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# A Comparison of Demand-Side Water Management Strategies Using Disaggregate Data

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Using data from Salt Lake City, Utah, for the years 1999-2002, a water demand model was developed, and the effects of price and nonprice public policies estimated. The demand for water is found to be price inelastic except in summer months. The effects of a public information campaign to reduce water use were also estimated and found to be moderately effective. The household level panel data used in this study give more accurate estimates of these elasticities than found in previous research.

***Keywords:*** *water demand; public information campaign*

## Introduction

The mechanisms to achieve efficient and fair allocation of municipal water have been long debated in the water policy literature. Historically, policy makers sought to expand water supplies to meet increasing demand. However, as increasing the supply of water became more expensive, water managers sought ways to curb water demand through a variety of instruments. Much research has been devoted to exploring the effects of water pricing on user demand. Other work has focused on alternative demand-side management programs such as public information campaigns and use of water-efficient technologies (Michelson, McGuckin, & Stumpf, 1999; Nieswiadomy, 1992; Renwick & Archibald, 1998; Renwick & Green, 2000; Taylor, McKean, & Young, 2004).

In this article, the effects of both price and nonprice mechanisms meant to curb urban water demand in Salt Lake City, Utah, are assessed. This region has experienced periodic drought throughout its history, and from 1999 to 2002, Utah's annual rainfall was below its 30-year average (Utah Division of Water Resources [UDWR], 2002). That, combined with rapid population growth, makes water allocation an important policy debate in the region (UDWR, 2003).

The municipal government of Salt Lake City started experimenting with demand-side management policies in 1995 by commissioning a panel to assess potential conservation from rate structure changes in its billing. The city's 2002 Summer Water Management Plan discussed the need for a "more aggressive water rate structure," and eventually, the city changed pricing in the summer of 2003 (Salt Lake City Department of Public Utilities [SLCDPU], 2002). Alternative (nonprice) demand-side management policies have also been introduced. Salt Lake City implemented a public information program to encourage conservation known as "Slow the Flow, Save $H_2O$" (SLCDPU, 2002; UDWR, 2002). This campaign included mailings, television and radio ads, and a Web page.

Results from this article add to the information available to water managers when deciding on conservation strategies. The wealth of household-level time series data provide a unique opportunity to model user responsiveness to these various policy alternatives (Arbués & Barberán, 2004; Brookshire, Burness, Chermak, & Krause, 2002; Danielson, 1979; Hanke, 1970; Hewitt & Hanneman, 2000). The most important contribution of this article is the estimation of the effects of a public information campaign on household-level water consumption.

## Literature Review

Howe and Linaweaver (1967) conducted one of the first aggregate studies of residential water demand by comparing a cross-section of cities throughout the United States. Using a simple linear regression model, they found indoor water demand to be relatively price inelastic. The authors also concluded that consumers react to average prices instead of marginal prices because few consumers know how to read water meters accurately. They argue that consumers are unaware of their water use within a block rate structure where different levels of use induce different marginal prices depending on consumption level. Following this study, other early water demand researchers also used ex post average prices (Nieswiadomy & Molina, 1989).

In his study of the electricity sector, Taylor (1975) argued that marginal and average prices should be used together for estimates in markets under block pricing. Nordin (1976) later modified Taylor's suggestion by requiring a "difference" variable instead of average price. The Taylor-Nordin difference variable, or rate premium, is defined as the difference between what consumers would pay had they been charged their ending marginal price all along and what they actually do pay. Because of inconsistent marginal prices under block rate pricing, consumer income deviates from what it would be if water were sold under constant marginal prices.[1]

Water is typically assumed price inelastic, at least at low quantities of consumption, but market demand curves for most functional forms are elastic in some regions and inelastic in others. Therefore, any statement of price elasticity of water must be qualified within a given price range. There is much variation in the estimates of the price elasticity of water; however, metastudies by Dziegielewski (2003) and Dalhuisen, Florax, de Groot, and Nijkamp (2003) conclude that residential water demand is relatively price inelastic (between 0 and −1). This implies that water use is moderately responsive to changes in prices—increasing the price of water by 1% is expected to reduce water consumption by something less than 1%.

