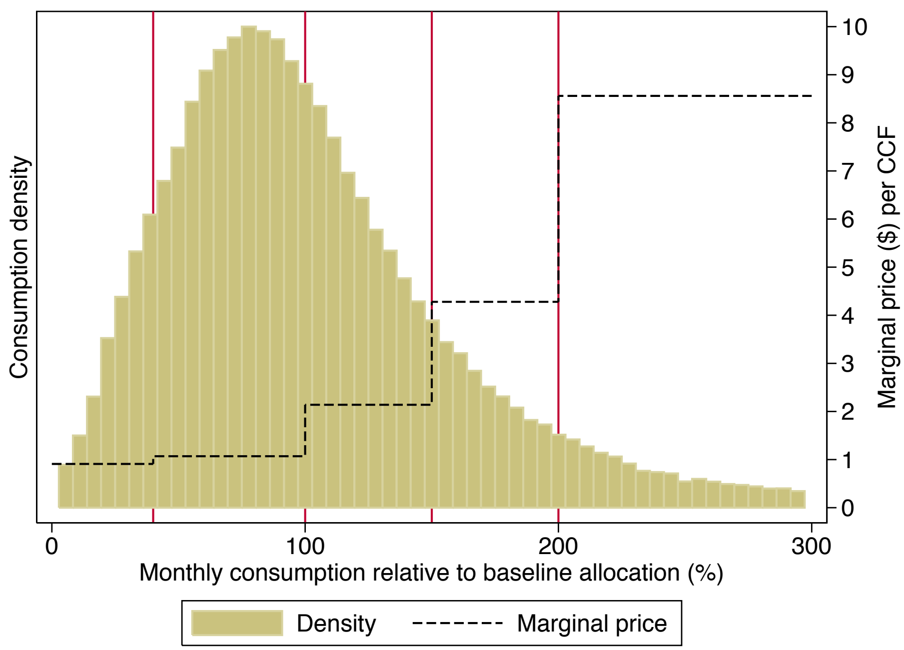
Notes: This figure shows an example of nonlinear price schedules along with demand curves. If consumer preferences are convex and smoothly distributed across the kink point k, many demand curves intersect the vertical part of the price schedule as illustrated in the figure. In other words, a disproportionally large number of indifference curves would intersect the kink of the nonlinear budget constraint. As a result, the distribution of consumption should show bunching of consumers across the kink points (Heckman (1983)) if consumers respond to the marginal price of water.

