Do Increasing Block Rate Water Budgets Reduce Residential Water Demand? A Case Study in Southern California

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Abstract

This study investigates the effect of introducing a fiscally neutral increasing block-rate water budget price structure on residential water demand. We estimate that demand was reduced by at least 18 percent, although the reduction was achieved gradually over more than three years. As intermediate steps the study derives estimates of price and income elasticities that rely only on longitudinal variability. We investigate how different subpopulations responded to the pricing change and find evidence that marginal, rather than average, prices may be driving consumption. Additionally, we derive alternative rate structures that might have been implemented, and assess the estimated demand effects of those rate structures.

1. Introduction

As urban water utilities confront increasingly scarce and less reliable water supplies due to population growth, environmental regulation, and climate variability, water managers are seeking opportunities to reduce residential water demand. While the adoption of non-price instruments (e.g., short-term water restrictions, subsidies for water-saving technologies, and public awareness campaigns) likely will continue to be widespread, volumetric pricing and, in particular, block-rate pricing is gaining traction. This is not surprising to economists who have long espoused the merits of pricing as an efficient and effective means to address water scarcity (e.g., Howe and Linaweaver 1967; Chesnutt and Beecher 1998; Renwick and Green 2000; Griffin 2001; Dalhuisen et al. 2003; Olmstead and Stavins 2009; Grafton et al. 2011). One challenge confronting water utilities that are considering switching to volumetric pricing is identifying the particular rate structure that is best suited to their needs. One structure that is increasingly being adopted by California water utilities is the increasing block-rate water budget.

Increasing block-rate (IBR) water budgets (which we refer to herein more simply as "water budgets") are a particular type of escalating tiered price structure in which the block sizes are based on household-specific characteristics (e.g., household size, irrigated area), environmental conditions (e.g., evapotranspiration), and a judgment by the water utility with regard to what constitutes "efficient" water use given those characteristics and conditions. This means that price structures can differ across households at any given time, and through time for any given household. Water budgets are a relatively new pricing tool. One of the earliest adopters was the Irvine Ranch Water District (IRWD) in Southern California, which instituted such pricing in the early 1990s (IRWD 2013).

Water budgets are thought to have significant advantages over more commonly used rate structures. A water budget creates a strong incentive for conservation by charging higher prices for additional water only when total consumption exceeds a household's "efficient" level of use for the current billing period (Mayer et al. 2008). The Irvine Ranch Water District reports that in the 13 years following the introduction of water budgets, average per-acre outdoor water use declined by 61 percent (IRWD 2013). Water budgets also can accommodate equity concerns by charging lower prices for the most essential uses of water such as drinking, cooking, and cleaning

(Mayer et al. 2008). Last, water budgets provide utilities with the ability to respond flexibly and immediately to evolving environmental and fiscal conditions with a price-based regulatory instrument (Mayer et al. 2008).

As of 2008, fewer than 14 California water utilities had implemented IBR water budgets (Mayer et al. 2008), even though around 50 percent of all California water utilities were utilizing IBR pricing as of 2005 (Hanak 2005). Recently, though, there appears to be renewed interest in water budgets. This trend has been driven, in part, by California's "20x2020 Water Conservation Plan," which aims to reduce statewide per-capita urban water use by 20 percent before 2020 (SWRCB 2010). Between 2008 and 2011, at least nine Southern California water utilities adopted IBR water budgets as part of their efforts to comply with the plan (Ash 2011).

Despite the potential advantages offered by water budgets and renewed interest by utilities, there remain widespread uncertainties and concerns about switching to such a price structure. A prominent concern, and the focus of this study, is the extent to which water budgets actually reduce demand. Statistics such as a 61 percent reduction in per-acre outdoor water use claimed by IRWD can be misleading because observed changes in demand are the product of multiple competing effects. For example, changes in the broader economy can drive per-capita water demand up or down as prices and incomes fluctuate. Changes in weather and climate, such as cyclical precipitation patterns or regional temperature trends, are important drivers of outdoor water use. Changes in the availability of, and preferences for, water conserving technologies (such as climate-controlled irrigation systems and low-flow toilets and sprinkler heads) can reduce demand. And even population *growth* can reduce per-capita demand if new homes must be built with such water-efficient technologies. To determine the effect of introducing an IBR water budget rate structure on demand, these other factors must be accounted for.

Another related issue is the transferability of results from one water utility, such as IRWD, to others. The extent to which a water budget rate structure impacts demand depends on the features of the rate structure and how those features compare to the rate structure that it replaces: water budgets with smaller blocks and higher prices should have greater effects on demand *ceteris paribus*. Therefore we might not expect the outcome for a particular water utility to be relevant for other utilities, unless those utilities intend to adopt similarly structured water budgets and have similar customer bases. Although rate structures clearly will differ across utilities, there is one fairly common feature that can be used as a convenient benchmark to increase the transferability of results across utilities. In many cases, such as the Southern California examples cited above, utilities will desire to maintain fiscal neutrality when switching from flat rates to water budgets in order to avoid incurring budgetary surpluses or deficits. Indeed it is often a requirement that utilities attempt to set their rates to match revenues with costs. Focusing on fiscally neutral rate structures thus narrows the scope of the investigation significantly while promoting broader applicability of the results.

With these issues in mind, this study estimates the effect of introducing a revenue-neutral IBR water budget rate structure on residential demand in the Eastern Municipal Water District (EMWD) of Southern California. The dataset follows more than 13,000 single-family households with continuous monthly water use records from 2003-2012. We account for socio-economic differences across households and through time with data from the U.S. Bureau of the Census and Bureau of Economic Analysis. We control for climate variability with spatially and temporally variable estimates of evapotranspiration. We include a time trend to capture changes in preferences and technologies, and we hold the housing stock fixed in our sample to control for vintage effects.

We estimate that EMWD reduced water demand by at least 18 percent by switching to IBR water budgets with no appreciable impact on its fiscal balance, although the reduction was achieved gradually over more than three years. As intermediate steps we derive estimates of price and income elasticities that rely only on the longitudinal variability in our panel dataset. We

investigate how different subpopulations of households responded to the pricing change and find convincing evidence that marginal, rather than average, prices may be driving consumption choices. We also use a discrete-continuous choice model of water demand under IBR pricing to derive alternative rate structures that might have been implemented, and compare their estimated demand effects with the actual rate structure that was implemented. We find that additional demand reductions could be achieved by increasing particular block prices or decreasing particular block volumes, or by removing, splitting, or adding additional blocks in simple ways, while maintaining stable revenue per unit. From these observations we draw some implications for water utilities that are considering implementing IBR water budgets and discuss directions for future work.

2. Related literature

The literature on residential water demand and pricing is large. Dalhuisen et al. (2003) provide an overview as part of their meta-analysis of 64 pricing studies between 1963 and 2001. A significant analytical innovation was provided by Hewitt and Hanemann (1995), who demonstrate how the discrete-continuous choice (DCC) framework of Burtless and Hausman (1978) can be applied to structural analysis of water demand under block-rate pricing. Recent empirical studies using the DCC framework include Pint (1999), Olmstead et al. (2007), Olmstead (2009), and Miyawaki et al. (2011). However many studies continue to use reduced-form demand estimation for block-rate analysis (Fordyce 2005, cited by Olmstead 2009), perhaps due to the computational difficulty of estimating the DCC model.