The literature has generally led to the conclusion that under block rate pricing, there is bias in ordinary least squares regression of single-equation water demand models because of the joint determination of water use and prices (Arbués, García-Valiñas, & Martínez-Espiñeira, 2003; Hewitt & Hanneman, 2000; Nieswiadomy & Molina, 1989; Renzetti, 2002). Instrumental variable (IV) techniques have generally been used to deal with this endogeneity.

A number of studies have also used alternative demand-side management policies such as public information campaigns and conservation programs as explanatory variables affecting water use (Michelson et al. 1999; Nieswiadomy 1992; Renwick & Archibald, 1998; Renwick & Green, 2000). For example, Renwick and Archibald (1998) look at the effects of the 1982-1992 California droughts on 119 households in the communities of Goleta and Santa Barbara. The cities tried several alternative demand-side management policies to curtail water use during and after the drought. Santa Barbara restricted irrigation use and Goleta allocated water quotas based on historic use and imposed stringent fee increases for quota violations. Subsidies for low-flow toilets and showerheads, retrofitting, and public information campaigns to inform citizens on water efficient irrigation technologies were also used in the region. Each policy alternative had a statistically significant effect on reduced water demand in the area.

Two years later, Renwick and Green (2000) extended the study to eight aggregated California water districts. Their goal was to assess the relative effectiveness of alternative policies in reducing water demand. They found that price responsiveness varied seasonally and that stringent mandatory nonprice policies, such as quotas, were more effective in reducing use than voluntary measures, such as rebates, retrofitting, and public information campaigns. Modest decreases in water use (5%-15%) can be achieved through price mechanisms or voluntary measures, but significant reduction (>15%) is best achieved through well-enforced rationing schemes. Table 1 gives results from studies using public information campaigns as explanatory variables. It shows that such campaigns may be somewhat effective at reducing demand.

**Table 1**
**Studies of Public Information Campaign Effectiveness**

| Study | Location | Effect on Mean Consumption (%)[a] |
|---|---|---|
| Michelson et al. (1999) | Los Angeles | −1.1** |
| | San Diego | −2.7** |
| | Denver | −2.0** |
| | Broomfield | 0.0 |
| | Albuquerque | −2.0** |
| | Santa Fe | −4.0** |
| | Las Cruces | 0.0 |
| Nieswiadomy (1992) | North Central United States | 1.9 |
| | Northeast United States | −4.24 |
| | Southern United States | 17.6 |
| | Western United States | −17.56* |
| Renwick and Green (2000) | 8 California cities | −8.0** |
| Taylor et al. (2004) | 34 Colorado districts | −1.26 |

[a]Effects from Michelson et al. (1999) and Renwick and Green (2000) are taken from the respective studies. To estimate the mean effect on consumption for Nieswiadomy (1992) and Taylor et al. (2004) we used Kennedy's (1981) technique: % Effect = 100 $\{\exp\{\beta - (V(\beta)/2] - 1\}$ where $\beta$ is the dummy variable regression coefficient for the public information campaign, and $V(\beta)$ is the variance of $\beta$.
Two-tailed hypothesis tests: $*p < .05$. $**p < .01$.

## Data

A complete database of Salt Lake City households' monthly water use during the period from February 1999 to October 2002 was obtained from the UDWR. Water use from the billing period is converted to 30-day averages. Quantity of water for connection $i$ in month $t$ ($Water_{it}$) is reported in hundred cubic feet (HCF) consumed. Marginal prices ($Price_{it}$) and the Taylor-Nordin difference variable ($Diff_{it}$) were calculated based on the city-mandated price structure. They are reported in dollars per HCF of water and have been adjusted for inflation.[2] Rates in summer months are higher than those in winter months and also increased from year to year during the study period.

Figure 1 shows real marginal water rates in the block beyond the 5 HCF allowance over time and average water consumption per connection. Both water consumption and block rates are cyclical in that more water is consumed at higher rates in summer months. If one did not account for the endogeneity of price, it would appear that prices are positively correlated with water use.

