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Defensive Investment in Water Hardness Reduction

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Defensive Investment in Municipal Water Hardness Reduction*

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Abstract

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We produce estimates of household's willingness to pay (WTP) for reduction in water hardness using a defensive investment framework. Using total dissolved solids (TDS) data observed in municipal water supplies in combination with product-by-store level point-of-sale scanner data on consumable water softening product sales, we provide among the first revealed preference estimates of WTP for water hardness reduction and quality control. Using instrumental variable regressions, we find that household's marginal WTP increases as the observed TDS in municipal water increases. Aggregating these estimated WTP at county level, we show how total WTP varies geographically, after controlling for income and fixed effects. Our estimations provide evidence that households have a non-negligible WTP for water hardness reduction, which has important policy implications for optimal water hardness management by municipal water authorities, and those policies aimed to target salinity management within surface and subsurface water supplies.

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1 Introduction

Water hardness in municipal water supplies can cause negative economic damages to households and industry. At the household level, these damages include a decrease in the efficacy of the soap and cleaning products, shortened service lives of the household appliances, and increased distaste and aesthetics of drinking water. In this study, we measure the willingness to pay (WTP) for the reduction of water hardness by households for reasons other than perceived or true health risk.

There are many contributing factors that cause high concentrations of hardness, such as discharge of subsurface saline groundwater, percolation through mineral-rich soils, agricultural return flows, municipal wastewater discharge, and atmospheric deposition. At the household level, increased hardness of water is related to increased consumption of laundry detergent, soap, shampoo, and other cleaning agents. This required increase in detergent and soap consumption is due to the presence of dissolved calcium and magnesium minerals as multivalent cations (Ca^{2+} and Mg^{2+}), which reduce the efficacy of detergent products by reducing their surfactant properties. The presence of these cations also causes soap scum (calcium or magnesium stearate), which is aesthetically displeasing and may encourage the formation of microbial biofilms (Kelley et al., 2004). Water hardness also contributes to shortened service lives of household appliances, as heating hard water causes the dissolved minerals to precipitate out of the solution, particularly as calcium carbonate ($CaCO_3$), causing scaling. This increase in soaps and other cleaning products in combination with shortened service lives of household capital can lead to an inefficient consumption of household resources for water consuming activities and an increase in resource use and household disutility related to water use.

When consumers purchase water softening systems, they tend to purchase these systems to reduce the damage to household capital (such as pipes or water heaters), or for aesthetic reasons (change in water taste or reduction of scales on pots and dishes). Consumers may also buy water softener additives for use in clothes washers or dishwashers to increase the efficacy of soaps and reduce the scaling within these appliances from calcium and magnesium salts. The demand for water softeners and water softening additives can provide valuable information on the estimation of WTP for water quality control and improvement, which can further be used as a guide for policy pertaining to decisions to invest in utility-scale desalination capital and management of the total salt system in water supplies.

Households generally use ion exchange to soften household water, which involves ion-exchanging beads that attract the calcium and magnesium ions, which are exchanged for sodium ions in the water. Looking beyond the household scale, water softening itself can contribute to the damages caused by excess salt in the larger water system. When individuals perform home water softening, they return both the salt that was present in the water originally (calcium and magnesium salts) as well as sodium salt in the water from the softeners used by the household. This occurs because once the ion-exchanging beads are saturated with calcium and magnesium, they are regenerated by soaking them in brine, and the calcium and magnesium are returned to the sewer or septic tank. At the same time, the water used by the household contains sodium salts, which is also returned to the sewer or septic tank. While calcium and magnesium salts are most damaging to households, sodium salts are most damaging to plant health, inhibiting water uptake in most plants (reducing both agricultural yields and urban landscaping plant growth). The effect of sodium salt within the water system has a knock-on effect, as soil that has been watered with brackish or saline water accumulates salt in the soil, so further watering or irrigation requires greater water application than would be necessary for healthy soils, known as soil leaching (Sheldon et al., 2004; Ayars et al., 2012).

Following Ito and Zhang (2016) and Berry (1994), we use a random utility model (RUM) in which consumers purchase consumable water softening supplies to reduce water hardness in household water. Based on this RUM, we build an empirical model to estimate household WTP for reductions in damages caused by water hardness.

Using this empirical framework, we determine revealed preference estimates of household WTP for water hardness reduction in municipal water. We use weekly store-product level panel data of water softener salt and water conditioner sales along with Total Dissolved Solids (TDS) measurements for 152 counties in Nevada, California and Texas, for the years 2006 to 2012. We focus on Nevada (NV), California (CA), and Texas (TX) in this analysis for two main reasons. First, these states provide the most easily obtainable data for measured TDS levels in drinking water, and second, all of these states have areas known to have issues with water hardness, while also having rich variation within each state for TDS levels.[1] Data on water softening salt and water conditioning additives sales are obtained from the Nielson Retail Scanner Database, and data on the level of water hardness in each county are obtained from the states' Drinking Water Watch (DWW) databases. Both of these data sources will be discussed in greater detail in Section 3.

Our identification strategy relies on instrumental variable regression because of the possible reverse causality problem since household softener purchase can affect softener price. To resolve this, we instrument price with two variables. The first instrument used is net income for all US manufacturers of chemical products. Because salt is a major input into chemical manufacturing, changes in the chemical manufacturing industry affect salt production through the supply side. Since net income of US manufacturers' of chemical products do not vary by counties, we include another instrument by interacting total US chemical manufactures' income with a dummy variable that represents county-level stringency in environmental regulation. We construct this dummy from the Environmental Protection Agency (EPA)'s National Ambient Air Quality Standards (NAAQS) index. The dummy variable indicates if the county has obtained NAAQS provided attainment

[1] The visual evidence presented in section 3 on TDS data also supports our claim that these regions suffer from water hardness issues.

status. This status is correlated with softener product price because chemical product plants benefit from lower air quality standards. Our identification relies on the assumption that both net income for all US manufacturers of chemical products and NAAQS index do not affect households' softener purchase in any other way except price. The instruments and the identification strategy are discussed in detail in Section 4.1.

Using the instrumental variable reduced form regression estimates we find that monthly marginal willingness to pay (MWTP) of each household on average is $7.5 when TDS level is 500 parts per million (ppm).[2] Extending monthly estimates to annual level, we find that on average a household is willing to pay $11.7 per annum given that the municipal water TDS level is greater or equal to 500 ppm.[3] When annual household level MWTP estimates are converted to county level, we find that on average a county in TX, NV, and CA is willing to pay $1.2 million annually to reduce damages from water hardness, when municipal water TDS level is greater than 500 ppm.

We contribute to the literature and to ongoing policy discussions in two channels. Firstly, to the best of the authors' knowledge, this study reveals the first estimates of WTP for reductions in water hardness. These results contribute to the literature on WTP estimates of point-of-use water treatment and our understanding of desalination policy and management. Many studies measure demand for point-of-use water treatment using revealed preference or experiments with subsidies or auctions (e.g. Ahuja et al. (2010); Berry et al. (2011)) and stated preference (e.g. Jeuland et al. (2016); Houtven (2011)). This study sets itself apart by specifically focusing on how elevated levels of water hardness affect people's preference for water treatment for reasons unrelated to health issues. Secondly, this paper has important policy implications for optimal water quality management. Given that water prices are often government regulated and desalination technology is expensive, water managers currently have little guide in determining the amount of desalination capital to invest in, and where these investments have been made, the amount of desalinated water to blend in with more brackish supplies. Where water hardness is a problem and large numbers of households using water softeners cause increased concentrations of salt, an understanding of the WTP for hardness reduction is also critical for the economically optimal management of system-wide salinity management. While an analysis of optimal salt system management is beyond the scope of this paper, the understanding gained here is a critical piece of understanding the larger system. Our WTP estimates provide a better understanding of the demand for water softness and aesthetic quality. This can help municipalities manage their decision making at the utility scale on hardness management and system-wide salinity management. While we focus on the United States for our analysis, the results and discussion in this paper have implications for water scarce regions around the world, particularly those that rely heavily on limited aquifer supplies. Examples of

[2] The value of 500 ppm is used as a threshold TDS level as this is the EPA's secondary drinking water standard (Environmental Protection Agency, 2009), which is a non-mandatory water quality standard for water hardness.