The DCC model has been critiqued recently by Strong and Smith (2010), who argue that applied welfare analysis is problematic within a DCC framework because the Marshallian demand function does not exist when the budget constraint is nonlinear (Bockstael and McConnell 1983). Strong and Smith instead propose estimating the structural parameters of the direct utility function for purposes of welfare analysis. However, largely due to the nature of their data, their approach stops short of a framework that permits individual consumers to locate at the kink points on their budget constraints, or that permits simulating changes in any aspect of the price structure, including scenarios that might cause consumers to move consumption to different facets of their budget constraints.[1]

The main thrust of the most recent empirical work on IBR water pricing has been investigations of consumer price responsiveness, and whether price elasticities appear to differ across price structures. Olmstead et al. (2007) find evidence that price elasticity does appear to differ between flat and block-rate price structures but they are unable to provide a definitive conclusion due to unresolved endogeneity issues in their data. The main focus of our study is related to but distinct from this work. Rather than comparing parameter estimates under flat and block-rate structures, we estimate a flat-rate model that then is used to predict what demand would have been if IBR water budgets had not been adopted. We then investigate the differences between observed and predicted demand to characterize the demand effect of IBR water budgets. To our knowledge this is the first study to utilize IBR *water budget* pricing data, and the first to estimate the demand effect of introducing such a price structure.

3. Empirical situation and data

The data for this study come from the Eastern Municipal Water District (EMWD) of Southern California. EMWD is a member agency of the Metropolitan Water District of Southern California, and serves a diverse region of western Riverside County that includes the cities of Moreno Valley,

[1] While the ability to conduct welfare analysis within the DCC framework is clearly a fundamental issue, and development of a theoretically consistent approach would be an important contribution, this study does not undertake welfare estimation and therefore adopts the established DCC model for block rate price analysis.

Perris, Hemet, Murrieta, and Temecula. This region covers 542 square miles and has a population of more than 768,000 (EMWD 2013). As of 2012, EMWD provided around 90,000 acre-feet of water to approximately 136,000 domestic water service accounts and a much smaller number of agricultural and irrigation water service accounts (EMWD 2013).

EMWD is trying to achieve a state-mandated 20 percent reduction in per-capita water use before 2020. Prior to April 2009, EMWD charged each household a fixed "daily service charge" (DSC) plus a flat price per unit of water consumed. Beginning in April 2009, EMWD changed from flat-rate pricing to household-specific IBR water budgets to help achieve the 20 percent reduction. There are four blocks in this IBR price structure. The cumulative block sizes are calculated as follows:[2]

Block 1. Indoor water use: $w_1 = (HHS \times PPA) \times DF + IV$
Block 2. Outdoor water use: $w_2 = w_1 + (ET \times CF \times IA + OV) \times DF$
Block 3. Excessive water use: $w_3 = 1.5 \times w_2$
Block 4. Wasteful water use: water use in excess of w_3

Variables used to calculate block sizes are household size (HHS), per-person allowance (PPA), drought factor (DF), indoor variance (IV), evapotranspiration (ET), conservation factor (CF), irrigated area (IA), and outdoor variance (OV). HHS is reported to EMWD by each household;[3] PPA is set by EMWD at 60 gallons per day; DF is set less than or equal to 1, depending on environmental conditions;[4] IV is negotiated between EMWD and households that report unusual indoor circumstances such as medical need or in-home daycare; ET is derived from real-time measurements for a reference crop which are then adapted to 50 designated microclimate zones within the EMWD service area; CF converts the reference crop ET to turfgrass ET;[5] IA is reported to EMWD by each household;[6] and OV is negotiated between EMWD and households that report unusual outdoor circumstances such as maintenance of large animals or turfgrass establishment.

Block-specific prices are set such that $p_1 < p_2 < p_3 < p_4$, where p_k is the price charged for block k. A household's "water budget" is defined as the first two blocks, or cumulative consumption of w_2. Consumption above w_2 is deemed to be "excessive" or "wasteful" and is thus charged a significantly higher price than consumption below w_2. It is worth emphasizing that w_2 and w_3 are functions of ET and thus fluctuate from month-to-month. When ET is high, households are allocated larger monthly water budgets (i.e., more water in blocks 2 and 3); when ET is low, households are allocated smaller budgets.

To analyze the demand effect of introducing IBR water budgets, we identified 13,565 residential accounts with uninterrupted monthly water consumption records between January 2003 and September 2012. The fact that these accounts remained open is a good indication that there were no tenancy changes in these households during this period.[7] In addition to monthly water consumption data, EMWD also provided information on prices paid by each account, the household size (HHS) and irrigated area (IA) associated with each account, dates when households were asked to increase their water conservation efforts (e.g., due to system maintenance or local supply scarcity), monthly ET during water budgeting for each of the 50 microclimates, and the relevant microclimate for each account. EMWD also provided the latitude and longitude of the

[2] The block labels (i.e., indoor, outdoor, excessive, and wasteful) are EMWD's terms.

[3] EMWD uses a default value of 3 if a household does not report the household size, and requires verification if a reported value exceeds 9 people.

[4] In our dataset, DF = 1 for all observations.

[5] Most water districts assume a baseline of turf grass given its high ET relative to most other grasses and plants; consequently, these districts are providing an overly-generous allocation for ET.

[6] EMWD uses Riverside County Assessor data to calculate a default value (up to a maximum of 6,000 sq-ft) if a household does not report the irrigated area, and requires verification if reported values seem excessive.

[7] An exception could be rental properties for which the utility accounts are registered to the owner rather than the tenants. We are not able to identify such accounts in our dataset.

meter for each account, which enables us to georeference against census data to obtain information on income and education at the tract level.

A crucial piece of missing data is microclimate ET during flat-rate pricing. During this period EMWD had no need for ET data and thus did not track it. Obtaining this data directly from the commercial provider was prohibitively costly, so we developed a simple but effective model to estimate it. First we obtained publicly available ET data from three CIMIS stations in western Riverside County.[8] We then regressed EMWD's available ET data for each of the 50 climate zones on the CIMIS ET data and a set of 12 monthly dummy variables as follows:

$$ET_{zt} = \beta_{zm} + \beta_{z1}ET_{1t} + \beta_{z2}ET_{2t} + \beta_{z3}ET_{3t} + \varepsilon_{zt}. \quad [1]$$

Here, ET_{zt} is observed ET for climate zone (z) during month (t); β_{zm} is a constant term that applies only to a given zone (z) and month (m) – in other words, there are 12 such coefficients for each zone; β_{z1} is a slope coefficient that is specific to zone (z) and that relates changes in ET at the first CIMIS station to observed changes in ET for zone (z); β_{z2} and β_{z3} are defined similarly for the other two CIMIS stations; ET_{1t} is monthly ET at the first CIMIS station, and similarly for the other stations; ε_t is the residual.

Equation 1 is estimated separately for each of the 50 climate zones using ordinary least squares to produce a set of coefficient estimates that is specific to each zone. Estimation results are very good. The mean absolute prediction error across all regressions is only 2.2 percent. The highest error for any month is 7 percent; the highest error for any zone is less than 4 percent. Adjusted R^2 values for the 50 zones are all between 0.976 and 0.992. We then use the coefficient estimates to predict ET values for the entire observation period and use these predictions in our analysis. Figure 1 presents a typical comparison of observed and predicted ET monthly values for a representative climate zone.