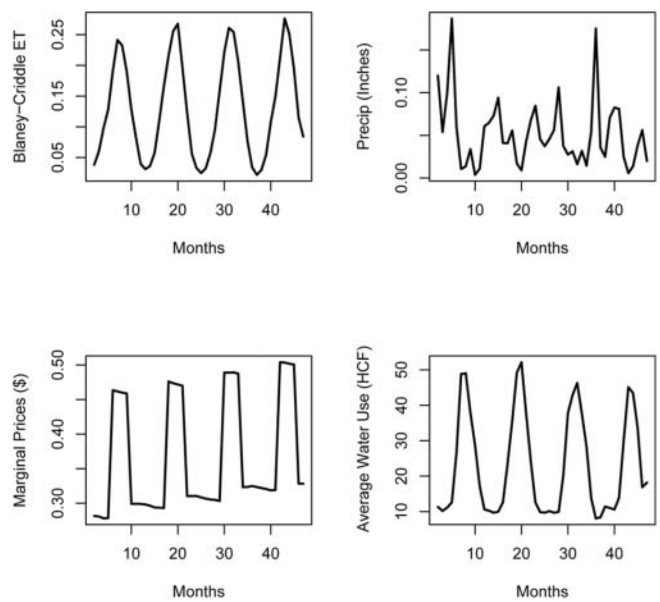
The state public information campaign started on September 1, 2001. The variable $STF_t$ (slow the flow) is coded as a dummy variable indicating whether the campaign is in effect (=1) or not (=0).

Unfortunately, no explicit measure of income was available. However, the Taylor-Nordin difference variable indicates an implicit income subsidy under increasing block rate pricing as in Salt Lake City. The difference variable should have an effect equal in magnitude and opposite in sign to an income effect (Hewitt & Hanneman, 2000; Nieswiadomy, 1992).[3]

Time invariant characteristics of the connections are implicitly controlled for in the fixed effects (FE) model outlined in the next section. Still, household level data are available on the taxable value of the property ($TaxVal_i$ in \$1,000), lot size ($LotSize_i$ in acres), and information on whether the connection is residential or not ($Residential_i$), all taken from the county recorder database.

Three weather stations were used to collect data for different weather experienced for each connection.[4] Using geographic information system software, connections are assigned to the nearest weather station, and daily average readings of precipitation and temperature are given to each household. Because readings are given daily, each household's climate variables perfectly match the days during the billing cycle. Evapotranspiration ($ET_{it}$) is then measured using the Blaney-Criddle method, suitable for desert-like climates similar to the Salt Lake Valley (Blaney & Criddle, 1950). Average monthly rainfall ($Precip_{it}$), measured in inches, is also used. The database includes approximately 1.5 million monthly observations of consumer water use. Table 2 lists descriptive statistics of the variables used in this study.

**Figure 1**
**Time Series of Selected Variables**




NOTE: Blaney-Criddle evapotranspiration measures the rate at which water evaporates from the ground in semiarid climates. Real marginal prices change relatively dramatically between summer and winter months, with more moderate changes across seasons through time. Average water use is quite cyclical, with the majority of use coming in summer months. Precipitation is countercyclical to seasonal patterns of the other three variables.

## Model

As previously discussed, the endogeneity of price under a block rate structure has been a major theme in the water demand literature. An IV model first used in the water demand literature by Nieswiadomy and Molina (1991) is followed here. The econometric model consists of two components: a first-stage expected water consumption equation to estimate a predicted marginal price and a second-stage water demand equation using predicted price from the first stage.

**Table 2**
**Descriptive Statistics**

| Variable | Mean | Standard Deviation |
|---|---|---|
| Water | 25.029 | 29.333 |
| Price | 0.329 | 0.160 |
| Diff | 2.737 | 1.058 |
| Precip | 0.050 | 0.045 |
| ET | 0.144 | 0.081 |
| Residential | 0.968 | 0.175 |
| TaxVal | 102.420 | 66.044 |
| LotSize | 0.197 | 0.189 |
| *N* | 1,547,539 | |

Let $\text{Price}_{it} = R_{it}(\text{Water}_{it})$ be the rate structure faced by connection $i$ in month $t$. In Salt Lake City's case,

$$R_{it}\,(\text{Water}_{it}) = \text{BlockPrice}_{it} \text{ if Water}_{it} \geq 5\text{HCF} \quad = 0 \text{ if Water}_{it} < 5\text{HCF}. \tag{1}$$

If water use is above the 5 HCF allowance, then the marginal price faced by the connection is that mandated for the month by city ordinance, $\text{BlockPrice}_{it}$. If water use falls below the allowance then the marginal price faced by the connection is simply 0.