[3] Given that average annual water utility bill for households in large U.S. cities is $300 The Hamilton Project (2014), our estimated annual household WTP represents approximately 4% of the annual water utility bill.

countries which face water hardness and desalination issues are, Israel, Saudia Arabia, and UAE. For a review on desalination plants and water salinity issues in the middle eastern and north African countries, see WorldBank (2004).

The remainder of the paper is organized as follows. Section 2 presents the theory model leading to the empirical framework. Section 3 discusses data and data sources. Section 4 analyses the estimates of marginal WTP (MWTP) for TDS reduction using two different methods. Section 5 concludes.

2 Model

The goal of this analysis is to obtain a revealed preference estimate of WTP for reductions in water hardness by analyzing demand for water softening products. Water softening products are differentiated products, so the basis of this analysis is a differentiated products model of random utility, following Ito and Zhang (2016) and Berry (1994). When consumers purchase water softening products, the consumer considers both the utility gain from the product attributes and disutility from the price. We consider two main types of water softening products: water softening salt for full water-system softeners, and appliance-level water softening additives. Full water-system softeners provide softened water to all water using appliances in a household, while appliance-level softeners provide water softening benefits to specific appliances, such as dishwashers or clothes washers.

The intuition behind our approach is that the extent to which consumers value the product specific water softening characteristic, along with the price elasticity of demand, provides insights into their WTP for water hardness improvements. Consider a consumer i in county c that faces a level of water hardness in their municipal supply of water, x_c (measured by total dissolved solids). The consumer can purchase water softening product j at price p_{jc} to reduce the total household impacts of water hardness by $x_{jc} = x_c \cdot e_j$, where the effectiveness of product j at reducing total household impacts of water hardness is denoted by $e_j \in [0, 1]$.

The conditional indirect utility of consumer i purchasing water softening supply j in county c is assumed to be:

$$u_{ijc} = \beta_i x_{jc} + \alpha_i p_{jc} + \lambda_c + \varepsilon_{ijc}, \tag{1}$$

where x_{jc} is the reduction in total household damages from water hardness, conditional on the purchase of product j, at price p_{jc}. County level fixed-effects are denoted by λ_c, which capture time-invariant effects at the county level, and ε_{ijc} is a mean-zero stochastic term. From this, β_i indicates the marginal utility for reduction in water hardness and α_i indicates the marginal disutility from price. This functional form assumes that all variables and errors enter the utility function linearly.

Consider a standard logit model. Consumer i purchases water softening product j if $u_{ijc} >$

u_{ikc}, $\forall\, k \neq j$. In this case, the market share of product j in county c is then:

$$s_{jc} = \frac{\exp(\beta x_{jc} + \alpha p_{jc} + \lambda_c)}{\sum_{k=0}^{J} \exp(\beta x_{kc} + \alpha p_{kc} + \lambda_c)} \tag{2}$$

where the outside option ($j = 0$) is to not buy water softening products. For the sake of simplicity in analysis, we further assume households face all water hardness impacts, and thus receive no utility if they do not buy water softening supplies. Then, the share of households that take the outside option can be calculated as the difference between the number of households in county c and the total number of sales in county c. Therefore, the difference between the log market share for product j and the outside option is

$$\ln s_{jc} - \ln s_{0c} = \beta x_{jc} + \alpha p_{jc} + \lambda_c. \tag{3}$$

Similar to Equation (1), β indicates the marginal utility for reductions in water hardness and α indicates the marginal disutility from price. From these estimated parameters, the marginal willingness to pay for one unit reduction in water hardness (again measured via TDS) can be obtained from $-\beta/\alpha$.

2.1 Empirical Model

Based on the theory model described in Section 2, we estimate marginal willingness to pay per household for reductions in water hardness. To estimate the equation of log market share of water softening products and the outside option, we estimate the following equation:

$$\ln s_{ijct} - \ln s_{0ct} = \alpha_0 + \beta_1 x_{jct} + \alpha_1 p_{jct} + \beta_2 y_{ct} + \lambda_c + \delta_t + \varepsilon_{ijct} \tag{4}$$

Here, $i = 1, 2, \ldots, N$(households); $j = 1, 2, \ldots, K$(softener products); $c = 1, 2, \ldots, L$(counties); $t = 2006, 2007, \ldots, 2012$(years);

The model in equation 4 includes spatial and temporal variation in terms of water hardness and households' purchase of water softening products. The dependent variable or left hand side (LHS) variable in equation 4, $\ln s_{ijct} - \ln s_{0ct}$, indicates the log difference between households that purchase water softening products and the outside option, which is to not purchase softening products. This LHS variable is same as the dependent variable in equation 3. The major difference between equation (3) and (4) is the former is a cross-sectional analysis, while the latter allows us to observe variation in shares of households that purchase softening products over time, as water softening supplies are consumable products.

We also include income, y_{ct}, in equation 4, because income is a major determinant of households' softener demand, which varies both by county and time. Not including income in the estimated equation as a control, may result in biased coefficient of softener price, p_{ijct}. The variable λ_c in equation 4 controls for time-invariant county level fixed effects. Examples of such time-invariant characteristics are geographical influence, county specific water and climate fixed effects, and store and product specific characteristics. The variable δ_t controls for time variant characteristics. Examples for such time-variant factors are technology, water softening specific regulations, etc. The variables ε_{ijct} is a random error term. Marginal willingness to pay per household to reduce water hardness as derived from Equation (4) is $-\beta_1/\alpha_1$.

3 Data

The source and description of the data used in our analysis is provided in the following subsections.

3.1 State Drinking Water Watch Databases

Data on the level of water hardness, measured as total dissolved solids (TDS) for our study is provided by states through databases known as "Drinking Water Watch" (DWW) databases. The exact data available through the DWW databases varies by state, but most states provide multiple measures of water quality which are meant to be used to provide information to residents about the number and severity of water quality rule violations. The measures available include not only measures of water hardness, as well as other measures such as coliform, *e. coli*, heavy metal concentration, PH, as examples.

The data at these sites are provided at the testing site level, and the number of testing sites varies by county based on the number of wells and other testing sites that exist in that county. Most individual sites are tested at least twice per year, but this can be as often as monthly, depending on the relative importance of that site to the integrity of the water system and to public safety.

As stated previously, not all states have a DWW site, and each site varies in terms of the complexity of data retrieval. For this study, we use data from California (CA), Texas (TX), and Nevada (NV), because the data from these states is easily obtainable, and all three states include large metropolitan areas that have been historically known to have issues with water hardness. Some other states that are not used in this study provide data in formats that rule them out as good data candidates, or have websites whose data retrieval policies explicitly forbid the use of the data scraping methods that were used in this study. These data can be accessed at California State Water Resources Control Board (2018), Texas Commission for Environmental Quality (2018), and Nevada Division of Environmental Protection (2018).

Data for reported TDS in parts per million (PPM) are available by site and were obtained in total for 152 counties: 48 of California's total 58 counties, 8 of Nevada's total 16 counties, and 96 of Texas's total 254 counties. The full TDS data includes 61,460 observations for TDS measurements, with an average of 844 tests per county in California, 86 tests per county in Nevada, and 49 tests per county in Texas. The data are averaged from the site level to the county level for each month in the analysis.

The average TDS values for each county used in this study can be seen in Figures 1 and 2. Data used in this study cover the years 2006 to 2012. Nevada has the highest average TDS concentration, at 525 ppm. The highest concentrations of TDS within the state are in Clark county. California has a slightly lower average TDS concentration, with an average of 471 ppm. The highest concentrations are found in Santa Barbara and Ventura counties. Texas has moderately lower TDS concentrations, with an average TDS concentration of 406 ppm. The highest TDS concentrations are found in the Panhandle and Gulf Coast regions. Note that because of the vast difference in size and population density between the counties in this study, some residents may obtain municipal water with significantly greater or lower concentrations of TDS than these averages.

Figure 4 shows average TDS values by state as they vary over time. Among the three states, Nevada has the highest average TDS level over all years. Average TDS values are fairly consistent over time, though increasing post-2010 for Nevada and California. Average TDS for Texas has a fluctuating trend through the analysis period 2006-2012.