Summary statistics for the data used in the regression analyses that follow are presented in Table 1.[9] Conservation requests refer to the fraction of months in which households were asked to increase water conservation efforts. Nominal and real prices are the prices charged per hundred cubic feet (CCF) of water (one flat rate from 2003 to 2008; four increasing block rates from 2009 to 2011). Under flat-rate pricing, these prices are the same as the average prices paid by households. However under water budgeting, the average price paid is a function of water consumed and thus is listed separately in the table. [10] As in Strong and Smith (2010), budgets are based on census income (Minnesota Population Center 2011) and are adjusted for the fraction of income typically spent on the category of "utilities, fuels, and public services." (U.S. Bureau of the Census 2012).[11] Budgets also are adjusted for temporal changes in per-capita personal income for the Ontario-Riverside-San Bernardino metropolitan statistical area (U.S. Bureau of Labor Statistics 2013). Education is expressed as the fraction of the census tract reporting "some college" or more education (U.S. Bureau of the Census 2012). Household size, irrigated area, and education are treated as constant characteristics, because we lack information on monthly changes in these variables.[12] Figure 2 presents selected summary statistics as relative trends through time, with 2003 values normalized to unity. As can be seen in the figure, ET and real budgets changed little during

[8] CIMIS is the California Irrigation Management Information System, developed and maintained by the California Department of Water Resources (www.cimis.water.ca.gov).

[9] Data for 2012 is from January through September only and is thus omitted from the table for purposes of comparison. However it is worth noting that nominal block prices in 2012 are unchanged from 2011 and thus real block prices in 2012 are slightly lower than for 2011. Data for 2012 is included in the regression analyses.

[10] Average price paid in 2009 is a blend of flat rates for January through March (nominally unchanged from 2008) and block rates for April through December (shown in the table).

[11] Using data from the 2010 Consumer Expenditure Survey, we estimate the following relationship between budget (y) and income (m) for the range of incomes observed in our sample: $y = 99.8941m^{0.3339}$, $R^2 = 0.9915$.

[12] Census data suggests that overall education levels in the study area remained fairly constant from 2000 to 2010.

the period of analysis, while there are noticeable changes in demand and prices, particularly after 2007.

4. Estimation strategy

To facilitate comparisons, our analysis is based on a log-linear demand model similar to that used in previous studies of block-rate water pricing (e.g., Hewitt and Hanemann 1995; Pint 1999; Olmstead et al. 2007; Olmstead 2009):

$$ln(w_{it}) = \delta z_{it} + \alpha ln(p_{it}) + \gamma ln(y_{it}) + \eta_i + \varepsilon_{it} \quad [2]$$

Here, w_{it} is demand by household (i) during month (t); z_{it} is a vector of household, economic, and environmental characteristics that are thought to affect demand; p_{it} is the marginal water price faced by the household; y_{it} is the household's budget for utilities and related expenditures; η_i captures unobserved preference heterogeneity; ε_{it} is an error term capturing the remaining unexplained variation in demand; and $\{\delta, \alpha, \gamma\}$ are parameters to be estimated.

Equation 2 forms the basis for two separate estimations: (1) a flat-rate demand model estimated using 2003-08 data, and (2) an IBR demand model estimated using 2009-12 water budget data.[13] For the flat-rate demand model, we model unobserved preference heterogeneity as fixed effects and derive parameter estimates from an OLS regression on deviations of the variables in equation 2 from their respective means.[14] The model is then used to predict demand during 2009-12 if flat-rate pricing had remained in effect. The predicted demand is then compared to the actual demand under water budgeting, and the difference is analyzed to estimate the demand effect of the water budget rate structure.

For the IBR demand model, we implement a standard DCC model that assumes the unobserved preference heterogeneity is randomly distributed. The DCC framework models demand as a joint choice involving selection of a price block and the amount to consume within that block. The framework allows a household to optimally select a consumption level within a block or at the edge of a block (also called a "kink point" because the consumer's budget constraint has an abrupt change of slope at these points). Within a block, demand is given by equation 2 but is implicitly conditional on the choice of that block and thus is referred to as a "conditional demand." For expositional purposes below, we rewrite equation 2 as: $\ln(w_{it}) = \ln(w_{it}^*) + \eta_i + \varepsilon_{it}$, where $w_{it}^* = \exp(\delta z_{it}) p_{it}^{\alpha} y_{it}^{\gamma}$ is estimated demand.

Under IBR pricing, the marginal water price p_{it} differs across blocks. Due to the nonlinear budget constraint, the effective household budget y_{it} also will differ across blocks to account for the fact that consumption is cheaper in the lower blocks. Thus unconditional demand with *K* price blocks can be written as (dropping the subscripts *i* and *t* for simplicity):

$$\ln w = \begin{cases} \ln w_0 + \varepsilon, & -\infty < \eta \le \ln w_0 - \ln w^*(p_1, y_1) \\ \ln w^*(p_1, y_1) + \eta + \varepsilon, & \ln w_0 - \ln w^*(p_1, y_1) < \eta \le \ln w_1 - \ln w^*(p_1, y_1) \\ \ln w_1 + \varepsilon, & \ln w_1 - \ln w^*(p_1, y_1) < \eta \le \ln w_1 - \ln w^*(p_2, y_2) \\ \ln w^*(p_2, y_2) + \eta + \varepsilon, & \ln w_1 - \ln w^*(p_2, y_2) < \eta \le \ln w_2 - \ln w^*(p_2, y_2) \\ \ln w_2 + \varepsilon, & \ln w_2 - \ln w^*(p_2, y_2) < \eta \le \ln w_2 - \ln w^*(p_3, y_3) \\ \vdots & \vdots \\ \ln w^*(p_K, y_K) + \eta + \varepsilon, & \ln w_{K-1} - \ln w^*(p_K, y_K) < \eta < \infty \end{cases} \quad [3]$$

[13] Olmstead et al. (2007) also use equation 2 as the basis for a combined estimation, including both flat- and block-rate pricing data, but find evidence that some parameter estimates (notably price and income elasticities) may differ across pricing structures. To allow for this possibility, we forego the combined estimation and perform two separate estimations.

[14] We also estimated a random effects flat-rate model, which is structurally more similar to the DCC framework. Coefficient estimates generally were similar to the fixed-effects estimates, but the fixed-effects model exhibits better overall predictive accuracy.

Here, p_k is the price associated with block k; y_k is the consumer's budget associated with block k; $w^*(p_k, y_k)$ is the estimated demand conditional on block k; w_k is the quantity associated with kink point k; and the other notation is the same as in equation 2. It is apparent from equation 3 that the unobserved preference heterogeneity (η) influences the block or kink point on which the consumer desires to consume; and the additional error term (ε) explains the deviation of actual consumption from estimated or "planned" consumption. Equation 3 is the basis for maximum likelihood estimation of the parameters in equation 2. Waldman (2000, 2005) provides a general statement of the likelihood function for the DCC model, which also forms the basis for predicting demand under IBR pricing. We also use this model to derive rate structures that generate equivalent revenue per unit, and compare their estimated demand effects against the actual rate structure that was implemented by EMWD.

5. Results and discussion

5.1 Flat-rate model

We estimated several different specifications of the demand model in equation 2, and found that the performance of a relatively simple specification with few regressors was nearly indistinguishable from that of more complicated (and, for the DCC model, computationally burdensome) specifications.[15] Table 2 shows the variables used in the analysis along with the parameter estimates and standard errors for the flat-rate model. Note that a constant term, education, household size, and irrigated area do not appear in the table because they drop out of the fixed effects estimation; however, these terms do appear later in the DCC model. Table 2 summarizes results for seven different samples: the full sample (all 13,565 accounts); high, moderate, and low-usage accounts (i.e., 2003-08 average usage in the top, middle, and bottom thirds); and high-, moderate-, and low-income accounts (i.e., 2010 census income in the top, middle, and bottom thirds). All estimated parameters are significantly different from zero at well above the 99 percent confidence level. Signs and magnitudes generally are intuitive and exhibit similarities across subsamples. Some noteworthy observations include the following:

Requests by the water district for increased water conservation efforts appear to produce a 5 percent reduction in demand during the month in which a request is made. This is not an insignificant response to a request for voluntary action to support a public good.