The first stage of the econometric model is then,

$$\begin{aligned} \hat{\text{Price}}_{it} &= R_{it}\,(\hat{\text{Water}}_{it}), \\ \hat{\text{Diff}}_{it} &= f(\hat{\text{Price}}_{it}, \text{FixFee}_{it}\ \text{Water}_{it}), \end{aligned} \tag{2}$$

where $\text{FixFee}_{it}$ is the fixed fee charged to each connection regardless of water use. $\text{Water}_{it}$ is the exponential of the predicted water use from the regression

$$\begin{aligned} \text{In}(\text{Water}_{it}) = \alpha_i^1 + \gamma_{\text{BP}}\text{BLockPrice}_{it} + \gamma_{\text{FF}}\ \text{FixFee}_{it} \\ + \gamma_{\text{STF}}\text{STF}_t + \gamma X_{it} + \eta_{it}. \end{aligned} \tag{3}$$

The variables in $X_{it}$ include the control variables for precipitation, evapotranspiration, and a summer months dummy variable ($\text{Summer}_t = 1$ for the months of June, July, August, and September; and is equal to zero otherwise) in the FE model. $X_{it}$ also includes time, the invariant variables taxable value, lot size, and a residential dummy for pooled and random effects (RE) models. This regression predicts water consumption from the independent variables and all possible prices the consumer faces. In our case, the consumer faces a fixed fee and one additional block price in each time period.

The semilogarithmic functional form is used following Arbués and Barberán (2004) and others because of its simplicity and its implication of nonconstant elasticities. The double-logarithmic specification is not used, because some of the observations in these data have zero price and difference values and because that form implies constant elasticities.

The second stage of the econometric model substitutes the predicted values $\hat{\text{Price}}_{it}$ and $\hat{\text{Diff}}_{it}$ for the actual values faced by the connection. Thus, the second stage equation is

$$\begin{aligned} \text{In}(\text{Water}_{it}) = \alpha_i^2 + \beta_{\text{p}}\hat{\text{Price}}_{it} + \beta_{\text{D}}\hat{\text{Diff}}_{it} + \beta_{\text{STF}}\,\text{STF}_t \\ + \beta X_{it} + \varepsilon_{it}. \end{aligned} \tag{4}$$

The estimation technique used in Equations 3 and 4 depends on the assumption of the individual specific effect $\alpha_i$, where $\alpha_i$ is a separately estimated intercept for each connection, and is the FE case. The pooled case refers to $\alpha_i = \alpha$, constant for all connections. If instead $\alpha_i$ is assumed to be a normally distributed error with constant mean and connection-specific error, this is the RE case. RE estimates are consistent only when individual intercept parameters are uncorrelated with the explanatory variables of interest. FE estimates are consistent whether or not individual intercept parameters are correlated with explanatory variables (Wooldridge, 2002). In this case, FE estimates are expected to be more appropriate because unobservable individual differences are likely correlated to price and public information campaign effects.

To estimate the long-run effects of policy variables, the following lag structure is used. First, an explanatory variable "1 month lagged water use" is included, so that the first and second stage equations now become

$$\begin{aligned} \text{In}(\text{Water}_{it}) &= \alpha_i^1 + \gamma_{\text{BP}}\text{BLockPrice}_{it} + \gamma_{\text{FF}}\ \text{FixFee}_{it} \\ &\quad + \gamma_{\text{STF}}\text{STF}_t + \gamma X_{it} + \delta^1\text{Water}_{it-1} + \eta_{it}, \\ \text{In}(\text{Water}_{it}) &= \alpha_i^2 + \beta_{\text{p}}\,\hat{\text{Price}}_{it}\,\beta_{\text{D}}\hat{\text{Diff}}_{it} + \beta_{\text{STF}}\,\text{STF}_t \\ &\quad + \beta X_{it} + \delta^2\,\text{Water}_{it-1} + \varepsilon_{it}. \end{aligned} \tag{5}$$