3.2 Nielsen Retail Scanner Database

The Nielsen Retail Scanner database provides weekly point-of-sale price and quantity data for 2.6 million individual UPC codes. The full dataset covers the entire United States, with more than half the total sales of US grocery and drugstores as well as more than 30% of all US mass merchandiser sales. Weekly point-of-sale data are provided at the county level as the total number of sales and price for those sales by UPC. The data coverage begins in 2006, and data through 2012 is used in this study.

For this study, the sales of interest include UPCs for products whose description matches with those of water softening salts, water softening additives, and water conditioners. The total number of weekly sales that match these descriptions include 941,459 observations, 70% of which are in California, 16% in Nevada, and 14% in Texas. Average weekly unit sales of products matching these descriptions can be seen in Figures 6 and 5. The highest average weekly sales within the dataset are in Andrews county, Texas, in the Panhandle region.

Average weekly price of the softener products can be seen in Figures 7 and 8 for Texas, Nevada, and California. While we do not observe much price difference in California and Nevada, some price differences are observed in Texas, specially around Dallas and Houston.

Summary statistics of the data used are provided in the Appendix in Table 4. The merged dataset is weekly store-product level data for the period 2006 through 2012.

3.3 Instruments and Controls

US Chemical Manufacturers' Total Income

Net income for all US manufacturers of chemical products is obtained from the US Census Quarterly Financial Report. These data are provided by corporations that have domestic assets of $250,000 and over, and we use data that corresponds to the chemical manufacturing NAICS code. This data is provided quarterly, and is reported in billion US$.

National Ambient Air Quality Standards (NAAQS) index

The NAAQS index was obtained from EPA's Green Book Data Download website (Environmental Protection Agency, 2018). The data provided indicate whether counties have met the NAAQS standard (have attainment status), by pollutant and year. We construct an index indicating whether a county has fallen into non-attainment by county for thirteen ambient air pollutants.[4] We do this by indicating with a one if a county has either wholly or partially fallen into non-attainment status for the thirteen pollutants for each year. Otherwise, the county is indicated with a zero for reaching attainment status. In this way we created an environmental regulation index which varies by counties and year for Texas, Nevada, and California.

Winter Weather Events

In Section 4.3, we use count of winter weather events as our second choice of instrument. Data for winter weather events are from the NOAA National Center for Environmental Information's Storm Events Database (National Oceanic and Atmospheric Administration, 2018). These data provide a count of extreme weather events by month for the United States. We take the total count for the United States for all storms labeled "winter weather" as our count of total storms that could necessitate the use of salt to clear sidewalks and roads.

County Wages

Since household level income is not available for this study, we use county level wages as reported by the Bureau of Labor Statistics' Quarterly Census of Employment & Wages (Bureau of Labor Statistics, 2018). These data are provided quarterly, are derived from quarterly contribution reports filed by employers, and wages are reported in millions of nominal dollars.

Household Statistics

Household statistics used in this analysis are obtained from Census Bureau, and all household statistics are from the 2010 census (United States Census Bureau, 2010). The data used in our

[4]The thirteen pollutants are, 1 hour ozone (1979), 8 hour ozone (1997), 8 hour ozone (2008), Carbon Monoxide (1971), Lead (1978), Lead (2008), Nitrogen Dioxide (1971), PM-10 (1987), Pm-2.5(1997), PM-2.5(2006), PM-2.5(2012), Sulfur Dioxide(1971), and Sulfur Dioxide(2010). The years in parentheses indicate the year the rule was enacted.

analysis are the count of total occupied housing units by county.

Drought Index

In Section 4.3, we include a drought index as a control for weather. The drought index used is the US Drought Monitor, a joint product of the National Drought Mitigation Center at the University of Nebraska-Lincoln, the National Oceanic and Atmospheric Administration, and the US Department of Agriculture (Tinker and Pugh, 2018). The US Drought Monitor provides weekly and monthly data at the county level for drought severity. The drought categories provided range from no drought, 'D0', indicating abnormally dry conditions, to 'D4' indicating exceptional drought. The index is largely based on Palmer Drought Severity Index, but also includes impacts from soil moisture, stream flow, precipitation, and objective drought indicators from local reporting. The data is provided as a percentage of the county that is classified at each level of drought severity, and a county can be in multiple drought categories at the same time.

4 Results

4.1 Identification

It is possible that Price, p_{jct}, in equation (4) is endogenous. This endogeneity could arise through changes in price affecting quantity of water softening supplies demanded, and this change in quantity demanded affecting price. To mitigate this potential problem, we instrument water softener prices with two variables.

The first instrument that we use is total net income for the US chemical manufacturing industry. Because the manufacturing of chemicals is a major consumer of salt, changes in chemical manufacturing activity provides shifts on the supply side to the salts and other inputs into water softening products. Figure 3 shows movement over time of both average net US chemical manufacturers' income and average prices of water softening products across TX, CA, and NV. From the figure, it can be seen that these two variables has been increasing together over 2006-2012, with the exception of the period during the global financial crisis of 2008-2009.

Net income for all US manufacturers of chemical products is aggregated to national-wide data. Therefore, this instrument varies by time, but does not vary by county. To resolve this issue, we use our constructed NAAQS index interacted with net income for the US chemical manufacturing industry as a second instrument for softener products price. The index indicates whether a county has either wholly or partially fallen into non-attainment status for any of the thirteen pollutants for each year. This index varies by counties and by years.

Our rationale for the inclusion of the EPA's NAAQS index as an instrument follows. If the ambient air quality standards in a state or county are more stringent than the federal standards set by the EPA, that region should be less likely to fall into non-attainment of the federal standards.

Because chemical manufacturing plants are among the sources of ambient air pollutants, an increase in attainment should indicate that these plants are facing more stringent regulation. We observe strong correlation between the NAAQS index and prices of water softening products.

Since both net US chemical manufacturers' income and the NAAQS index do not affect household softener purchase in any way other than price, both of these instruments fulfill the exclusion restriction condition. In the reduced form regression, we use net chemical manufactures' income and its interaction with the NAAQS indicator dummy as instruments. Because US chemical manufacturers' income only varies by time and NAAQS index dummy varies by both county and year, the interaction variable varies by both county and year. Hence, the first-stage regression of our empirical model is,

$$\begin{aligned} p_{jct} = \gamma_0 + \gamma_1 x_{jct} + \gamma_2 y_{ct} + \gamma_3(\text{Chemical Manuf. Income})_t \\ + \gamma_4(\text{Chemical Manuf. Income})_t * (\text{NAAQS Index Dummmy})_{ct} + \lambda_c + \delta_t + \epsilon_{jct} \end{aligned} \tag{5}$$

Here, $j = 1, 2, \ldots, K$(softener products); $c = 1, 2, \ldots, L$(counties); $t = 2006, 2007, \ldots, 2012$(years);

4.2 Instrumental Variable Regression Results

The second-stage reduced-form instrumental regression results based on equation (4) are summarized in Table 1. The dependent variable in the regressions is the percent change in the share of households purchasing softeners, that is, ln(share HH purchasing softening)- ln(share HH not purchasing softening). Covariates include prices of water softening supplies, damages from TDS that avoided by those purchases, and county wages. Damages avoided are measured by county level TDS. [5]

Column (1) shows the results of a fixed-effects regression without month fixed effects, and Column (2) shows the results of a fixed-effects regression with month fixed effects. Price is instrumented in all three regressions by US net chemical manufacturing income and our constructed NAAQS index interacted with net income for the US chemical manufacturing industry.[6] A regression that

[5] Consumers that purchase water softening products can either use water softening salt in a full water system softener, which prevents all damages caused by TDS to household appliances. Consumers, in some cases, also use appliance specific softening additives, which prevent damages to only that appliance. Therefore, we define the reduction in damages from water softening purchases, $x_{jc} = x_c \cdot e_j$, based on the type of water softening product purchased. The estimated effectiveness of water softening salt is assumed to be 100%, so all TDS damages are prevented. The effectiveness of other water softening additives is assumed to be equal to the share of total household damages prevented by each additive. These estimates are calculated by the average cost of the intended household appliance divided by the average cost of all household water-using appliances, based on the cost estimates from Michelsen et al. (2009).