Figure 7: Consumption Density in 1994 and 2008: Bunching Around Kink Points

Panel A. Consumption density and price schedule in 1994

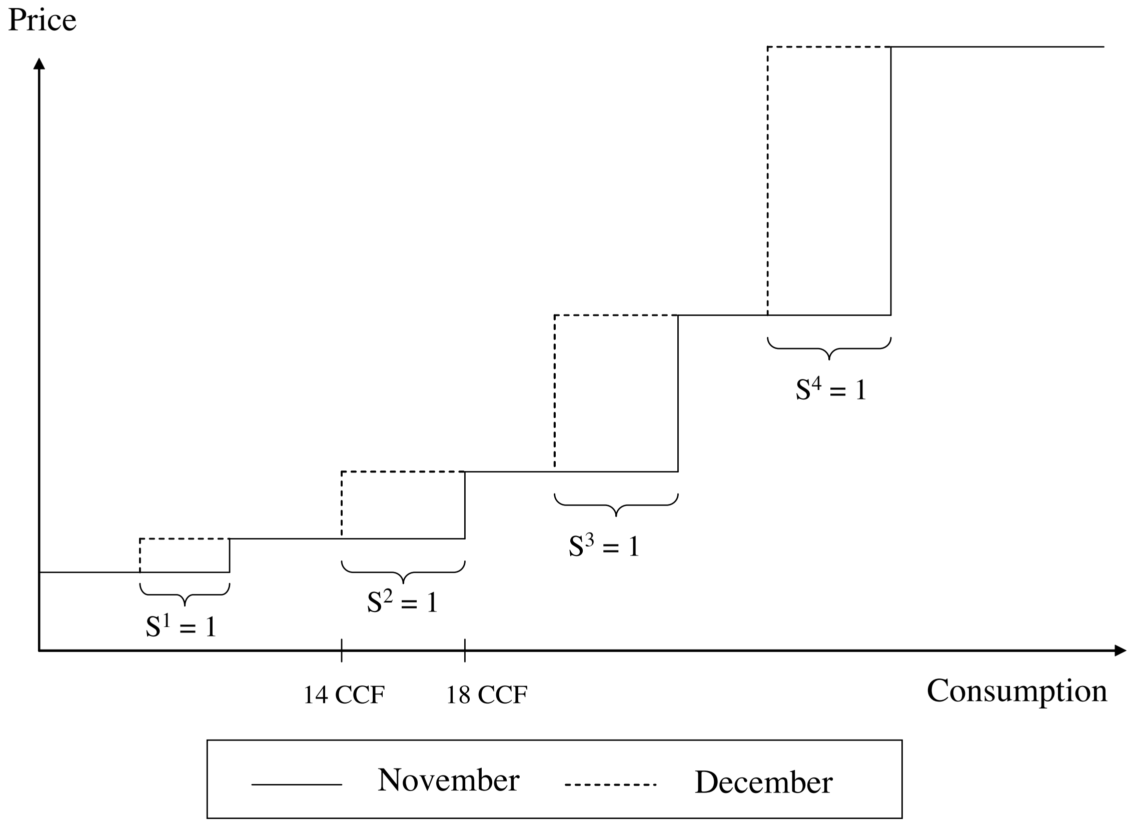


Panel B. Consumption density and price schedule in 2008



Notes: The figures display the histogram of household-level monthly water consumption for Irvine Ranch Water District in 1994 (Panel A) and 2008 (Panel B). The horizontal axis shows consumption relative to the baseline allocation. The bin size is 5% of the baseline consumption quantity. The figures also show the marginal price. The solid lines present the locations of the kinks in the five-tier increasing block price schedules. The distribution is smooth and does not have visible bunching of customers around the kink points.

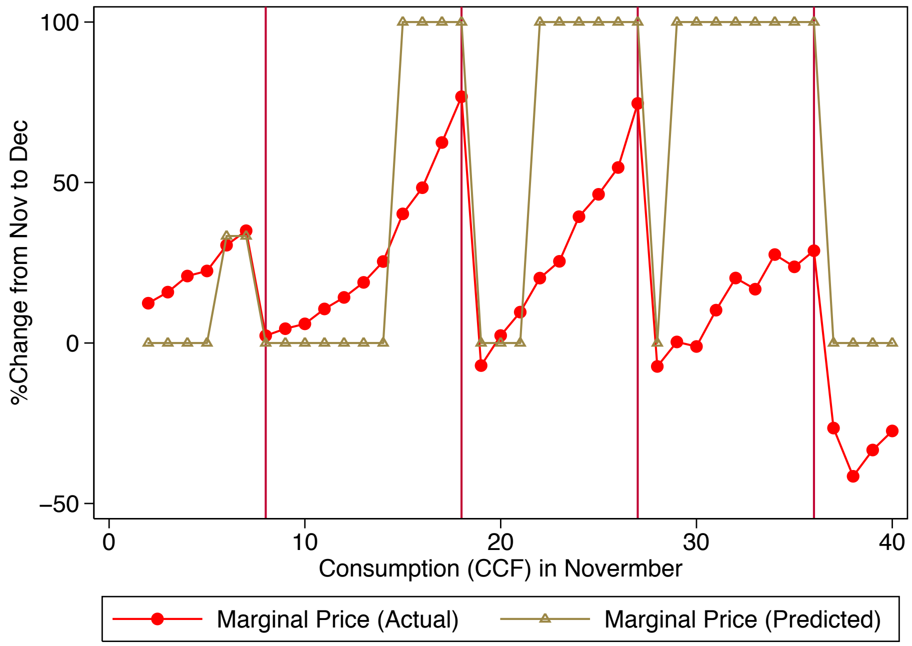
Figure 8: Instrumental Variables for the RD design to estimate the response to marginal price



