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Estimating Water Demand Elasticity at the Intensive and Extensive Margin

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Abstract

I exploit a unique panel dataset of monthly water metering records and annual landscape choices from satellite data for more than 170,000 households over 12 years to estimate price elasticity at the intensive and extensive margin. Higher water prices significantly increase the probability of adopting water conserving landscapes. The extensive margin only accounts for 2-3% of total elasticity in the short run and this increases to 6-24% in the long run. As cities transition away from water-intensive landscapes aggregate demand becomes less elastic and future conservation in the face of droughts becomes more challenging.

JEL classification: Q21, Q25, Q54

Keywords: water demand; extensive margin elasticity; satellite data; landscape conversion

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1 Introduction

Public water utilities, particularly those in arid regions such as the western United States, face pressure to fulfill demand with diminished and uncertain supplies. As of the summer of 2014 California was suffering through one of the worst droughts on record, which prompted California's governor to declare a state of emergency in January 2014.[1] Internationally, the east coast of Australia recently experienced a one thousand year drought, and the west coast is facing a new paradigm of a permanently strained water supply. Despite the growing severity of water scarcity there are glaring gaps in the economic analysis of water demand, particularly with respect to the complementary goods that use water as an input. Demand for municipal water is primarily derived from complementary goods, such as washing machines, toilets, showers, and gardens that collectively comprise the capital stock for water. In the residential sector landscape is the most important complementary good. The lack of knowledge is concerning given the resources specifically devoted to upgrading complementary goods, as evidenced by the approximately $450 million spent on removing turf grass by the Metropolitan Water District of Souther California.

Adjustments to the water capital stock represent changes along the extensive margin, while the intensive margin constitutes behavioral changes conditional on a fixed set of complementary goods. The conventional treatment of the extensive margin in the water demand literature relies on the assumption that households cannot fully respond to prices in the short run due to frictions that prevent the immediate replacement of complementary goods. Therefore, the long run equilibrium, where full adjustment takes place, encompasses changes along both the intensive and extensive margins. While explicit treatment of the capital stock has been studied in energy markets (Dubin and McFadden, 1984; Vaage, 2000; Goulder et al., 2009; Knittel and Sandler, 2010; Gillingham, 2012, 2014) there is little research devoted to changes in the water capital stock.

This paper has three objectives. First, in order to isolate the intensive margin elasticity

[1] See details at http://ca.gov/drought/.

I estimate conditional demand functions for households that maintain a fixed landscape over the course of the sample. Second, I examine the role of water rates on changes in the capital stock of water durables through a discrete choice model of landscape conversion. Combining the results of the discrete choice model with estimates for the effect of landscape conversions on water demand produces explicit estimates of the extensive margin elasticity. Lastly, I evaluate the role of landscape conversions on long run demand. The primary barrier to addressing these objectives in the literature is the need to observe changes in both water consumption and landscape over time. My approach merges a spatially explicit time series of satellite data capturing vegetative cover at the parcel level to monthly water metering records and structural characteristics of the home. The result is a novel panel dataset of nearly 25 million observations of water and landscape for over 170,000 households in City of Phoenix. This is complemented with a dataset on landscape, housing characteristics, and water rates for over 370,000 households spanning eight municipalities in the Phoenix metropolitan area.

The distinction between the intensive and extensive margin of water demand elasticity in the water economics literature is addressed through the divergence of short-run and long-run elasticity. Early water demand research employs partial adjustment models that include lagged consumption in the demand equation (Billings and Agthe, 1980; Carver and Boland, 1980; Dandy et al., 1997). The long run elasticity is calculated by dividing the price coefficient by one minus the autoregressive, or flow adjustment, coefficient. More recent studies improve on this general approach and using more advanced econometric methodology and micro-level data (Pint, 1999; Nauges and Thomas, 2003; Bell and Griffin, 2011). The studies that apply a variant of the flow-adjustment model find that the autoregressive coefficient is generally positive and less than unity, producing values for long-run elasticity that exceed the short-run elasticity in absolute value. The notion that demand is more elastic in the long run is a standard result from economic theory, and implies that there are meaningful reductions in water consumption along the extensive margin by replacing complementary goods such as turf lawn. The partial adjustment models are appealing because they provide simple estimates for both short-run and long-run elasticities, but they also impose significant structure on the adjustment process. Caballero and Engel (1992) suggest that partial adjustment models do not appropriately model large shocks, and Kamerschen and Porter (2004) find that a simultaneous equation model outperforms a flow adjustment model for electricity demand. The limitation of the flow-adjustment models is that they estimate changes along the extensive margin implicitly through a parametric specification of demand. The contribution of this research to the literature is to explicitly estimate both intensive and extensive margin elasticity.