There appears to be a slight *upward* trend in overall water consumption through time (0.6 percent per year) after controlling for other variables affecting demand; however, the high-usage subsample exhibits a downward trend. For the full sample, this amounts to a 3.6 percent *increase* in household demand during the observation period. This unexpected result could reflect the housing bubble of the mid 2000s, to the extent that rapidly rising home values create an additional income effect and/or increase the perceived marginal benefit of investing in one's home (including landscaping and swimming pools).

The estimated price elasticity (coefficient on $ln(p_{it})$) for the full sample is -0.69. This estimate and the others for the subsamples are consistent with, though somewhat higher than, estimates from previous work that tend to average around -0.4 to -0.5, or around -0.6 for longer time periods (Espey et al. 1997, Dalhuisen et al. 2003). Considering the subsample regressions, price elasticity appears to decrease monotonically with usage but exhibits a non-monotonic trend with income. In absolute terms, we estimate that a 1 percent price increase would produce expected reductions of 0.138 CCF/month from a high usage account, 0.123 CCF/month from a moderate usage account,

[15] It is also worth noting that both the flat-rate and water budget models include the appropriate Slutsky restriction as a constraint on the estimation to ensure the integrability conditions are satisfied. Slutsky restrictions are not always imposed on standard demand models (or, at least, not discussed in the subsequent analysis), but here it plays an essential role in proper estimation of the DCC framework. In both models the restriction binds; without it, income effects appear much larger and some of the estimated block probabilities in equation 3 are negative.

and 0.099 CCF/month from a low usage account. Thus the high-usage group is the most responsive in absolute terms, even though its price elasticity is lowest. The observed pattern in price elasticities across usage groups may reflect differing preferences for outdoor water use. Average irrigated areas for the high-, moderate-, and low-usage groups are 5,985, 3,512, and 3,034 square feet, respectively. The high-usage group appears qualitatively different in this regard, suggesting that it may be composed of households with strong preferences for outdoor landscaping who are more reluctant to reduce irrigation in response to price increases.

Income elasticities are estimated by interacting the budget elasticity (coefficient on $ln(y_{it})$) with the derived relationship between budget and income (see footnote 11). The estimated income elasticity for the full sample is 0.0009. This is notably lower than most previous estimates: in a meta-dataset used by Dalhuisen et al. (2003), the mean and median income elasticities were 0.43 and 0.24, respectively. Our estimate is about one-half of one standard deviation below this mean. Although our analysis exhibits several of the characteristics that were found by Dalhuisen et al. (2003) to be significantly correlated with *higher*-income elasticity estimates, it appears that the Slutsky restriction is causing our estimate to be lower.[16]

The model generally fits the data well, particularly when we consider average consumption through time, which is important for generating predictions beyond the observation period. Figure 3 shows the observed and predicted usage for the full sample, both annually and monthly. The prediction error for 2005 looks large but is only 2.9 percent in relative terms. Analogous graphs for the six usage and income subsamples (not shown) exhibit similarly good predictions.

5.2 Demand effect of water budgets

The flat-rate model can be used to estimate the demand effect of introducing IBR water budgets in 2009. To do this, we create a new dataset that includes the same explanatory variables as in Table 2 but with values updated for the prediction period (2009-2012). We update conservation requests, ET, and household budgets accordingly. We also create new seasonal dummies and extrapolate the time trend into the prediction period. Finally, we set prices equal to the annual average real prices paid under water budgeting (shown in Table 1). Predicted demand thus corresponds to the hypothetical case in which flat-rate pricing continued beyond 2008, and prices were increased such that they matched the average annual prices paid under water budgeting. From the perspective of a water utility, this is a useful baseline from which to judge the demand effect of IBR water budgets, since such a flat-rate structure would produce revenues equal to those of the water budget structure under the null hypothesis that there is no demand effect.

Figure 4 summarizes the estimated demand effect. The figure shows, beginning one year after the implementation of IBR water budgets, the average difference between observed and predicted (i.e., equivalent flat rate) demand for the previous 12 months. During the first year of implementation, IBR water budgets had a relatively small effect on residential water demand: between April 2009 and March 2010, observed demand is only 5.8 percent lower than predicted demand. However, the demand effect appears to grow through time. As of March 2011, two years after implementation, the 12-month moving average for observed demand is 10.3 percent below that for predicted demand. As of March 2012, three years after implementation, there is a 17.3 percent difference. More recently, as of September 2012, the difference grows to 20.1 percent after plateauing around 18 percent for nearly a year.[17] Water budgeting appears to have had a significant effect on demand; however, it has required a substantial amount of time for that effect to be realized. This result is consistent with Dalhuisen et al. (2000), who find that households appear more responsive to price changes when they have had more time to adapt.

[16] When we relax the Slutsky restriction, the estimated income elasticity for the full sample is 1.16.

[17] Omitting the time trend from the predictions decreases these estimates by less than 2 percent.

Another way to gauge the water budget effect is as follows. During the most recent 12-month period in our data, the average price paid per CCF under water budgeting is 3.7 percent higher (in real terms) than the average price paid in 2008. Our model predicts that flat rates would have had to increase by nearly 48 percent to achieve the same level of demand observed during this period. Notably, the average *marginal* price paid during this period is 34 percent higher than in 2008. This suggests that marginal prices may be having a stronger influence on consumption than average prices, and helps to inform the ongoing debate on this subject.[18] Also of interest, average prices paid under water budgeting were *higher* prior to this most recent 12-month period, but the estimated demand effect was *smaller*. This suggests that under water budgeting, households may be gradually adopting relatively permanent water conservation habits as they learn how to use water more efficiently – habits that are retained even when prices subsequently decrease. This observation could motivate adding a subjective learning component to Borenstein's (2009) hypothesis about utility demand being driven by consumption "rules" that are fixed prior to a consumption period and updated only when feedback is received in the form of a bill.

Results for the high and moderate usage and income subsamples are generally the same as for the full sample: the introduction of water budgets caused consumption to decrease more than predicted if flat rates had been set equal to the average prices paid under block rates. For the low-usage and income subsamples, the water budget effect was strong enough to overcome *decreases* in average prices paid by these groups under increasing block rates. In other words, our model predicts increased demand by these groups if flat rates were set equal to average prices paid under block rates, but we observe decreased demand. Not surprisingly, average *marginal* prices paid by these groups did increase under block rates. This again is strongly suggestive of the importance of marginal rather than average prices in determining residential water consumption levels.

5.3 Block-rate model

Estimation results for the DCC model are shown in Table 3. Parameter estimates can be interpreted directly as the effect of each regressor on *conditional* demand (i.e., holding block choice fixed); simulations are needed to interpret the effect of each regressor on unconditional demand. As with the flat-rate model, the parameter estimates generally have intuitive signs and magnitudes and are all significantly different from zero at well above the 99 percent level. Similar to Gilg and Barr (2006), we find a positive relationship between water use and education and, somewhat unexpectedly, a slightly larger coefficient on the fall dummy than on the summer dummy. Conservation requests appear to have a larger effect under water budgeting (though only one such request was made, in January 2011), and the time trend is now negative.