[6] The sales data used in this analysis is weekly. The county-level TDS data, however, is monthly. We include

does not use instrumental variables is shown in the appendix in Table 5.

In both regressions, the price elasticity of demand is negative, and increases in water hardness increase the share of households that purchase water softening supplies. Wages are not statistically significant for any regression. For each regression, The marginal willingness to pay (MWTP) for a one-unit reduction in water hardness are calculated as the ratio of -(Damages Avoided/Price) via the delta method, as discussed in section 2.1. Because water softening supplies in our data are consumable products, and we assume that the purchase of water softening supplies will be consumed in a month, MWTP estimates can be interpreted as a monthly estimate of the average MWTP for a 1 ppm reduction in water hardness.[7] Based on the MWTP estimates from regression results in Column (2), households are willing to spend roughly 1.5 cents per month to reduce 1 ppm of TDS. For a more meaningful interpretation, households are willing to pay $7.50 per month to reduce water hardness by 500 ppm on average.

We interpret the marginal willingness to pay estimates as a lower bound for the true values, based on two major factors. Firstly, and most importantly, our data for softening supply sales does not cover all sales of these supplies, so our estimates of the shares of households purchasing these products is likely to be lower in many counties than in reality. Secondly, some households may use reverse osmosis technology to reduce hardness in drinking water. Reverse osmosis systems reduce the aesthetic damage from drinking water, but we do not observe sales of these systems.

First-stage regression results of Table 1 are shown in Table 6 in the appendix.

4.3 Robustness Checks

4.3.1 Winter Weather as an Instrument for Price

In this section, we perform robustness checks on our analysis in Section 4.2 using a different instrument for price than income for chemical manufacturers, namely winter weather events. Because a major use of salt is for clearing streets and sidewalks during winter weather events, this use is one of the largest consumers of salt. Increases in the number of winter storms that necessitate the clearing of snow and ice should cause shifts in salt supply for reasons unrelated to water softening demands.

Table 2 summarizes instrumental variable regression results that control for county-level fixed effects, and has the same specification as Table 1. Column (1) shows results without month fixed effects, and column (2) shows the same specification, but with the inclusion of month fixed effects. The dependent variable is the same as in the regressions shown in Table 1. In both regressions, price is instrumented with winter weather along with chemical manufacturing income.

The results again show a negative price elasticity of demand and positive relation between

month fixed effect to capture monthly time variation.

[7] see Idaho Water Solutions (2018) or Linton (2014) as examples of suggestions on this point in popular press.

damages avoided and the share of households that buy water softening products. Results for both regressions are not statistically different than those found in Table 1. In this case, households are willing to pay roughly 1.4 cents per month to reduce TDS levels in water by 1 ppm. Extrapolating to a 500 ppm reduction, households are willing to pay nearly $7 per month.

First stage regression results of Table 2 are shown in Table 7 in the Appendix.

4.3.2 Including Drought Index and Winter Weather as Instrument

In Table 3, we show robustness checks for the inclusion of weather controls. Table 3 is identical to Table 1, except that both regressions include a drought index as a control for severe dry weather periods. In Table 3 Column (1), the regression has no month fixed effects, where Column (2) does include month fixed effects. The variables used to instrument price are identical to those in the regressions found in Table 1.

As with the previous robustness checks, these results are not statistically different from the results shown in Table 1. The first two drought categories, associated with "abnormally dry" conditions and "moderate drought", respectively, are both statistically significant and negative. This may indicate a reduction in household water consumption as a result of municipal water conservation campaigns, or that utilities draw upon sources of water that differ from those used in non-drought conditions. The lack of significance for the last two drought categories, associated with "extreme drought" and "exceptional drought" is likely due to their relative infrequency in the data set. Only 10% of the observations in the data have non-zero levels of category 3 drought, and less than 2% of observations have category 4.

First stage regression results of Table 3 are shown in Table 8 in the Appendix.

4.4 Further Analysis of Marginal Willingness to Pay

While these MWTP values are seemingly small, water hardness can vary dramatically across regions as discussed in the data section. To determine the total willingness to pay (TWTP) for households, we calculate this by multiplying our MWTP estimate from Table 1 Column (2) by the level of water hardness that exceeds 500 ppm for each county. The value of 500 ppm is used as a threshold TDS level as this is the EPA's secondary drinking water standard (Environmental Protection Agency, 2009), which is a non-mandatory water quality standard for water hardness.

We convert the monthly household TWTP estimates shown in Table 1, to an annual estimate by multiplying by twelve. The assumption that we make is that water softening products that are purchased by household will be consumed within a month. From our calculation, at the household level, the average annual TWTP is $11.7, with a standard deviation of $26.7. Half of households have no positive willingness to pay to reduce water hardness, due to their water not exceeding the 500 ppm limit. However, the 75th percentile value of TWTP is $9 per year, which rises to $118 per year at the 99th percentile. The highest household TWTP is found to be as high as $259.3 annually for Midland county, Texas, the county in our sample with the highest level of water hardness. Figure 9 shows box plots of the distribution of household annual willingness to pay estimates.

Extending these values to the county level is performed by multiplying the household annual TWTP estimates by the number of total households per county, providing a county-wide estimate of total willingness to pay. As before, 50% of the counties in our sample do not face water hardness that exceeds the 500 ppm secondary standard limit. The average annual county WTP is $ 1.2 million, with a standard deviation of $93.5 million. At the 75th percentile, the county-level TWTP is $0.2 million, rising to $19.6 million at the 99th percentile. The county with the highest county-level TWTP is Dallas county in Texas, with a TWTP of $33.9 million, due to its large population that faces relatively hard water. Figure 10 shows box plots of the distribution of county-level estimates of willingness to pay.

These household- and county-level estimates of TWTP can provide guidance to policy and decision makers in the operation of desalination plants as well as decisions on capital outlays for desalination plants and the choice of water sources. Because many freshwater aquifers are stressed, have limited capacity for recharge, and are expected to be drawn upon more heavily in the future, understanding the demand for water quality in hardness terms can be a critical component of understanding how to manage current and potential water sources. Currently, there is little guidance for utilities in terms of operation with the perspective of quality demands when it comes to optimal level of compliance with secondary standards such as water hardness.

In regions where the cost of providing softer water by blending in desalinated supplies is lower than the WTP of residents for that water, there are possibilities for welfare gains. The public provisioning of private water softness can improve societal welfare as it reduces the damages from the return to the system of extra sodium salts through individual water softening decisions (as discussed in Section 1).

5 Discussion and Conclusion

The purpose of this study is to determine revealed preference estimates of WTP for water quality control and water hardness reduction due to the increased presence of total dissolved solids (TDS) in the municipal water. We develop a random utility model in which consumers purchase water softening products to reduce water hardness in household water supplies. Extending this random utility framework, we calculate the WTP of the households to reduce water hardness and control for water quality. To conduct this analysis, we use a detailed weekly panel data of observed TDS in the municipal water and water softening product sales for the years 2006 to 2012. Our fixed effect estimations reveal that households would be willing to pay an average $11.7 per year to meet the EPA's secondary drinking water standard for TDS of 500 ppm. This average value is low because not all households face TDS levels above 500 ppm. Among households that do, the average annual total willingness to pay is \$11.7, and the highest total willingness to pay is as high as \$259.3. When estimates of total willingness to pay are performed at the county level, the average county-level willingness to pay among counties with TDS levels above 500 ppm is \$1.2 million, and is as high as \$33.9 million. These results provide important policy implications for the water utilities in their operation of current and potential desalination capital.

This analysis has shown that consumers do have a non-negligible willingness to pay for reductions in water hardness. This result sheds light on the optimal management of water hardness from the utility perspective. In general, the utilization of desalination plants in the United States has been divorced from an economic perspective; most utilities simply have a TDS measure target that they strive to meet through blending with fresh supplies, but use no information on consumer demands for softer water. This analysis can shed light on the desires that consumers have and provide evidence for optimal management of desalination capital, as well as desalination capital outlay decisions.