I focus on landscape due to it's critical role in residential water demand, which is defined by three important characteristics. First, irrigation for landscapes consumes massive quantities of water. In cities with an arid climate, such as the southwestern United States, outdoor water use represents 50% or more of aggregate demand, of which up to 90% is for landscape (Dandy et al., 1997; Wentz and Gober, 2007; Balling et al., 2008). Second, residential irrigation is a discretionary use as opposed to water for drinking and sanitation.[2] Lastly, demand for landscape irrigation is countercyclical to supply with demand rising during droughts and heat waves when water supplies are stressed.

Understanding the interaction between landscape and water demand has important implications for water management during droughts. There are multiple studies that measure the efficacy of demand side management policies that come into effect during water shortages (Grafton and Ward, 2008; Klaiber et al., 2014; Mansur and Olmstead, 2012; Nataraj and Hanemann, 2011). One of the most common command and control policies is limiting outdoor water use for lawns and gardens during times of drought. Estimates of the welfare loss from using mandatory restrictions as opposed to prices range from $96 to $152 per household per season (Grafton and Ward, 2008; Mansur and Olmstead, 2012). Water

[2]This limits concerns about pricing water that is considered a human rights. The United Nations, through Resolution 64-292, deemed clean drinking water and sanitation to be a human right, while water for discretionary uses is widely considered to be an economic good (Perry et al., 1997).

managers face the challenge of quickly reducing demand under the constraint that water consumption is a function of the quasi-fixed complementary goods. Given the importance of managing outdoor water use during droughts, and the welfare loss associated with traditional policies, it is critical to assess the ability of the price mechanism to curtail outdoor water use through landscape conversions. Despite the importance of demand for residential irrigation during drought conditions, there is no research that directly incorporates changes in landscape into water demand by modeling the landscape conversion decision.[3] The decision to maintain a lush green landscape, or switch to drought-resistant vegetation, alters the behavioral response to water rates and weather conditions leading to structural changes in demand.

Households that maintain a dry landscape are significantly less price elastic than the general population. In aggregate households that keep a wet landscape are less price elastic though this stems from a group of households that receive subsidized irrigation water. Excluding this group the intensive margin elasticity for wet households is larger than the total elasticity for the general population, though this difference is not statistically significant. This result indicates that more elastic outdoor use (Barrios García and Rodríguez Hernández, 2008; Martínez-Espiñeira and Nauges, 2004; Mansur and Olmstead, 2012) dominates the fixed commitment to wet landscapes.[4]

In a discrete choice model I estimate factors that impact the decision to convert from a wet to dry landscape. The short run effect of price on landscape conversion is statistically significant but small in magnitude, comprising 2-3% of total elasticity, whereas the long run effect is larger in magnitude ranging between 6-24% of total elasticity. The results are robust to several model specifications and a boundary discontinuity analysis that restricts the sample to households near utility borders. Neighbors' landscape choices are also positive and significant determinants in the conversion decision. This result reinforces anecdotal evidence

[3]Tchigriaeva et al. (2014) does address heterogeneity due to landscape, but does not incorporate changing landscape over time.

[4]The intuition behind this result is simple; households will not stop drinking and bathing as the price of water goes up but they are more likely to reduce discretionary uses such as irrigation.

of the importance of social peer effects that lead to the transition towards drought-resistant landscapes as social norms evolve. The results demonstrate that the price mechanism, as opposed to commonly employed mandatory watering restrictions, can effectively curtail outdoor water use; an outcome that economists have shown improves social welfare (Grafton and Ward, 2008; Mansur and Olmstead, 2012).[5] However, the price response is not immediate, which has implications for water managers required to immediately reduce water demand during critical droughts.