At the household level, the model fit is not particularly good. When we evaluate expected household consumption as $\widehat{w}_{it} = E_{\eta,\varepsilon}[w_{it}^{*} \exp(\eta) \exp(\varepsilon)]$, where $w_{it}^{*} = \exp(\delta z_{it}) p_{it}^{\alpha} y_{it}^{\gamma}$ and different portions of the distribution of η correspond to different conditional demand curves, we get an adjusted R^2 value less than zero.[19] When we set η and ε equal to their means (zero) and evaluate expected household consumption as $\widehat{w}_{it} = w_{it}^{*}$, we get an adjusted R^2 value of 0.1661. Although the first approach is the correct one, close inspection of the results reveals that the disturbance term simulations, in conjunction with our increasing convex demand function, produce

[18] Ito (2012) finds strong evidence of consumer responsiveness to average rather than marginal prices for the case of electricity demand. Borenstein (2009) also finds evidence that electricity consumers are responding either to average price or expected marginal price (which entails averaging over uncertain consumption) rather than the actual marginal price paid. Nataraj and Hanemann (2011) conclude that water consumers do respond to changes in marginal price. The extent to which these discrepancies are due to fundamental differences between water and electricity consumption, and/or between the price structures under investigation, is a topic for future work.

[19] We use multidimensional quadrature (Judd 1999) to evaluate the expectation. We use Gauss-Legendre quadrature to integrate over the piecewise distribution of η and Gauss-Hermite quadrature to integrate over ε.

some very large simulated consumption values that tend to reduce the model fitness. However, this approach provides a good fit to the average monthly data, as can be seen in Figure 5.

Price and income elasticities are estimated by simulating the demand effects of a 1 percent increase in all prices, and a 1 percent increase in household incomes, throughout the water budget observation period. Results are shown in Table 3. The price elasticity estimate (-0.58) is close to that for the full sample flat-rate model, but the income elasticity estimate (0.05) is substantially larger than its flat-rate counterpart though still small in magnitude. Our block-rate income elasticity estimate is close to that estimated by Olmstead et al. (2007) in a random-effects model of flat-rate pricing (~0.04) but below their DCC estimates for IBR pricing (~0.18), all of which they note are low compared to previous estimates. Those authors cite evidence that omitting household characteristics from the regression (as is common in previous studies) tends to increase the estimated income elasticity due to correlations between those characteristics and income. Because our fixed (flat rate) and random effects (water budgets) panel data specifications implicitly capture all constant household characteristics, this may help to explain our relatively low-income elasticity estimates.

5.4 Demand effects of alternative block-rate structures

As described above, EMWD has implemented a relatively sophisticated water budget rate structure with four blocks that vary in magnitude across households and through time. The IBR water budget structure was designed, in part, to be fiscally neutral. Although we cannot use our limited sample to rigorously test for fiscal neutrality, our data nonetheless appears consistent with it: the real average price paid (revenue received) per CCF in our dataset increased by less than 4 percent over more than three years since the pricing change. A natural question that arises is: could the existing rate structure be modified such that demand is further reduced while the average revenue per unit is maintained?

There are obviously many alternatives to consider. Here we focus on some relatively simple modifications to the existing rate structure that intuitively might be of interest to water utilities. For each scenario, we find the parameters of the hypothetical rate structure that produce the same expected revenue per CCF as the current rate structure, and we compare the associated expected demand against that for the current rate structure. For all scenarios, we use the data from the most recent 12-month period in our dataset as the basis for the simulations.

Figure 6 summarizes the effects of several rate structures that reduce demand below the current baseline while maintaining stable revenue per unit.[20] Scenarios 1-7 maintain the existing rate structure but make changes to its quantity and price parameters. A simple but effective alternative is scenario 2 (20 percent decrease in block 2 size), which would decrease expected demand by 4.3 percent while maintaining stable revenues per unit of water consumed. This has about the same demand effect as scenario 5, which reallocates one-quarter of block 2 into block 3 but leaves the sum of blocks 2 and 3 unchanged (whereas scenario 2 reduces this sum by decreasing the size of block 2). Scenarios 6-7 examine the demand effect of reallocating additional block 2 water into block 3, and show that the effect increases sharply. Reallocations like these might be justified by a water utility as a means to incentivize turf grass removal if lawns are deemed "excessive" in certain climates. Scenario 8 considers simplifying the rate structure by removing the "wasteful" water use block, and shows that a simultaneous 35 percent increase in the block 3 price would reduce demand slightly while maintaining stable average revenue. Alternatively, scenario 9 considers complicating the rate structure by adding a new block between blocks 2 and 3 with a price that maintains the increasing block-rate structure and finds a demand effect similar to that in scenario 8.

[20] In all cases the expected revenue per CCF is within 0.5 percent of the baseline. We investigated other rate structures that ultimately could not maintain similar revenue per unit and are thus not reported here.

Overall these simulations suggest that there are relatively small conservation gains to be realized from fundamentally changing the existing rate structure by adding or removing blocks when fiscal neutrality must be maintained. Rather, most of the conservation potential appears to be associated with changes in the existing blocks 2 and 3. This is perhaps not surprising because the marginal consumption of most households occurs within these blocks.

6. Conclusions and implications

This study utilizes a high-quality panel dataset of household water consumption for a large Southern California water district to estimate the demand effect of switching from flat-rate pricing to increasing block-rate water budgets. More than three years after the rate structure changed, we estimate that demand under IBR water budgets was at least 18 percent below the level it would have been under a comparable flat-rate price structure. Whereas average prices paid rose by less than 4 percent under the block-rate structure, average prices paid under the flat-rate structure would have had to rise by nearly 48 percent to achieve the same demand reduction. These results suggest that IBR water budgets are potentially a highly effective conservation tool, although a substantial amount of time is required for demand reductions to be realized. Furthermore, to the extent that more complicated IBR water budget structures are both more costly to implement and harder for consumers to understand (and thus respond to), our findings suggest that utilities can safely pursue relatively simpler rate structures, with perhaps only three tiers, without foregoing significant conservation opportunities.

Our analysis also finds some evidence of a price-induced "ratcheting effect," whereby households that are faced with higher water prices – particularly higher *marginal* prices that are characteristic of IBR structures – learn how to be more water efficient, adopt those new habits, and thus are less prone to "back-sliding," if and when prices decline in the future. This finding, although somewhat circumstantial, is consistent with Borenstein's (2009) hypothesis about the formation of consumption "rules" in electricity demand analysis and lends additional legitimacy to related modeling efforts, including formal investigations of learning and habit formation in utility demand contexts.

For water utilities that are considering adopting IBR water budgets as a conservation tool, this study provides strong support for doing so, with the caveat that conservation goals may take years to achieve. Efforts to promote quicker re-learning of water consumption habits should hasten the attainment of those goals, but exactly how to go about doing this is a topic for future work. A potentially fruitful line of research would investigate the extent to which non-price instruments and/or neighborhood effects influence learning and habit formation. Some water utilities have begun reporting local average water consumption on individual bills to give households a better idea of how their own consumption compares to a relevant peer group. Such information, combined with a high marginal price for "excessive" water use, could prove to be a highly effective approach to encouraging urban water conservation.

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Table 1: Summary statistics.