Further, the demand for water softness is not devoid from environmental impact. When consumers install and operate home water softening systems, they introduce *more* salinity to the water system than was there previous. In the operation of a home water softening system, magnesium and calcium cations are exchanged for sodium cations. When the sodium ions are exhausted in the ion-exchange beads, the softening process requires that the magnesium and calcium ions (that were removed from the household water) be removed from the beads, flushed from the system, and replaced again with sodium ions. This means that waste water with the same TDS is returned to wastewater systems, along with the sodium-containing water from the softened water. In a sense, a household with a home water softening system returns wastewater with twice the salinity that it received.

This can be contrasted with a utility operated desalination plant, where the waste salts can be managed at a single point. Given this perspective, the water hardness decisions of the utility, along with the demand for water softness at a household level become a unified system for local or basin-wide salinity management, which has implications beyond municipal level decisions.

Some challenges to this analysis include data paucity and additional outside options that households have in management of water hardness impacts. Further research should be conducted on larger samples and include other products that households consider, such as bottled water or reverse osmosis technologies. However, this is among, if not the first study to consider revealed preference analysis of willingness to pay for softer water supplies.

Growing populations, climate change, demographic change, and competition for scarce water resources are among the largest challenges for policy makers in the realm of water policy. Desalination can be a useful piece of an overall water management plan for a utility – one that is not impacted nearly as heavily as surface waters that will potentially face increasing competition. This analysis has shown that consumers have a non-negligible willingness to pay for reductions in water hardness. These results in conjunction with the impacts that consumer decisions in the realm of water softening can have on system wide outcomes should be considered when the operation of or planning of desalination sites is undertaken.

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6 Tables and Figures

Table 1: IV Regression Results: Households' WTP to reduce Water Hardness 2006-2012

	(1) IV-FE	(2) IV-FE
Price of Softening Products (US$)	-0.0922**	-0.0912**
	(0.0428)	(0.0445)
Damages Avoided (TDS)	0.00135***	0.00137***
	(0.000256)	(0.000271)
County Wages (Thousand US$)	0.000306	0.00676
	(0.00266)	(0.00532)
Constant	-12.38***	-12.47***
	(0.180)	(0.226)
MWTP	0.0147***	0.0150
	(0.0054772)	(0.0062808)
Month FE	No	Yes
Observations	982,378	982,378
No. Groups	153	153
No. Clusters	153	153
First-stage F statistic	111.99	90.74

Notes: Dependent variable: ln(HH share purchasing softeners)- ln(HH share not purchasing softeners).
Standard Errors (in parentheses) are clustered by counties. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
MWTP estimates calculated as -(Damages Avoided/Price) via the delta method.
First-stage F statistics exceed Stock-Yogo weak identification F test critical values. The critical F value for 10% maximal IV size with one endogenous variable and two instruments is 19.93.

Table 2: Robustness Check: Households' WTP to reduce Water Hardness 2006-2012, Winter Weather Instrumenting Price

	(1)	(2)
Price of Softening Products (US$)	-0.102**	-0.0962**
	(0.0439)	(0.0457)
Damages Avoided (TDS)	0.00138***	0.00139***
	(0.000254)	(0.000269)
County Wages (Thousand US$)	0.00115	0.00682
	(0.00284)	(0.00567)
Constant	-12.35***	-12.45***
	(0.191)	(0.232)
MWTP	0.0136***	0.0144**
	(0.0047022)	(0.0058568)
Month FE	No	Yes
Observations	955,734	955,734
No. Groups	153	153
No. Clusters	153	153
First-stage F statistic	52.22	77.75

Notes: Dependent variable: ln(HH share purchasing softeners)- ln(HH share not purchasing softeners).
Standard Errors (in parentheses) are clustered by counties. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
MWTP estimates calculated as -(Damages Avoided/Price) via the delta method.
First-stage F statistics exceed Stock-Yogo weak identification F test critical values. The critical F value for 10% maximal IV size with one endogenous variable and two instruments is 19.93.

Table 3: Robustness Check: Households' WTP to reduce Water Hardness 2006-2012, controlling for drought

	(1)	(2)
Price of Softening Products (US$)	-0.0898**	-0.0848*
	(0.0423)	(0.0449)
Damages Avoided (TDS)	0.00136***	0.00137***
	(0.000254)	(0.000270)
County Wages (Thousand US$)	0.000555	0.00692
	(0.00278)	(0.00559)
Drought Category 1	-0.000274**	-0.000310**
	(0.000121)	(0.000128)
Drought Category 2	-0.000295***	-0.000299**
	(0.000115)	(0.000140)
Drought Category 3	0.000130	0.000100
	(0.000301)	(0.000324)
Drought Category 4	-0.000344	-0.000438
	(0.000278)	(0.000287)
Constant	-12.39***	-12.49***
	(0.180)	(0.231)
MWTP	0.0151***	0.0161**
	(0.0057811)	(0.0074468)
Month FE	No	Yes
Observations	982,378	982,378
No. Groups	153	153
No. Clusters	153	153
First-stage F statistic	90.50	90.96

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable: ln(HH share purchasing softeners)- ln(HH share not purchasing softeners).
Standard Errors (in parentheses) are clustered by counties. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
MWTP estimates calculated as -(Damages Avoided/Price) via the delta method.
First-stage F statistics exceed Stock-Yogo weak identification F test critical values. The critical F value for 10% maximal IV size with one endogenous variable and two instruments is 19.93.

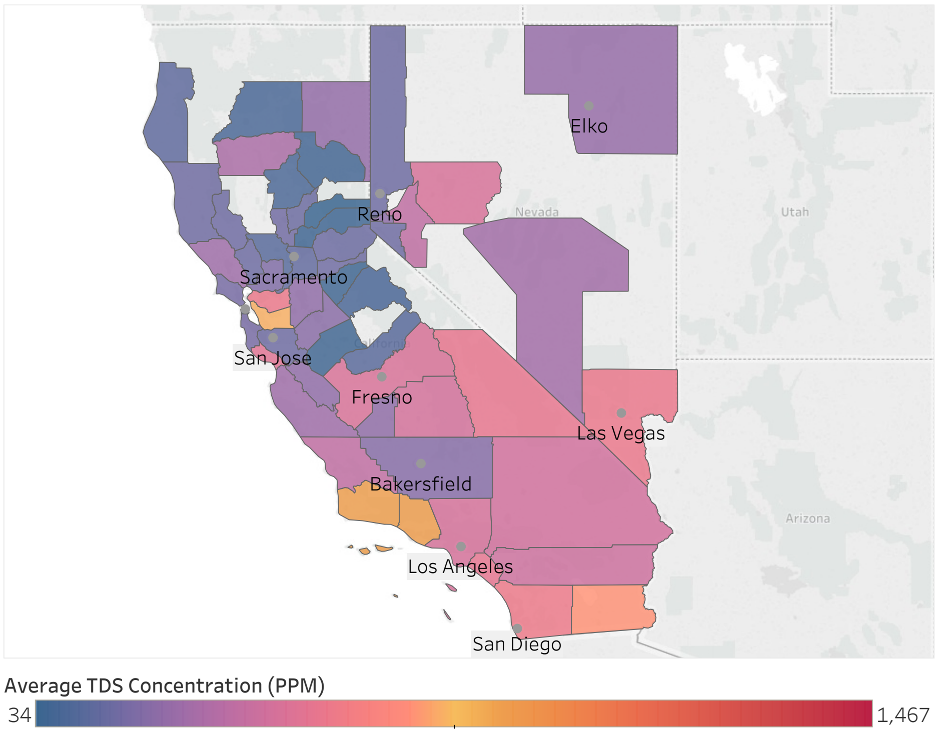

Figure 1: Average TDS Measures by County in Nevada and California 2006–2012
Source: Nevada Division of Environmental Protection – Drinking Water Watch
California Water Boards – Drinking Water Watch