Landscape conversions have long run implications for water demand since water-intensive landscapes act as an additional source of supply that can be drawn down during times of drought through reductions in irrigation. The empirical results indicate that demand parameters such as the responsiveness to price and weather variables evolve as the composition of residential landscapes changes. As consumers transition to water-efficient landscapes aggregate demand becomes less elastic, and there will be less capacity to rapidly reduce consumption during droughts. Since climate change is anticipated to increase the probability of severe sustained droughts, it is critical to measure the distribution of green landscapes and understand the heterogeneity of consumer response to policy interventions. Utilizing satellite data adds depth to water demand estimation and informs policy makers about the long run effects of rate increases, and how consumers will respond to future price changes.

2 Background & Data

2.1 Water and landscape in Phoenix

Phoenix lies in an arid climate and its history is inextricably tied to importing water from external sources. The prodigious water infrastructure projects conducted by the U.S. Bureau of Reclamation in the early 20th century enabled the development of a strong agricultural sector by securing water rights from the Colorado via the Central Arizona Project, with additional water sourced from the Verde and Salt Rivers via the Salt River Project.

[5] One advantage of using mandatory restrictions instead of prices during droughts is that restrictions produce an immediate decrease in consumption, while consumers may take time to adjust to prices.

The experience of engineering solutions for water scarcity by transporting and storing vast volumes of water has been replicated in many Western regions, and facilitated rapid population growth in the southwestern United States.[6] During Phoenix's transition into a major metropolis in the second half of the 20th century, the water rights freed up from converted agricultural land allowed residential developments to establish lush green landscapes with immense water requirements. As water rates rise and environmental issues related to water scarcity become more prominent, households are now converting their green landscapes to drought-resistant native vegetation, known as xeriscape or xeric landscape.

Supply constraints are stressed during the summer peak demand period, and for this reason I focus on summer demand, defined as June through September. Additionally, the link between landscape and water demand is strongest during the summer.[7] Landscape conversions normally take place from October-May in order to avoid the extreme heat of the summer months making observations of the landscape at any point between May and September good indicators of the landscape during the summer season. Additionally, while summer landscape can be viewed as an irreversible decision due to the high fixed costs of conversion; winter landscape does not have the same features. Bermuda turf, the most common grass in the Phoenix area, lies dormant in the winter and consumers need to reseed each season in order to have a green lawn in the winter.[8] Therefore some households' green summer lawns will appear dry in the winter even if they still have turf grass. The reverse situation is not true since dry summer landscapes generally require removing turf grass, making summer landscape an appropriate measure of the water capital stock.[9]

A key feature of water demand in the Phoenix metropolitan area is the Salt River Project

[6] According to data from the 2010 census, Phoenix was the sixth largest city in the U.S., with nearly 1.5 million inhabitants and a metro area that includes 6 other municipalities with over 200,000 people.

[7] Additionally, there is evidence summer water demand is inherently different and lumping winter and summer demand together is not appropriate (Dalhuisen et al., 2003; Espey et al., 1997; Bell and Griffin, 2011).

[8] Average yard size is approximately 7000 square feet (lot size less square footage of house). If half of that the yard is turf and conversion costs range between \$1.5-\$2.5 per square foot, then conversion costs range from \$5,250-\$8,750; from http://www.mesaaz.gov/conservation/convert.aspx.

[9] Households can refrain from watering their lawns in the summer, which will have the same satellite signature as a xeric landscape.

(SRP). The SRP provides irrigation water to households within its service area through a system of canals. Water is delivered to households approximately every two weeks in the summer via flood irrigation, where the lawn is flooded with several inches of water. Residential customers pay an annual fee of roughly $60 for this service that covers a base quantity of water, which is sufficient for most households' landscape irrigation. Not all households within the SRP service area sign up for this service since the flood irrigation requires a depressed lawn in order to hold the water and is known to attract pests. Households within the SRP water still use municipal water for indoor use, filling pools, and supplemental landscape irrigation. Since the SRP fundamentally affects water use on both the intensive and extensive I incorporate this source of heterogeneity in the analysis. See Figure 1 for the geographical boundaries of the SRP.