Baltagi (2003) has shown that panel estimates of this dynamic model are inconsistent. General method of moments and IV techniques have been developed to deal with this problem (Arbués & Barberán, 2004). Here, the large sample size precludes general method of moments estimation, so the IV technique is used instead. Next, the $\alpha_i$ are eliminated through the first-differenced (FD) transformation. After the FD transformation, the first and second stage equations become

$$\begin{aligned}\ln(\text{Water}_{it}) - \ln(\text{Water}_{it-1}) = {} & \gamma_{BP}(\text{BLockPrice}_{it} - \text{BLockPrice}_{it-1}) \\ & + \gamma_{FF}(\text{FixFee}_{it} - \text{FixFee}_{it-1}) \\ & + \gamma_{STF}(\text{STF}_t - \text{STF}_t) \\ & + \gamma(X_{it} - X_{it-1}) \\ & + \delta^1(\text{Water}_{it-1} - \text{Water}_{it-2}) \\ & + \eta_{it} + \eta_{it-1}, \end{aligned} \tag{6}$$

$$\begin{aligned}\ln(\text{Water}_{it}) - \ln(\text{Water}_{it-1}) = {} & \beta_p(\hat{\text{Price}}_{it} - \hat{\text{Price}}_{it-1}) \\ & + \beta_D(\hat{\text{Diff}}_{it} - \beta_D\hat{\text{Diff}}_{it-1}) \\ & + \beta_{STF}(\text{STF}_t - \text{STF}_t) \\ & + \beta(X_{it} - X_{it-1}) \\ & + \delta^2(\text{Water}_{it-1} - \text{Water}_{it-2}) \\ & + \varepsilon_{it} - \varepsilon_{it-1}. \end{aligned}$$

Finally, the variable Water is lagged for 2 to 12 months, and these variables are used as instruments for the still endogenous explanatory FD-lagged Water variable.[5] Note that this IV estimation technique is used at both stages of the two-stage model.

Of particular interest is the effect of the public information campaign, $\beta_{STF}$. This effect is measured in an interrupted time series framework (see Shadish, Cook, & Campbell, 2002, chap. 6). The measured effect accounts for an intercept shift in water use during the months of the campaign.

## Results

Three different sets of model estimates are compared in this section: static and dynamic models; different panel-data models, and residential and seasonal models. The results of the control variables are briefly discussed below before turning to estimated policy effects in each model. Table 3 reports a summary of the effects of the policy variables measured in this article.

Precipitation and evapotranspiration have the anticipated signs and are of a reasonable magnitude. In the static model reported in Table 4, it is seen that a standard deviation increase in precipitation (0.045 inches) decreases water use by about 15% (0.045 × 3.369), holding all else constant. This effect remains relatively constant across the models with the exception of the model for nonresidential users for which the effect is smaller.

Evapotranspiration, or the rate at which water evaporates from the ground, is positively associated with water use as expected. In the static model, a standard deviation increase in ET (0.081) increases water use by about 43% (0.081 × 5.259), holding all else constant. This is a very large effect and consistent across models. However, the effect is again much smaller for nonresidential users.

**Table 3**
**Estimated Effects of Policy Variables in FE-IV Models**

| | Price Elasticity[a] | Income Elasticity[a] | STF Effect on Mean Consumption (%)[b] |
|---|---|---|---|
| Time | | | |
| Long run | −0.485 | 0.126 | −1.269 |
| Short run | −0.391 | 0.271 | −6.673 |
| Season | | | |
| Summer | −1.445 | 0.268 | −1.192 |
| Winter | −0.378 | 0.213 | −4.687 |
| Connection type | | | |
| Residential | −0.413 | 0.268 | −6.761 |
| Nonresidential | −0.665 | 0.222 | −1.784 |

NOTE: FE = fixed effects; IV = instrumental variable.
[a]Elasticity estimates calculated at the mean. Each estimate is significant at the .001 level. Significance for long-run estimates is calculated via the delta method for the nonlinear combination of coefficients.
[b]The percentage reduction in water consumption resulting from the public information campaign is calculated via the Kennedy (1981) technique as discussed in Table 1.

Water use is greater in summer months than in winter months. Users consume about 52% {100 × [exp (0.421) − 1]} more water in summer months than in winter months in the static model, holding all else constant. Again, this measure seems stable across models.

### Static and Dynamic Models

The parameters in the water demand Equation 4, the static model, are estimated using FE and reported in Table 4. The parameters in the water demand Equation 6, the dynamic model, are also estimated using FE and are reported in Table 5. Again, the lagged value of water is endogenous in Equation 6 so all variables were FD, and then lagged values of water for 2 to 12 months as instruments for $\text{Water}_{t-1}$ were used. Tables using these instruments to predict $\text{Water}_{t-1}$, however, are not included.

It must be noted first that price estimates in the FE model in both the static and dynamic case, without controlling for price endogeneity, are clearly biased. The positive coefficients merely represent the fact that connections consuming beyond the fixed allowance are being charged a higher marginal price than zero. Once endogeneity of price is controlled for, coefficient estimates are negative.