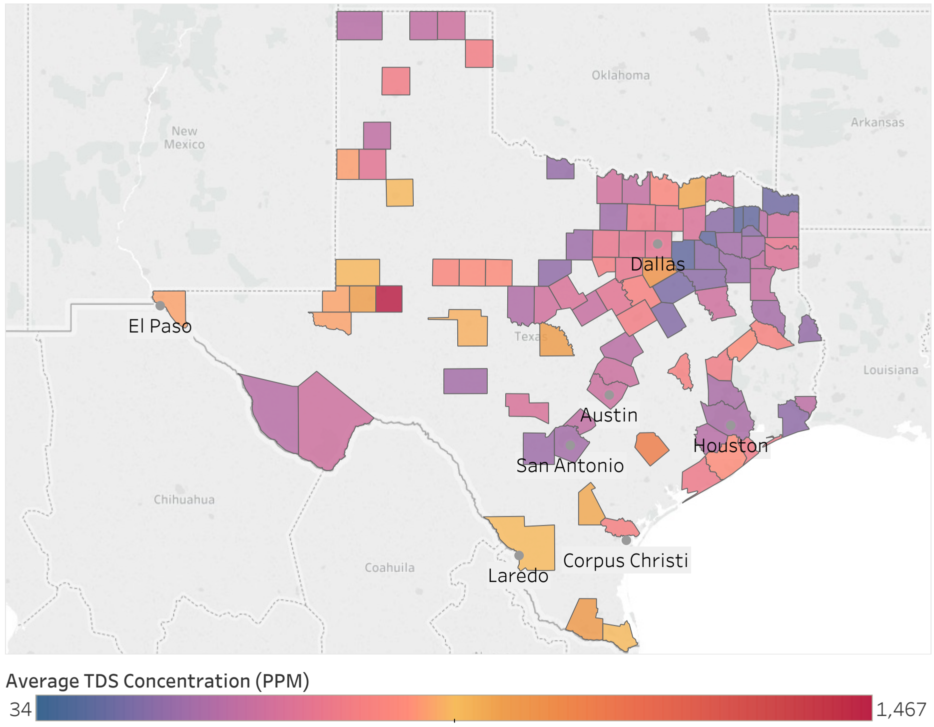

Figure 2: Average TDS Measures by County in Texas 2006–2012
Source: Texas Commission on Environmental Quality – Drinking Water Watch

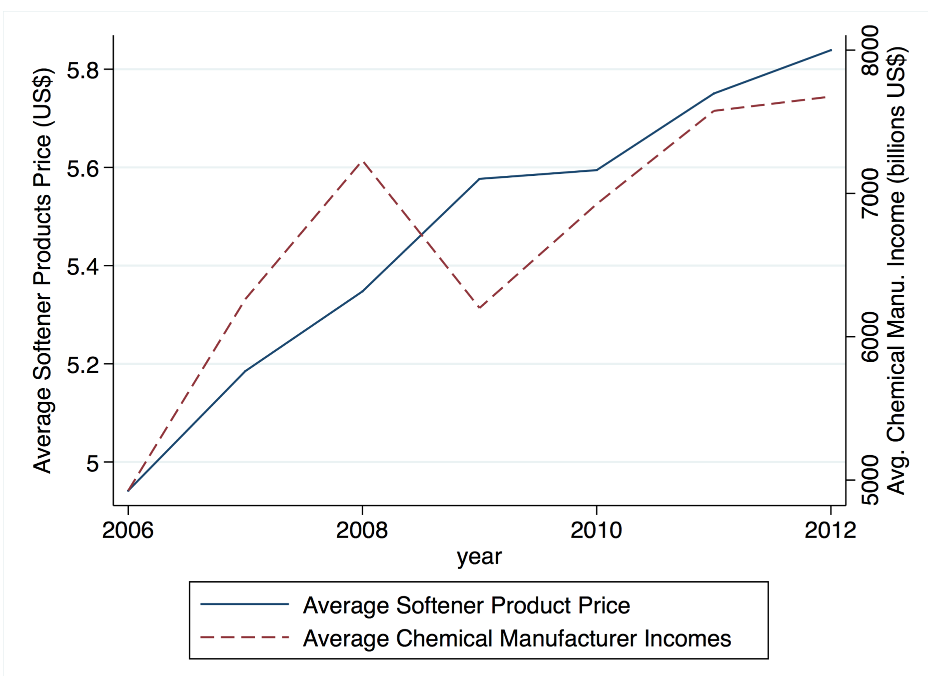

Figure 3: Average Price and Average Net US Chemical Manufacturers' Income , 2006-2012
Source: Nielsen Scanner Data and US Census Quarterly Financial report

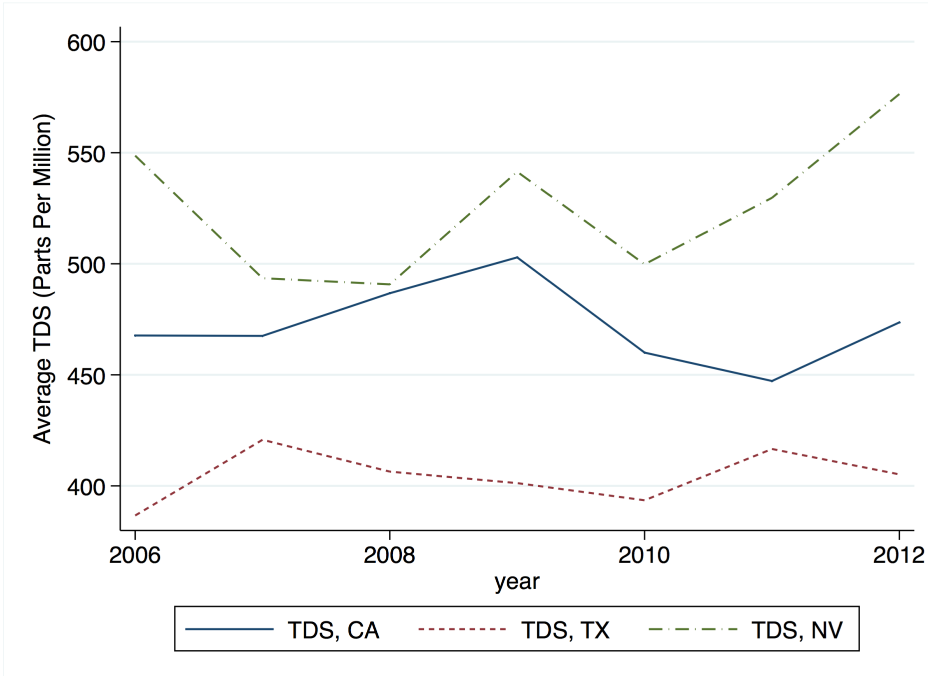

Figure 4: Average TDS Measures by State over Years, 2006-2012

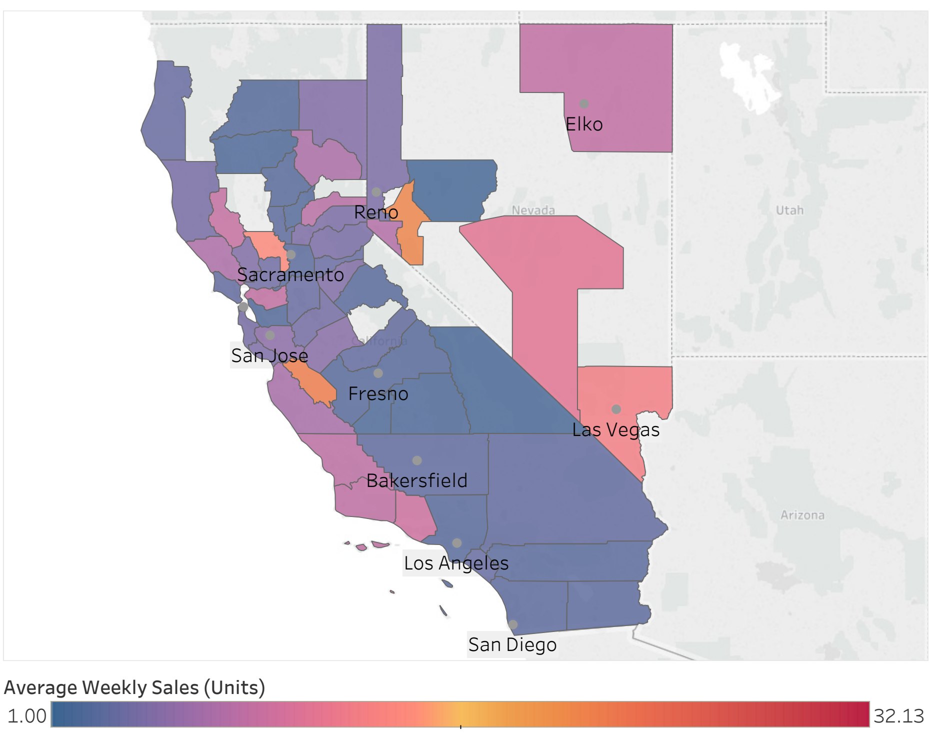

Figure 5: Average Weekly Unit Sales by County in California and Nevada 2006–2012
Source: Nielsen Retail Scanner Database