2.2 Data

Data limitations constrain existing empirical studies of water demand. Many studies estimate long-run demand using time series data aggregated for entire municipalities (Bell and Griffin, 2011; Carver and Boland, 1980; Musolesi and Nosvelli, 2011; Nauges and Thomas, 2003). Household level datasets often have small sample sizes and are recycled for different research applications (Agthe and Billings, 1980; Billings and Agthe, 1980; Agthe et al., 1986). The lack of data prevents researchers from observing important complementary goods and water consumption simultaneously; a goal established early in the literature (Agthe et al., 1986). In order to incorporate capital goods into water demand I utilize a time series of satellite data obtained from the National Aeronautics and Space Administration's (NASA) Landsat 5 Thematic Mapper series, henceforth referred to as Landsat.[10] The Normalized Difference Vegetation Index (NDVI), one of the most common measures of vegetative cover, serves as a proxy for landscape choices (Aggarwal et al., 2012; Stefanov and Netzband, 2005; Stefanov et al., 2001).

Since Phoenix is an arid environment with few cloudy days I can acquire high-quality

[10] Landsat data, publicly available for download from the USGS Glovis system at http://glovis.usgs.gov/.

images for each year in summer and winter. For each year I use two images per season to capture the average landscaping patterns, and to limit the impact of random weather events.[11] Each image represents an observation at one point in time and there are several steps to process the data to ensure comparability over time and space, described in detail in Section A.1 of the Appendix. The final landscape dataset is a panel where the cross-sectional unit is geographical location and the time series is the year. Although there is a continuum of landscaping options in the Metro area the two overarching categories are drought-resistant native plants, (xeric), and lush green vegetation, usually comprising turf lawn, defined as mesic. The key distinction for this research is that xeric landscapes are much less water-intensive than mesic landscapes. Exact classification is not the primary concern; rather I develop a variable that captures the general water requirements for landscaping at the parcel level. Since NDVI captures the intensity of vegetation for a given area, and water is required to maintain almost all vibrant green vegetation in Phoenix, the index is appropriate for this coarse classification. For the rest of the paper, xeric and dry will be used interchangeably to define low-NDVI landscapes as will mesic, green, and wet for high-NDVI landscapes. In order to obtain accurate landscape classifications I compare quantiles of NDVI, which ranges from -1 to 1, with the data from a widely-cited existing remote sensing study Stefanov et al. (2001).[12] NDVI performs well in classifying landscape at the tails of the distribution, and is less accurate in the middle of the distributions. Table A.2 displays the comparison of NDVI quantiles with the classification of Stefanov et al. (2001).

A limitation of validating the use of NDVI for landscape classification in this study is that data in Stefanov et al. (2001) are only available for one year, and the purpose of this research is to observe both water and landscape over time. Comparing quantiles of NDVI over time is problematic because NDVI is correlated with time-varying weather conditions.In order to improve comparability of NDVI across years I regress NDVI on weather variables to parse out the variation due to weather. Section A.2 [CHECK] of the Appendix describes the

[11] There were two valid images in the summer for every year except 1998, where only one image was used.

[12] As of 10/15/2015 Stefanov et al. (2001) had 282 citations in Google Scholar.

normalization procedure and presents results from the weather normalization regressions. Using the residuals from the weather normalization regressions I create quantiles over the full distribution of normalized NDVI. Weather data are collected from three sources: the National Oceanic and Atmospheric Administration's National Climatic Data Center, Oregon State University's PRISM Climate Group, and the University of Arizona's AZMET Weather Data.[13]

In addition to the landscape and weather data I obtain geo-referenced parcel characteristics from the Maricopa County Assessor, socioeconomic data and census boundaries from the U.S. Census, and water metering records from the City of Phoenix. These data sources produce two final datasets: a monthly panel of water metering records for 172,314 households in the City of Phoenix and a yearly panel of landscape choices for 370,781 households in the Phoenix metro areas that span eight distinct municipal water providers. Figure 1 shows a map of the sample area including the parcels, metropolitan areas (with Phoenix outlined in bold red), and the border of the Salt River Project.