**Table 4**
**FE Static Models**

| | FE | First-Stage FE | IV-FE |
|---|---|---|---|
| Price | 2.920*** (0.00) | | –1.188*** (0.01) |
| Diff | –0.050*** (0.00) | | –0.099*** (0.00) |
| STF | –0.095*** (0.00) | –0.079*** (0.00) | –0.069*** (0.00) |
| Precip | –2.177*** (0.01) | –2.945*** (0.01) | –3.369*** (0.01) |
| ET | 4.021*** (0.01) | 5.694*** (0.01) | 5.259*** (0.01) |
| Summer | –0.227*** (0.00) | 0.255*** (0.01) | 0.421*** (0.00) |
| BlockPrice | | –0.004 (0.05) | |
| FixFee | | –0.042*** (0.00) | |
| Constant | 1.554*** (0.00) | 2.165*** (0.02) | 2.701*** (0.00) |
| $R^2$ | 0.694 | 0.570 | 0.583 |
| $N$ | 1,654,037 | 1,654,037 | 1,654,037 |

NOTE: Standard errors in parentheses. FE = fixed effects; IV = instrumental variable.
Two-sided hypothesis tests:*$p < .05$. **$p < .01$. ***$p < .001$.

**Table 5**
**FD Dynamic Models[a]**

| | Dynamic FD | First-Stage Dynamic FD | Dynamic FD-IV |
|---|---|---|---|
| ln(Water$_{t-1}$) | 0.255*** (0.00) | 0.328*** (0.00) | 0.361*** (0.00) |
| Price | 2.336*** (0.01) | | –0.942*** (0.01) |
| Diff | –0.068*** (0.00) | | –0.029*** (0.00) |
| STF | –0.022*** (0.00) | 0.045*** (0.00) | –0.008* (0.00) |
| Precip | –1.461*** (0.01) | –2.060*** (0.01) | –2.154*** (0.01) |
| ET | 3.886*** (0.02) | 4.814*** (0.02) | 4.455*** (0.02) |
| Summer | –0.287*** (0.00) | –1.715*** (0.02) | 0.135*** (0.00) |
| BlockPrice | | 10.596*** (0.13) | |
| FixFee | | –0.051*** (0.00) | |
| Constant | –0.005*** (0.00) | –0.017*** (0.00) | –0.010*** (0.00) |
| $R^2$ | 0.749 | 0.637 | 0.675 |
| $N$ | 1,089,902 | 1,089,902 | 1,089,902 |

NOTE: Standard errors in parentheses. FD = first differenced; IV = instrumental variable.
[a]Regression equations using lagged water use for 2 to 12 months are omitted from this table. Results are available on request from the author.
Two-sided hypothesis tests:*$p < .05$, **$p < .01$, ***$p < .001$.

The coefficient, $\delta^2$, on the lagged dependent variable Water$_{it-1}$ lies between 0 and 1 as expected. The long-run price elasticity is defined as $\varepsilon_{\text{Price}} = [\beta_p/(1 - \delta^2)]$ (Price). The estimated long-run elasticity of price calculated at the mean is –0.485 and is significant at the .001 level. The estimated short-run elasticity calculated at the mean is –0.391 and is also significant at the .001 level. As anticipated, the long-run elasticity is greater than the short-run elasticity. This reflects the fact that in the long run, consumers can change to more water-efficient consumer durables such as more efficient washing machines, dishwashers, and plumbing fixtures.

The difference variable, which is equal in magnitude and opposite in sign to the income effect, shows a relatively inelastic income effect. The short-run income elasticity calculated at the mean is 0.271, and the long-run income elasticity is 0.126.

The STF variable is also significant. It appears that water use decreased in the months when the campaign was active. In the short run, the campaign reduced water consumption by 6.673%, holding all else constant. However, in the long run, the campaign only reduced consumption by 1.269%.