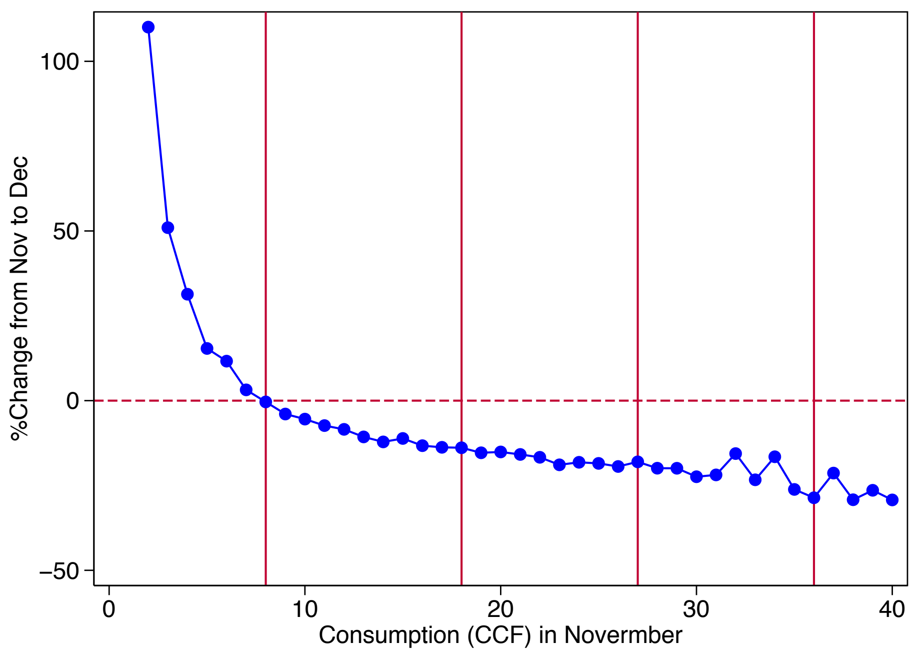
Notes: This figure illustrates the instrumental variables that I use for my regression discontinuity estimation in equation (6). The solid line shows the five-tier increasing block price schedule in November. The dashed line shows the price schedule in December. From November to December, the baseline allocation changes from 18 CCF to 14 CCF. As a result of this change, households whose November consumption is near the top-end of a tier are more likely to experience an increase in marginal price in December compared to households whose November consumption is near the bottom part of a tier. Each of the four instruments equal one if a consumer's November consumption falls in its range and zero otherwise.

Figure 9: Changes in Marginal Price and Consumption from November to December 1996