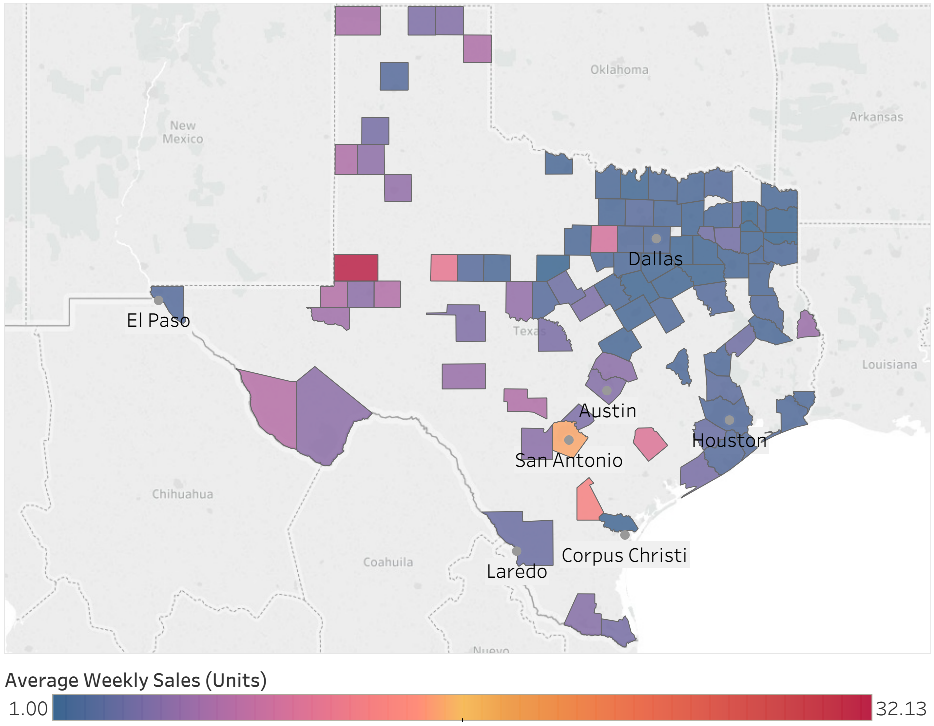

Figure 6: Average Weekly Unit Sales by County in Texas 2006–2012
Source: Nielsen Retail Scanner Database

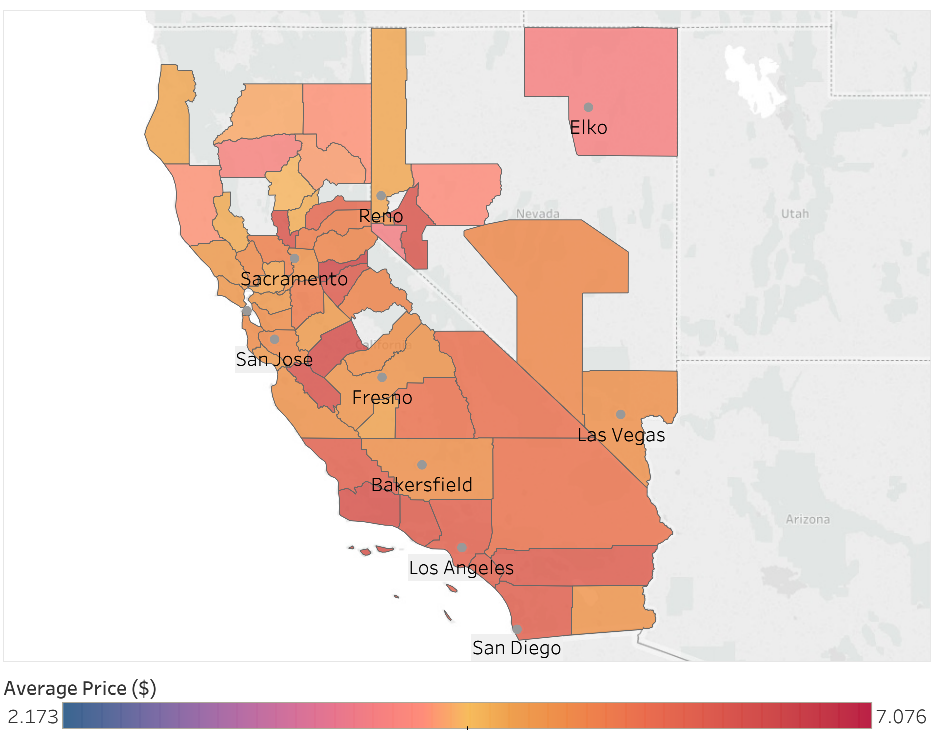

Figure 7: Average Price for Water Softening Products by County in California and Nevada 2006–2012
Source: Nielsen Retail Scanner Database

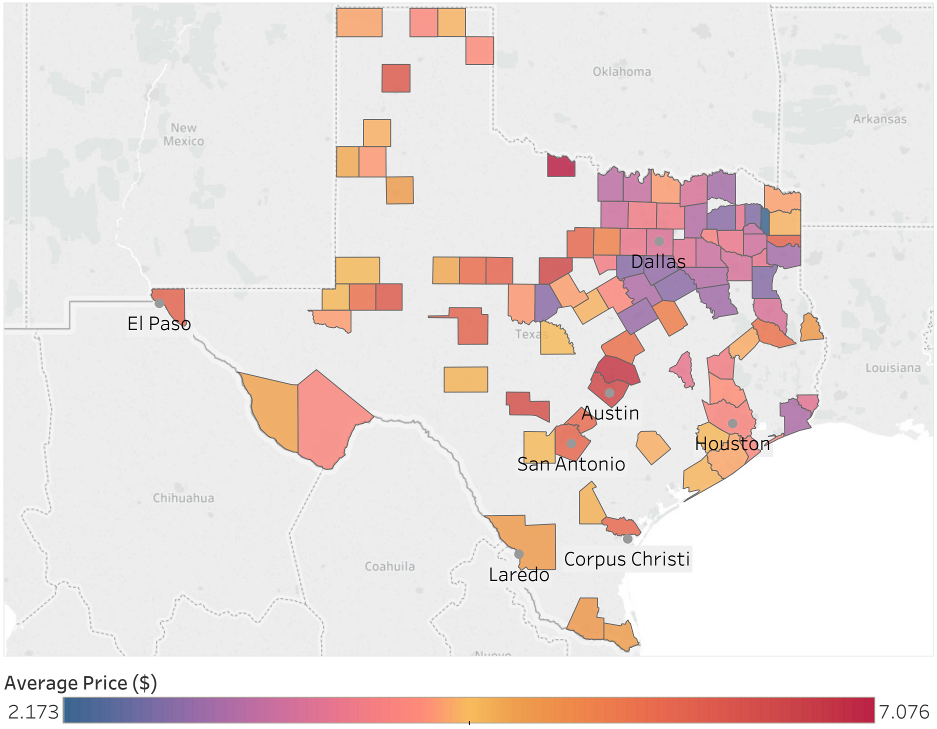

Figure 8: Average Price for Water Softening Products by County in Texas 2006–2012
Source: Nielsen Retail Scanner Database