## Panel Data Models

Static IV models were also estimated in RE and pooled frameworks. Table 6 reports these results. Here, estimated price elasticities in the RE and pooled models are similar to

**Table 6**
**Static Panel Models**

| | FE-IV | RE-IV | Pooled-IV |
|---|---|---|---|
| Price | –1.188*** (0.01) | –1.582*** (0.01) | –1.592*** (0.02) |
| Diff | –0.099*** (0.00) | –0.100***(0.00) | –0.103*** (0.00) |
| STF | –0.069*** (0.00) | –0.067*** (0.00) | –0.067*** (0.00) |
| Precip | –3.369*** (0.01) | –3.552*** (0.01) | –3.408*** (0.02) |
| ET | 5.259*** (0.01) | 5.334*** (0.01) | 5.319*** (0.01) |
| Summer | 0.421*** (0.00) | 0.478*** (0.00) | 0.478*** (0.00) |
| Residential | | –0.331*** (0.01) | –0.405*** (0.00) |
| TaxVal | | 0.003*** (0.00) | 0.003*** (0.00) |
| LotSize | | 0.361*** (0.01) | 0.363*** (0.00) |
| Constant | 2.701*** (0.00) | 2.717*** (0.02) | 2.806*** (0.01) |
| $R^2$ | 0.583 | 0.585 | 0.475 |
| $N$ | 1,654,037 | 1,654,037 | 1,654,037 |

NOTE: Standard errors in parentheses. FE = fixed effects; IV = instrumental variable; RE = random effects.
Two-sided hypothesis tests: *$p < .05$. **$p < .01$. ***$p < .001$.

**Table 7**
**Static Fixed-Effect Season- and Connection-Type Models**

| | Summer | Winter | Residential | Nonresidential |
|---|---|---|---|---|
| Price | –4.392*** (0.06) | –1.150*** (0.01) | –1.256*** (0.01) | –2.020*** (0.29) |
| Diff | –0.116*** (0.00) | –0.078*** (0.00) | –0.098*** (0.00) | –0.081*** (0.00) |
| STF | –0.012*** (0.00) | –0.048*** (0.00) | –0.070*** (0.00) | –0.018* (0.01) |
| Precip | –3.713*** (0.04) | –3.308*** (0.01) | –3.483*** (0.01) | –1.697*** (0.07) |
| ET | 4.664*** (0.02) | 5.748*** (0.01) | 5.371*** (0.01) | 2.546*** (0.07) |
| Summer | | | 0.433*** (0.00) | 0.482*** (0.05) |
| Constant | 4.830*** (0.02) | 2.573*** (0.01) | 2.691*** (0.00) | 3.810*** (0.09) |
| $R^2$ | 0.253 | 0.281 | 0.594 | 0.265 |
| $N$ | 631,499 | 1,022,538 | 1,601,186 | 52,851 |

NOTE: Standard errors in parentheses.
Two-sided hypothesis tests:*$p < .05$, **$p < .01$, ***$p < .001$.

each other, albeit slightly larger in absolute value than the FE estimates. The price elasticity calculated at the mean for the RE model, for example, is –0.520 as compared with –0.391 in the static FE model. Because the FE estimates are consistent regardless of whether time invariant connection heterogeneity is correlated with the explanatory variables, those estimates seem more reliable. However, the FE estimates cannot identify the effects of connection level variables of LotSize, TaxVal, and Residential. Estimates of these variables in the RE and pooled models are reported, but readers are cautioned of their potential inconsistency. Income elasticities and the effects of the public information campaign are similar across different panel models.

## Season- and Connection-Type Models

The last part of the analysis partitions the data in terms of residential and nonresidential users, and summer and winter use. Static FE-IV estimates from these models are reported in Table 7. The partition of the data allows separate estimates of all variables effects in each category. The price elasticity, estimated at the mean, for nonresidential users is –0.665, whereas the price elasticity, estimated at the mean, for residential users is –0.413. This indicates that nonresidential water consumers are more responsive to changes in price. In addition, the income elasticity, which might be thought of as a subsidy elasticity, is 0.268 for residential users and 0.222 for nonresidential users, calculated at the mean. This implies that residential users are slightly more responsive to subsidies than nonresidential users. In addition, it appears that the public information campaign had its greatest effect on residential users, decreasing consumption by 6.761%, while decreasing consumption among nonresidential users by only 1.784%.

Perhaps most striking in the results are the differences in policy effects by season. Water consumption appears quite elastic to price in summer months. The estimated price elasticity calculated at the mean in summer months is −1.445. Whereas this estimate of price elasticity is large in absolute value, it is well within the range of values found in the meta-analysis of price elasticities conducted by Dalhuisen et al. (2003). The magnitude of this effect may be because of the fact that water use in Salt Lake City is very discretionary in summer months. Average water use increases dramatically in the summer, mostly driven by discretionary watering of lawns. The UDWR (2004) estimates that 65% of household water consumption is for landscaping.