Panel A. Changes in actual and predicted marginal price

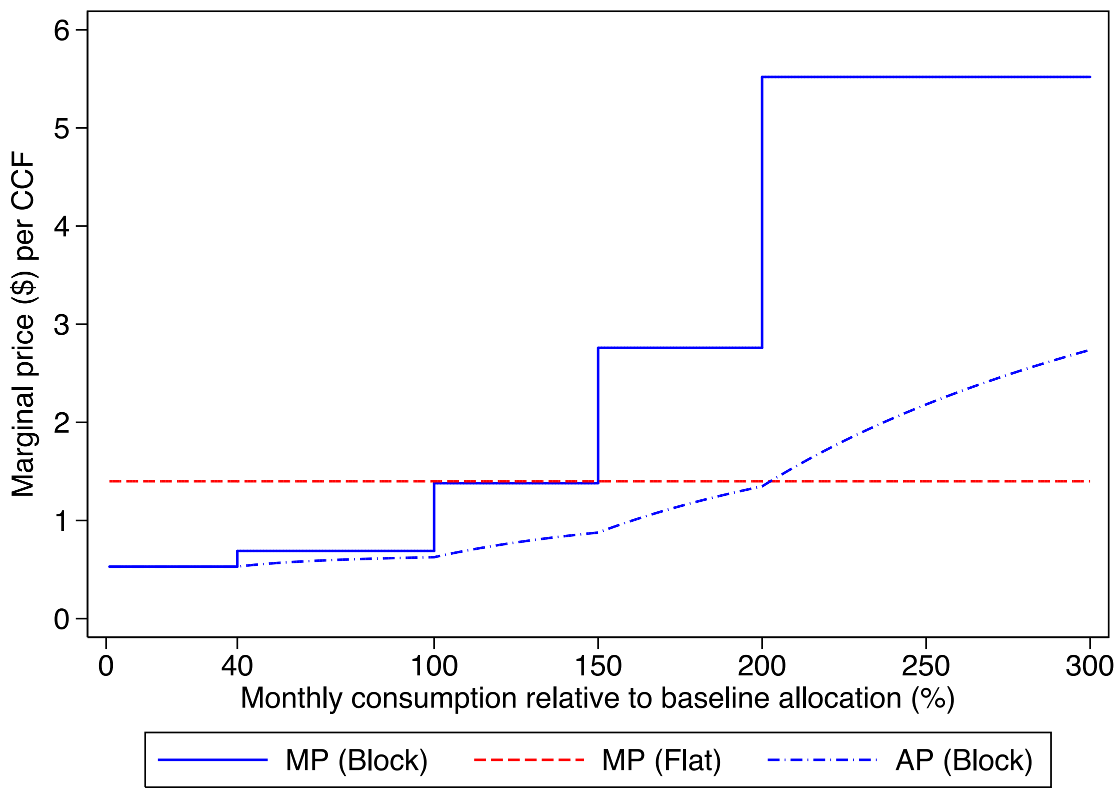


Panel B. Changes in consumption



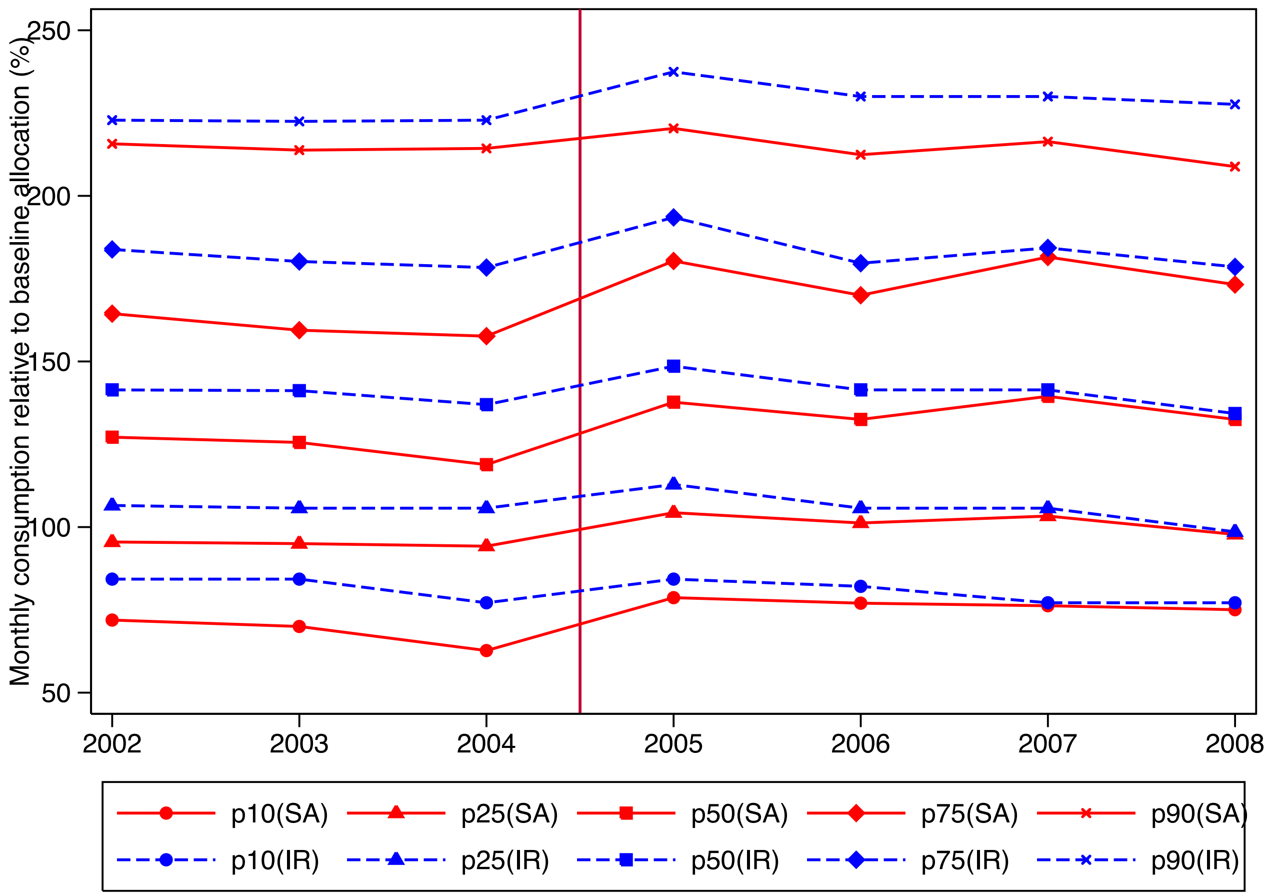
Notes: Panel A shows the mean percent change in marginal price and predicted marginal price from November to December in 1996 over November consumption levels. I calculate the mean of the percentage change in predicted marginal price, $[mp_t(x_{it_0}) - mp_{t_0}(x_{it_0})]/m_{t_0}(x_{it_0})$ and the mean of the percentage change in actual marginal price, $[mp_t(x_{it_0}) - mp_{t_0}(x_{it_0})]/m_{t_0}(x_{it_0})$. Panel B shows the percent change in consumption, $(x_{it} - x_{it_0})/x_{it_0}$, over November consumption levels.