Variable	2003	2004	2005	2006	2007	2008	2009	2010	2011
Consumption (CCF/month)[a]	20.70	21.14	20.12	20.77	20.99	19.74	17.77	15.99	15.73
ET (in/month)[b]	4.67	4.87	4.59	4.73	4.87	4.81	4.70	4.55	4.85
Conservation requests	0.17	0.00	0.08	0.25	0.08	0.08	0.08	0.00	0.08
Nominal price ($/CCF)	1.43	1.46	1.53	1.62	1.69	1.85	1.27 2.33 4.17 7.63	1.43 2.61 4.68 8.56	1.44 2.64 4.73 8.65
Nominal average price paid ($/CCF)							1.93	2.10	2.05
Real price (2010$/CCF)	1.66	1.66	1.68	1.72	1.77	1.86	1.30 2.37 4.25 7.78	1.43 2.61 4.68 8.56	1.39 2.54 4.55 8.33
Real average price paid (2010$/CCF)							1.98	2.10	1.98
Real budget (2010$/month)	316.26	317.45	318.05	319.20	320.78	316.70	311.07	309.96	309.44
Household size (#)	3.53								
Irrigated area (sq-ft)	4,177								
Education	0.50								

[a] CCF = hundred cubic feet.

[b] A principle components analysis on all available weather data during the observation period for one of the CIMIS stations reveals that ET captures 94 percent of the total weather variability.

Table 2: Flat-rate model parameter estimates and standard errors.

Variable	Description	Full Sample	High Usage	Moderate Usage	Low Usage	High Income	Moderate Income	Low Income
Spring	Dummy for Apr-Jun	0.1588 (0.0016)	0.1812 (0.0023)	0.1698 (0.0029)	0.1290 (0.0028)	0.1845 (0.0030)	0.1525 (0.0028)	0.1414 (0.0027)
Summer	Dummy for Jul-Sep	0.4317 (0.0019)	0.4737 (0.0035)	0.4615 (0.0034)	0.3743 (0.0033)	0.4887 (0.0036)	0.4146 (0.0033)	0.3951 (0.0033)
Fall	Dummy for Oct-Dec	0.3357 (0.0011)	0.3821 (0.0020)	0.3459 (0.0019)	0.2779 (0.0020)	0.4062 (0.0020)	0.3112 (0.0020)	0.2933 (0.0019)
Conserve	Dummy for conservation request	-0.0511 (0.0006)	-0.0550 (0.0024)	-0.0521 (0.0024)	-0.0455 (0.0023)	-0.0547 (0.0021)	-0.0441 (0.0020)	-0.0537 (0.0023)
ET	ET (in/month)	0.0994 (0.0006)	0.1123 (0.0008)	0.1023 (0.0008)	0.0819 (0.0008)	0.1082 (0.0009)	0.0991 (0.0008)	0.0911 (0.0008)
Time trend	Linear annual increments	0.0059 (0.0004)	-0.0186 (0.0006)	0.0045 (0.0005)	0.0279 (0.0007)	0.0130 (0.0005)	0.0039 (0.0006)	0.0033 (0.0006)
$\ln(p_{it})$	log real price	-0.6920 (0.0123)	-0.4409 (0.0191)	-0.6258 (0.0212)	-0.8598 (0.0256)	-0.7627 (0.0206)	-0.6801 (0.0217)	-0.7292 (0.0236)
$\ln(y_{it})$	log real budget	0.0028 (0.0001)	0.0016 (0.0006)	0.0078 (0.0008)	0.0189 (0.0012)	0.0044 (0.0009)	0.0039 (0.0006)	0.0030 (0.0006)
Adjusted R^2	Model fit	0.3438	0.3860	0.3838	0.2721	0.3905	0.3460	0.4000
Income elasticity	1% change in income	0.0009	0.0005	0.0026	0.0063	0.0015	0.0013	0.0010

Table 3: Block-rate model parameter estimates and standard errors.

Variable	Description	Estimate (Std Err)
Constant	Constant	0.1135 (0.0134)
Education	Fraction of census tract residents reporting "at least some college" or more education	0.5355 (0.0087)
HHS	Household size (# of persons)	0.1309 (0.0012)
IA	Irrigated area (1000 sq ft)	0.0303 (0.0006)
Spring	Dummy for Apr-Jun	0.2392 (0.0053)
Summer	Dummy for Jul-Sep	0.5352 (0.0072)
Fall	Dummy for Oct-Dec	0.5731 (0.0051)
Conserve	Dummy for conservation request	-0.1412 (0.0053)
ET	ET (in/month)	0.1545 (0.0016)
Time trend	Linear annual increments	-0.0906 (0.0031)
$\ln(p_{it})$	log real price	-1.0505 (0.0090)
$\ln(y_{it})$	log real budget	0.2921 (0.0022)
σ_η	Standard deviation for η	0.8486 (0.0025)
σ_ε	Standard deviation for ε	0.2998 (0.0017)
Price elasticity	Demand response to 1% change in all prices	-0.5759
Income elasticity	Demand response to 1% change in income	0.0520