However, although prices seem effective at curbing this discretionary use, the public information campaign is not. Water consumption in summer months during which the campaign was in effect was only 1.192% less than in summer months in which the campaign was not in effect, holding the other variables constant.

## Discussion and Conclusions

In this article, static and dynamic econometric models of urban water demand were developed to compare policy alternatives to curb water consumption. The abundance of data at the household level provides a unique opportunity to test water use responsiveness to policies during the study period.

Estimated income elasticities from different models consistently fall within the range of previous studies (Dalhuisen et al., 2003). Moderate price elasticities for most models during the study period (between −0.378 and −0.665) were found. However, large price elasticities were estimated during the summer months. Thus, increasing water prices may be quite effective at reducing water use especially in the summer.

The public information campaign had a statistically significant effect at reducing water consumption; however, substantively, this effect appears quite small. In all models, water consumption decreases by no more than 7% as a result of the campaign, controlling for other factors. This confirms the work by Renwick and Green (2000) who found that public information campaigns only modestly reduced demand by 8% in California. These modest decreases in consumption confirm results from other research as well, as reported in Table 1. The campaign is most effective in the short run and with residential users.

Water scarcity and the need for demand-side management of water use is now seen as a viable tool for managing municipal water (Renwick & Archibald, 1998; Renwick & Green, 2000). Policy makers must choose among a variety of tools to achieve goals of reduced water use. There are costs to using each of these tools. Public information campaigns can be expensive and their efficacy hard to measure. Raising water prices is politically unpopular, but the analysis here indicates that both public information campaigns and price changes may be effective at reducing water use. Large estimates of price elasticity imply that this tool may be especially effective at reducing use. This analysis could help policy makers better assess the potential trade-offs of a particular tool in light of its costs.

## Notes

1. Note that a decreasing block rate structure implies an implicit income tax (Renwick & Green, 2000), an increasing block rate structure implies an implicit income subsidy, and the effect of income on water consumption should be equal in magnitude and opposite in sign to the difference variable (Nieswiadomy, 1992). The water demand literature has generally incorporated the Taylor-Nordin specification, but some studies have tried to empirically test whether consumers react to marginal or average prices (Shin, 1985; Taylor, McKean, & Young, 2004). Nieswiadomy (1992), following Shin (1985), used a "perceived price," which is simply a combination of average and marginal prices. Opaluch (1984) suggests using a new price variable, defined as the difference between average and marginal prices, and develops a limited test for inference of the appropriate variable. This specification was later used by Nauges and Thomas (2000), Arbués and Barberán (2004), and others.

2. The first determinant of the bill is the connection size of the pipe for incoming water. Based on that size, the city charges a flat fee for the first 500 cubic feet of water consumed. In other words, the 500 cubic foot allowance has a marginal price of 0. Each HCF of water consumed in excess of the allowance is charged a marginal rate, which depends on the time of the bill. Again, summer water use has higher rates than winter, and overall rates increased in the study period. Almost 98% of monthly water use exceeded the 500 cubic foot allowance. All aspects of the water bill, including marginal, average, and difference prices are inferred from total usage, connection size, time of reading, and pricing determined by city ordinance. Real prices are reported as 1980-1982 dollars based on the consumer price index for western, urban consumers, all products.

3. Some studies have used property values as a proxy for income (Arbués & Barberán, 2004; Hewitt & Hanneman, 2000). The proposed model uses fixed household effects, so that any time-invariant proxy for income is implicitly controlled for in the model.

4. The weather stations are located at the Salt Lake Airport, Hogel Zoo, and Murray Golf Course. The dispersion of the stations fortunately offers a range of accurate climate measurements across the valley. The Salt Lake Airport is located on the west side of the valley at a relatively lower altitude than the others. The Murray Golf Course,

on the other hand, is on the eastern side of the valley on the benches of the Wasatch Mountain Range. Differences in elevation are then implicit in climatic measurement, especially important for measuring precipitation. The Hogel Zoo, located in the middle of downtown Salt Lake City, provides additional moderation.

5. Figure 1 shows that monthly water use approximately follows a 12-month cyclical pattern. Other lag structures were also estimated. Contact the author for these results.

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