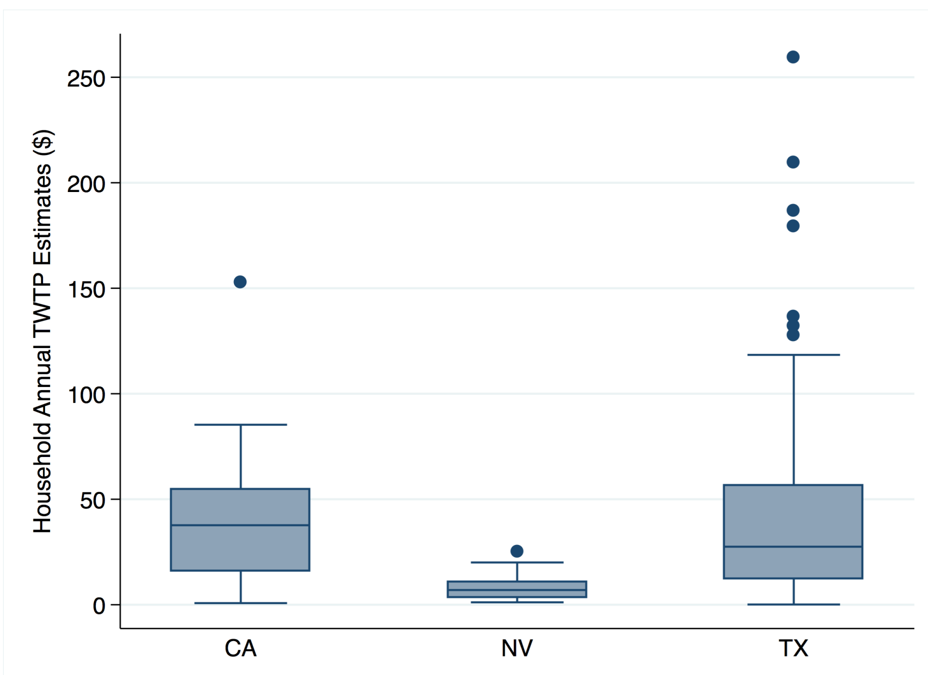

Figure 9: Box Plot of Household Annual Willingness to Pay Estimates

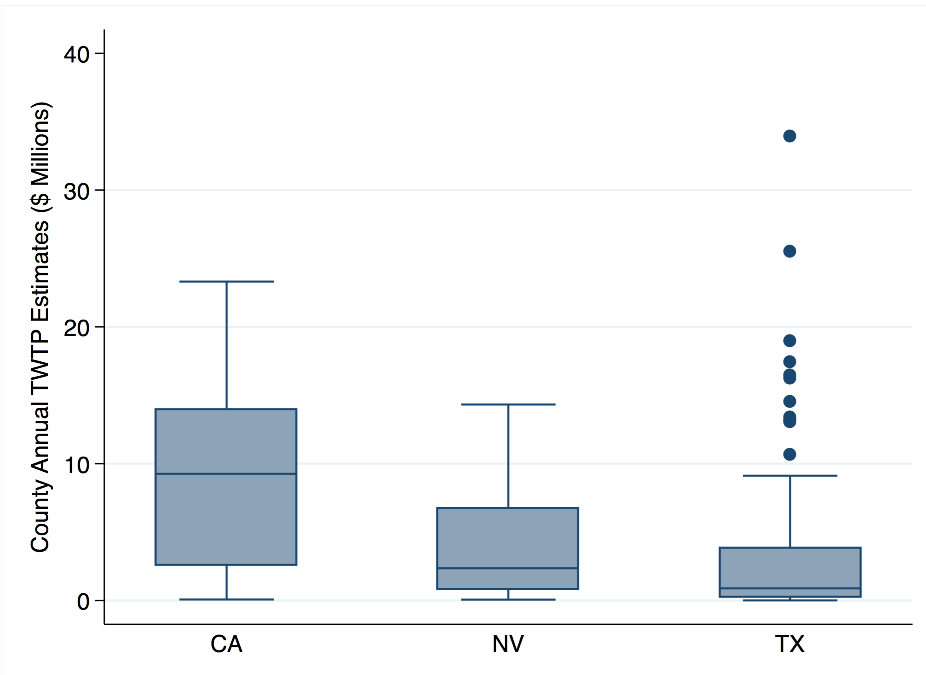

Figure 10: Box Plot of County-level Annual WTP Estimates

7 Appendix

7.1 Additional Tables

Table 4: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Water Softening Units Sold	1,257,236	5.506	10.332	1	462
Price	1,257,236	5.416	2.430	0.01	38.05
Occupied Housing Units	1,257,236	895,457.7	964,854.1	1,367	3,241,204
County Wages (Thousand US$)	1,257,236	1.43×10^7	1.62×10^7	7,792	6.26ex 10^7
TDS	941,385	472.812	200.739	0	2,500
Extreme Weather Events	1,222,122	259.466	385.550	0	1,511
Chemical Manufacturing Income	1,257,236	6,562.701	1,228.045	4,336	9,034

Table 5: Non-instrumented Regression Results: Households' WTP to reduce Water Hardness

	(1)
Price of Softening Products (US$)	-0.0415***
	(0.0112)
Damages Avoided (TDS)	0.00134***
	(0.000264)
County Wages (Thousand US$)	0.00557
	(0.00535)
Constant	-12.71***
	(0.104)
Month FE	Yes
County FE	Yes
MWTP	0.032323***
	(0.004354)
Observations	982,378
R^2	0.071
Number of groups (counties)	153
Number of clusters (counties)	153

Notes: Dependent variable: ln(HH share purchasing softeners)- ln(HH share not purchasing softeners). Standard Errors (in parentheses) are clustered by counties. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: First Stage Regression Results: Households' WTP to reduce Water Hardness 2006-2012

	(1)	(2)
Net Chemical Manufacturers' Income (billion US$)	0.000183***	0.000212***
	(0.0000228)	(0.0000270)
Chemical Income $\cdot$ NAAQS Index Dummy	-0.00000792	-0.00000206
	(0.00000800)	(0.00000851)
Damages Avoided (TDS)	0.000488	0.000485
	(0.000300)	(0.000305)
County Wages (Thousand US$)	-0.0101	-0.0179
	(0.00753)	(0.0110)
Constant	4.299***	4.376***
	(0.106)	(0.109)
Month FE	No	Yes
Observations	982378	982378
R^2	0.010	0.011
Number of Groups (counties)	153	153
Number of clusters (counties)	153	153
F statistic	111.99	90.74

Notes: Dependent variable: Price of softener products. Standard Errors (in parentheses) are clustered by counties. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: First Stage Regression Results: Households' WTP to reduce Water Hardness 2006-2012

	(1)	(2)
Net Chemical Manufacturers' Income (billion US$)	0.0001826***	0.0001972***
	(0.000022)	(0.0000243)
Extreme Winter Weather Events	0.0001551***	0.0001558***
	(0.0000261)	(0.0000267)
Damages Avoided (TDS)	0.0005438*	0.00054*
	(0.0003017)	(0.0003053)
County Wages (Thousand US$)	-0.0147312*	-0.0174637*
	(0.0080874)	(0.010012)
Constant	4.319***	4.299***
	(0.1053)	(0.1087097)
Month FE	No	Yes
Observations	955,734	955,734
R^2	0.0025	0.0017
Number of groups (store-products)	153	153
Number of clusters (stores)	153	153
F statistic	52.22	77.75

Notes: Dependent variable: Price of softener products. Standard Errors (in parentheses) are clustered by stores. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: First Stage Regression Results: Households' WTP to reduce Water Hardness 2006-2012

	(1)	(2)
Net Chemical Manufacturers' Income (billion US$)	0.0001836***	0.0002131***
	(0.0000231)	(0.0000261)
Chemical Income · NAAQS Index Dummy	6.89 x 10^{-6}	6.52x 10^{-7}
	(7.97 x 10^{-6})	(8.24 x 10^{-6})
Damages Avoided (TDS)	0.0004802	0.0004839
	(0.0003046)	(0.0003082)
County Wages (Million US$)	-0.008021	-0.014574
	(0.0069434)	(0.0101439)
Drought Category 1	-0.000192	-0.0005705
	(0.000358)	(0.0004339)
Drought Category 2	0.001306***	0.0012942***
	(0.000455)	(0.0004192)
Drought Category 3	-0.002639***	-0.0024285***
	(0.000233)	(0.0002259)
Drought Category 4	-0.0003351	-0.0005267
	(0.0005974)	(0.0005581)
Constant	4.267***	4.324***
	(0.1034)	(0.1053)
Month FE	Yes	Yes
Observations	982,378	982,378
R^2	0.0061	0.0025
Number of groups (store-products)	153	153
Number of clusters (stores)	153	153
F statistic	90.50	90.96

Notes: Dependent variable: Price of softener products. Standard Errors (in parentheses) are clustered by stores. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.