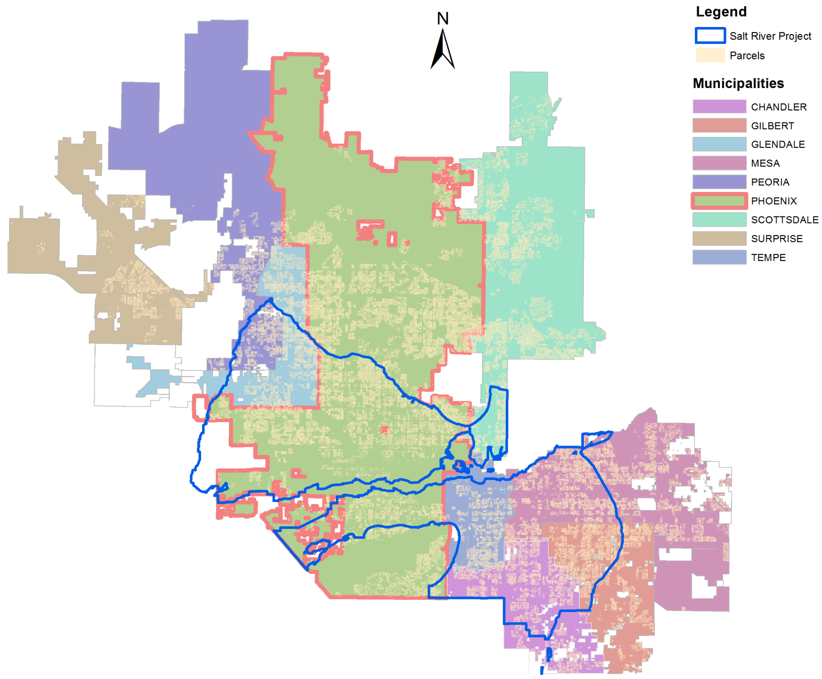
Water Dataset

Water consumption data are only available within the City of Phoenix (CoP), and therefore all water demand models are estimated exclusively within CoP. Water consumption is observed though monthly metering records for single-family homes in the CoP Water Department's service area from 1998-2009. This rich dataset is a balanced panel containing nearly 25 million observations. Since this period corresponds with the collapse of the housing market, using data from *active* accounts ensures that dry landscapes in the CoP data are not merely neglected lawns of foreclosed homes. I spatially merge NDVI, structural housing characteristics, selected census demographic variables, and weather variables for each single family residential parcel in CoP to the time series of water metering records and water rates.[14] The resulting dataset is a panel with two sources of time-varying data. Water

[13]The data are all publicly available at the following websites: http://www.ncdc.noaa.gov/ (NOAA), http://www.prism.oregonstate.edu/ (PRISM), http://ag.arizona.edu/azmet/azdata.htm/ (AZMET).

[14]According to a confidentiality agreement with the City of Phoenix I merge the NDVI values at the parcel level and then City officials attached it to an anonymous identifier representing a water account.

Figure 1: Phoenix Metro Area



Note: The map shows the the parcels used in the analysis along with the municipality geographies and the SRP boundary.

consumption, water rates, and weather all vary at the monthly level, whereas NDVI varies annually. Structural characteristics of the house are recorded at the time of the sale and thus can vary over time, but the vast majority of the structural features of the house remain constant during the sample.[15]

In the CoP data I form three groups based on the time series of satellite data: Wet, Dry, and Mixed. The Wet and Dry groups contain households that, for every year in the sample, have a normalized NDVI value above the 80th percentile or below the 30th percentile respectively.[16] The Mixed group makes up the remainder of the sample and consists of households that converted from wet to dry landscapes, converted from dry to wet, or have at least one normalized NDVI observation that lies between the 30th and 80th percentiles. It is possible

[15] I can only observe changes in structural housing characteristics for homes that are sold multiple times in the sample, which comprise 43% of the sample. Within this subset of homes most structural characteristics do not change. For example only 0.8% of households in the sample are observed either adding or removing a pool.