Figure 10: Five-Tier Block Price Schedule and Flat Marginal Price Schedule in August 2002



Notes: This figure shows the five-tier increasing block price schedule in IRWD in August 2002. The figure also shows the flat marginal price schedule in Santa Ana Heights service area. Finally, the figure includes the average price of water for the five-tier increasing block price schedule. Consumers in Santa Ana Heights service area had the flat marginal price schedule until 2004 and their price schedule was transformed into the five-tier increasing block price schedule. For the block price schedule, IRWD allocates "baseline allocation" to a customer, and the customer's marginal price depends on consumption relative to the baseline allocation. The marginal price equals the first tier rate up to 40% of the baseline, the second tier rate up to 100%, the third tier rate up to 150%, the fourth tier rate up to 200%, and the fifth tier rate over 200% of the baseline.

Figure 11: Changes in the Consumption Distributions in the Border Samples



Notes: This figure shows five percentiles (percentile 10, 25, 50, 75, and 90) of consumption for the households within one mile of the service area border between Santa Ana Heights service area (SA) and Irvine service area (IR). The vertical axis is the monthly consumption relative to the baseline allocation (%).

Table 1: Descriptive Statistics

	All samples	Households within 1 mile of the border of Santa Ana Heights service area		
		Santa Ana Heights' Side	Irvine's side	T-stat
Number of customers in 2008	64601	2750	3235	
Mean Square Footage	3609.55	4977.14	5039.72	-0.24
Mean water use (CCF) in 2008:				
January	12.79	13.93	14.15	-0.33
February	11.00	11.63	12.35	-1.28
March	12.42	13.53	14.87	-1.50
April	14.99	17.95	18.13	-0.12
May	16.65	21.13	20.96	0.08
June	17.48	22.52	21.35	0.52
July	18.89	25.11	23.14	0.73
August	18.20	23.45	22.84	0.26
September	18.61	23.18	22.95	0.09
October	17.49	20.74	22.02	-0.60
November	16.33	20.03	19.36	0.34
December	13.98	16.32	15.28	0.78

Notes: The first column shows the statistics for all samples, and the second and third columns present the statistics for households within one mile of the border between the Santa Ana Heights service area and Irvine service area. The last column presents t-statistics for the difference in the means between the two groups in the border sample.