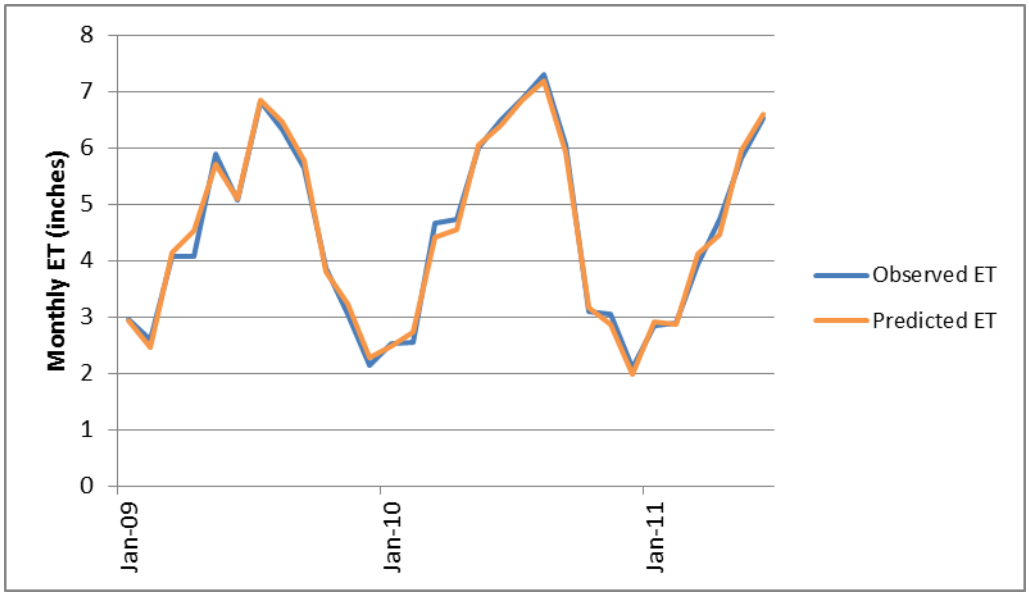


Figure 1: Comparison of observed and predicted ET for a sample climate zone

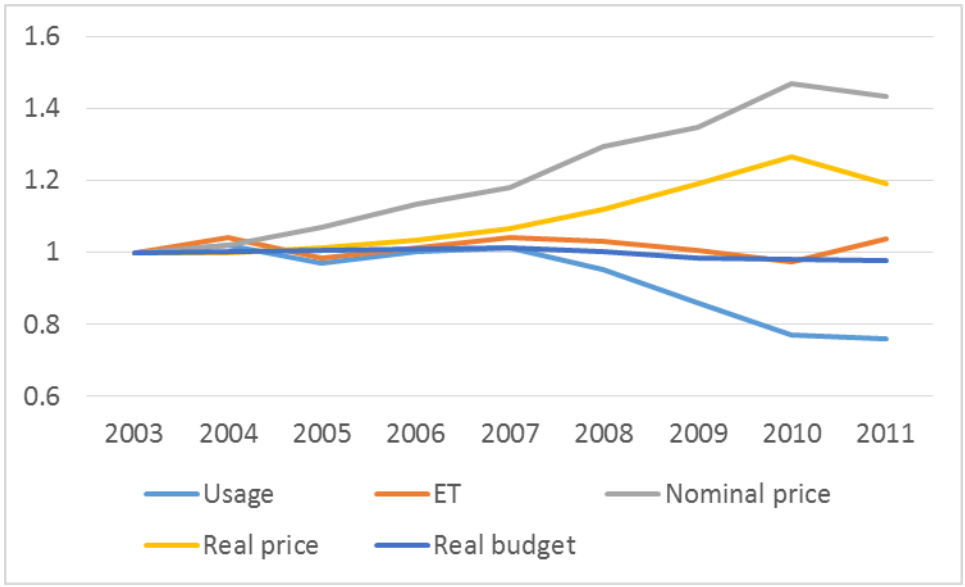
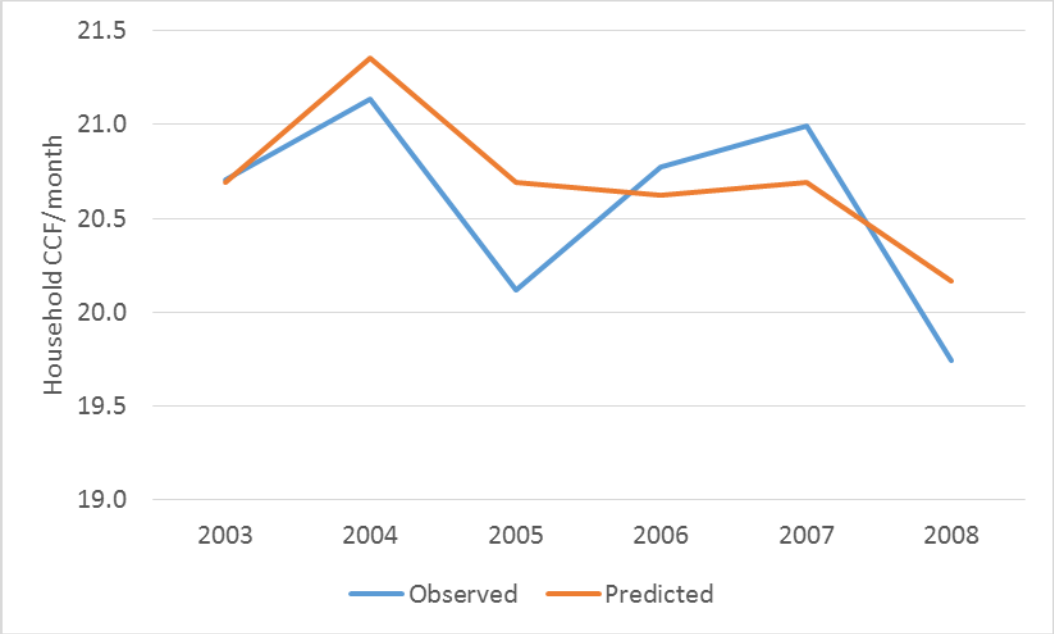


Figure 2: Selected statistics in relative terms.

Panel A: average annual usage.



Panel B: average monthly usage.

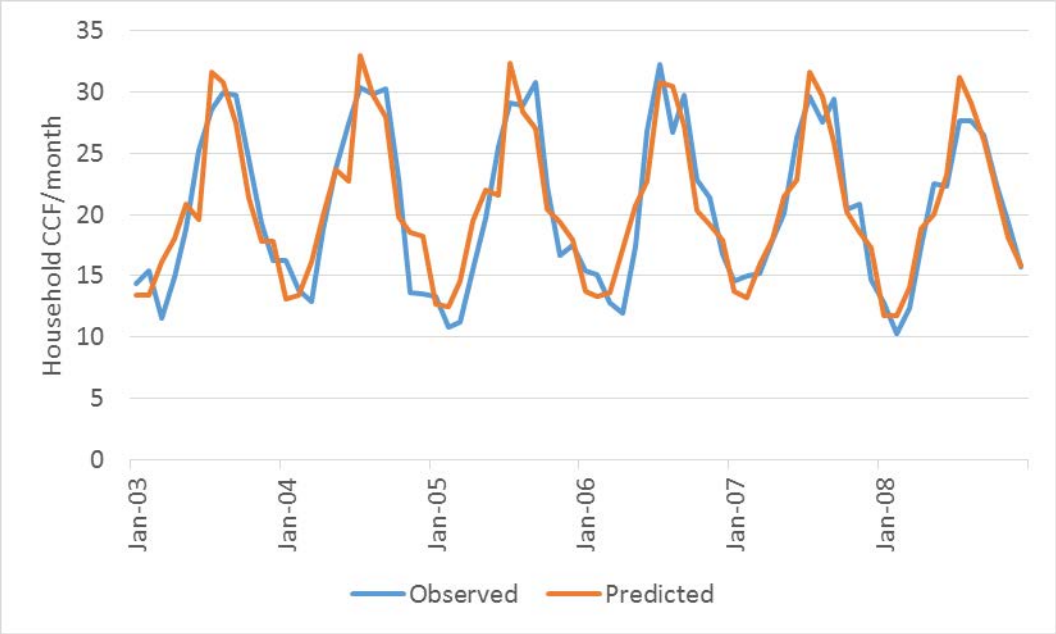


Figure 3: Observed and predicted consumption for the full sample under flat-rate pricing.

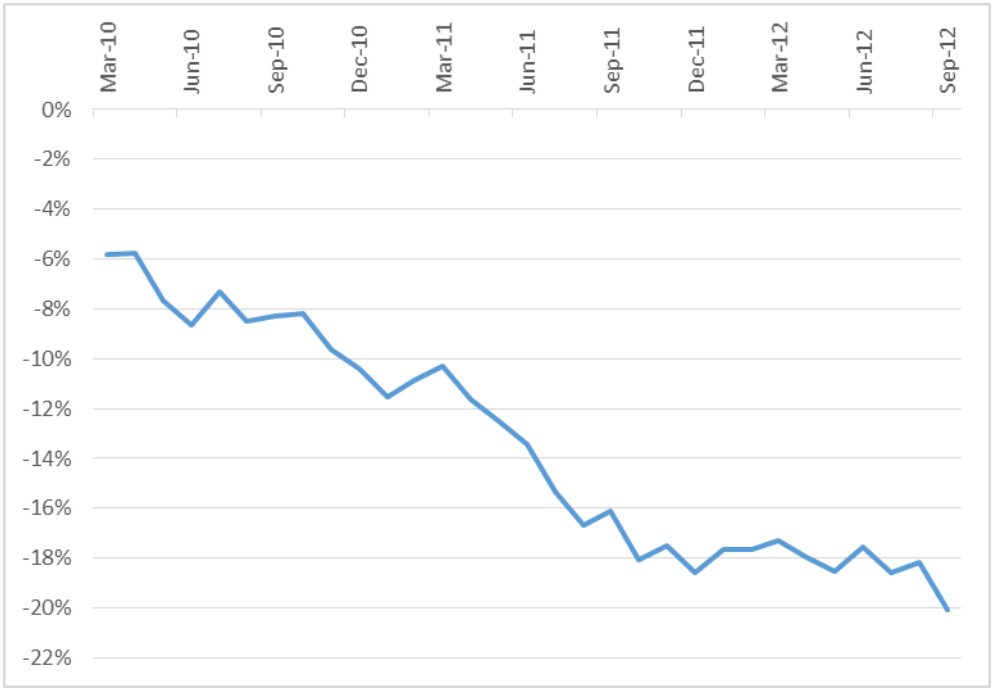
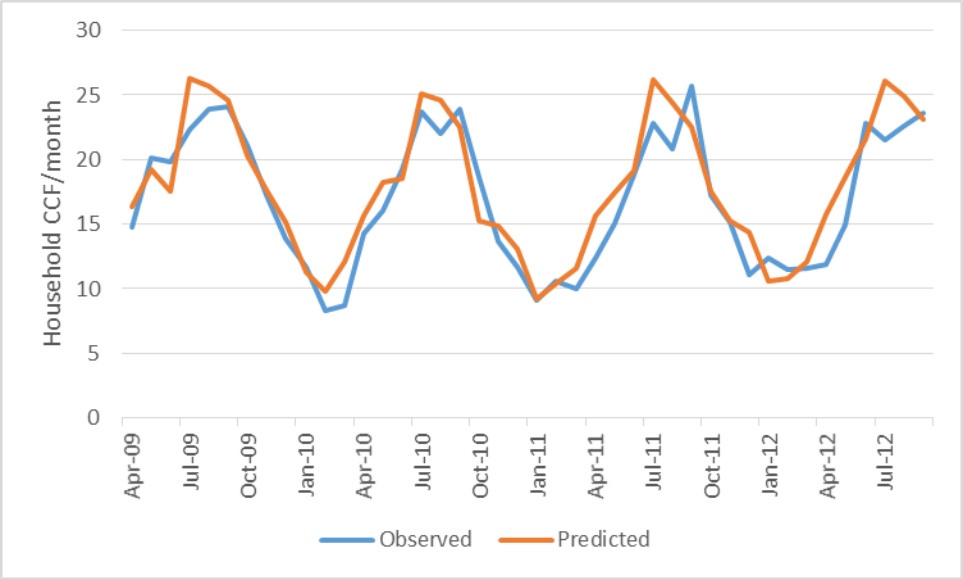


Figure 4: Estimated demand effect of IBR water budgets, 12-month moving average.[a]

[a] Measured as the difference between observed demand under IBR water budgets and predicted demand under comparable flat-rate pricing.

Panel A: time trends.



Panel B: linear regression of predicted average values on observed average values.

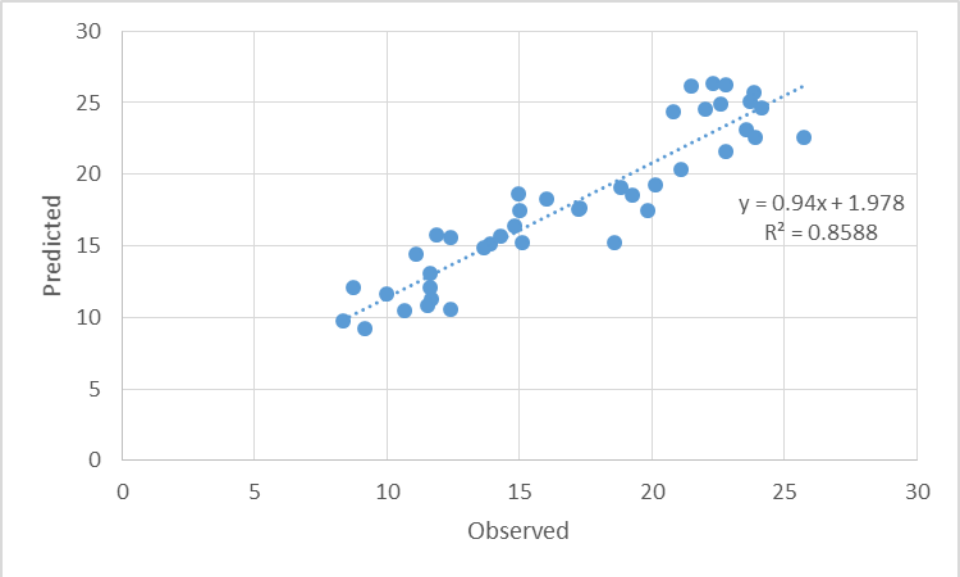


Figure 5: Observed and predicted average monthly consumption under block-rate pricing.

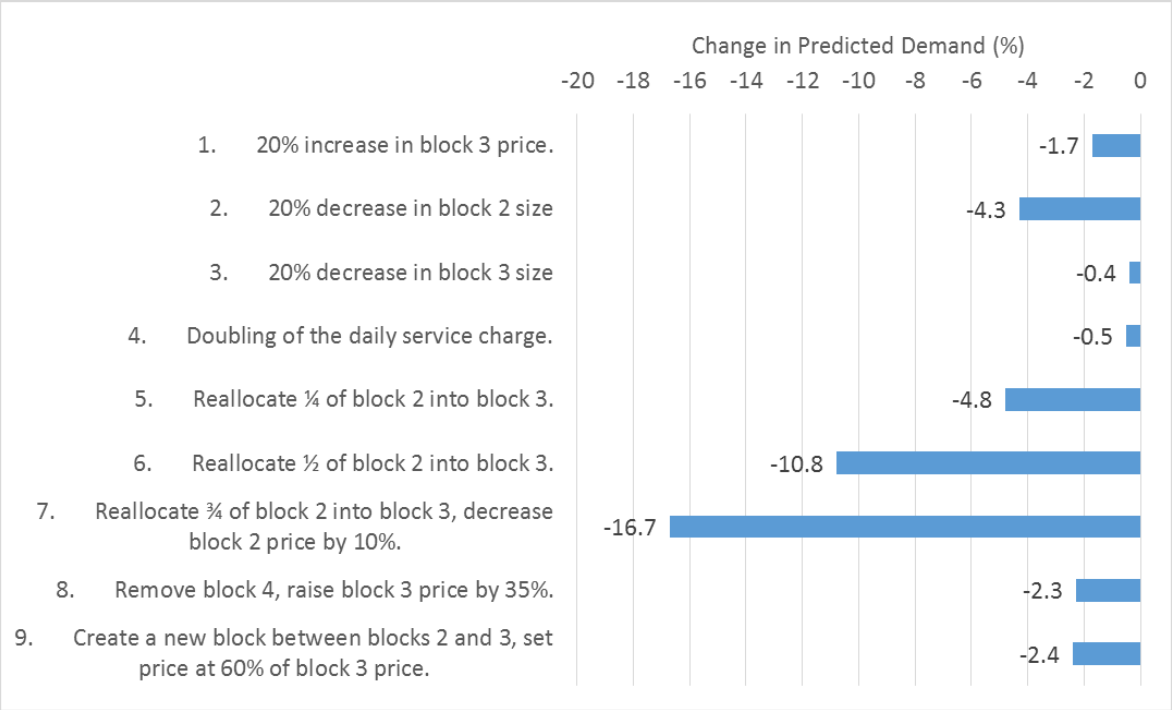


Figure 6: Demand effect of alternative block-rate structures.