Table 2: Regression Discontinuity Estimates of Price Elasticity with Respect to Marginal Price

	November - December		April - May	
	Full sample	±3 CCF of kinks	Full sample	±3 CCF of kinks
	(1)	(2)	(4)	(5)
$\triangle$ln(MP)	0.008	0.007	0.001	-0.0021
	(0.014)	(0.012)	(0.011)	(0.012)
x_{t_0}	-14.431	-12.406	-10.046	-9.354
	(1.032)	(3.878)	(0.838)	(3.946)
${x^2}_{t_0}$	0.933	0.809	0.633	0.608
	(0.093)	(0.318)	(0.073)	(0.321)
${x^3}_{t_0}$	-0.027	-0.023	-0.018	-0.018
	(0.003)	(0.011)	(0.003)	(0.011)
Constant	69.260	57.809	44.272	39.915
	(3.901)	(15.581)	(3.255)	(15.958)
Observations	40150	13032	39780	12190

Notes: This table presents results of the 2SLS regression in equation (6). The unit of observation is household-level monthly water bills. The dependent variable is the log change in daily average water consumption during a billing month. The regression uses data from 1996, but results do not change when data from other year are used.
The first two columns use November and December consumption data. The first and third columns include the full sample. The second and fourth columns include samples whose November (April for the fourth column) consumption falls between plus or minus 3 CCF from the kink points of the nonlinear price schedule. To control for the mean reversion in consumption, I include the first, second, and third order of polynomials of x_{it_0}.
Adding higher orders of polynomials does not change the estimate of the price elasticity. Standard errors are adjusted for clustering at the zip code level.

Table 3: Price Elasticity Estimation (Summer, Short-run)

	(1)	(2)	(3)	(4)	(5)
ln(MP)	-.094			-.010	
	(.034)			(.022)	
ln(EMP)		-.081			-.012
		(.019)			(.020)
ln(AP)			-.127	-.120	-.121
			(.016)	(.022)	(.018)
Observations			251,370		

Notes: This table presents results of the 2SLS regressions in equation (8), (9), and (10). The unit of observation is a household-level monthly water bill. The dependent variable is log of daily average water consumption during a billing month. The data include the summer billing months (May to October) from 2002 to 2008. Standard errors are adjusted for clustering at the zip code by decile level.

Table 4: Price Elasticity Estimation (Winter, Short-run)

	(1)	(2)	(3)	(4)	(5)
ln(MP)	-.042			.003	
	(.007)			(.012)	
ln(EMP)		-.027			-.009
		(.014)			(.013)
ln(AP)			-.097	-.098	-.100
			(.012)	(.014)	(.013)
Observations	multicolumn 5c251,370				

Notes: This table presents results of the 2SLS regressions in equation (8), (9), and (10). The unit of observation is a household-level monthly water bill. The dependent variable is log of daily average water consumption during a billing month. The data include the winter billing months (November to April) from 2002 to 2008. Standard errors are adjusted for clustering at the zip code by decile level.

Table 5: Price Elasticity Estimation (Summer, Long-run)

	(1)	(2)	(3)	(4)	(5)
ln(MP)	-.171			.003	
	(.019)			(.012)	
ln(EMP)		-.152			-.040
		(.023)			(.020)
ln(AP)			-.203	-.177	-.184
			(.015)	(.022)	(.018)
Observations	multicolumn 5c251,370				

Notes: This table presents results of the 2SLS regressions in equation (8), (9), and (10). The unit of observation is a household-level monthly water bill. The dependent variable is log of daily average water consumption during a billing month. The data include the summer billing months (May to October) from 2002 to 2008. In these regressions, the price variables are the mean of the twelve-month lagged variable. Standard errors are adjusted for clustering at the zip code by decile level.

Table 6: Price Elasticity Estimation (Winter, Long-run)

	(1)	(2)	(3)	(4)	(5)
ln(MP)	-.068			.005	
	(.015)			(.012)	
ln(EMP)		-.042			.013
		(.019)			(.014)
ln(AP)			-.154	-.157	-.158
			(.012)	(.014)	(.013)
Observations	multicolumn 5c251,370				

Notes: This table presents results of the 2SLS regressions in equation (8), (9), and (10). The unit of observation is a household-level monthly water bill. The dependent variable is log of daily average water consumption during a billing month. The data include the winter billing months (November to April) from 2002 to 2008. In these regressions, the price variables are the mean of the twelve-month lagged variable. Standard errors are adjusted for clustering at the zip code by decile level.