[16] The results from the classification diagnostics in Section A.3 of the Appendix reveal that performance of NDVI for dry extends out from the tails to a greater degree than for wet. For this reason, and in order to obtain a relatively balanced group for wet and dry, I have non-symmetrical cutoffs for landscape classification. Additionally, this classification allows for similarly sized groups for Wet and Dry.

that the Mixed group has a combination of turf grass and native vegetation, but I cannot distinguish different landscape patterns within a parcel with the Landsat remote sensing data. To clarify the notation, wet/dry are general descriptors or refer to an observation at one point in time, whereas the capitalized versions Wet/Dry correspond to the formal groups in the sample that are consistently wet or dry. Examining summary statistics for each of the three landscape groups in Table 1a reveals that the landscape groups differ by several variables that impact water consumption, and may affect demand elasticity. Unsurprisingly, the Wet group on average uses 40% more than the Mixed group and roughly twice as much as the Dry group. Additionally, the Wet group lives in larger, older, and more expensive homes. Therefore there may be unobservables driving differences in water demand as well, and for these reasons I run models that control for selection into each landscape group.

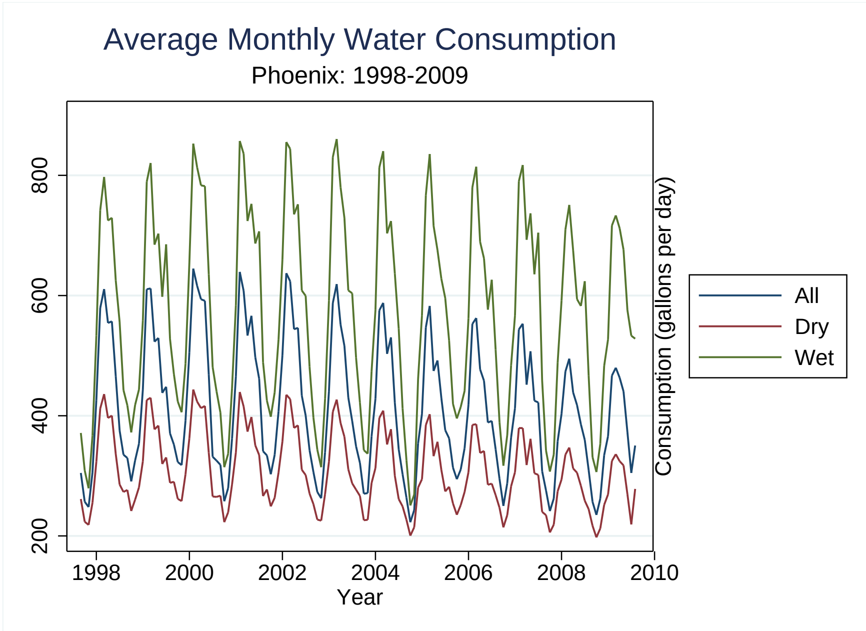
In addition to the classification diagnostics with respect to the Stefanov et al. (2001) study, merging the landscape data with water consumption records confirms that the satellite data performs well as a proxy for landscape. Figure 2 shows the average historical consumption for the three groups. While all groups have a cyclical dimension to consumption, seasonality is much stronger for the Wet group, and in fact these households are the primary driver of peak summer demand. In the winter months all three groups converge while there are extreme differences in summer usage. To put these consumption figures in perspective according to the U.S. Environmental Protection Agency average household consumption is approximately 300 gallons per day.[17] So while the Dry group still uses more water in the summer relative to the U.S. average, the Wet group's summer usage is more than twice the average U.S. household.

Landscape Conversion Dataset

In order to augment the CoP dataset and increase cross-sectional variation in water rates I incorporate data from the surrounding municipalities in the Phoenix metropolitan area (Metro) when estimating the landscape conversion model, which constitutes the central

[17]Estimates from the U.S. Environmental Protection Agency are available at http://www.epa.gov/watersense/our_water/water_use_today.html.

Figure 2: Water Consumption by Landscape Group



Note: Wet and Dry groups are determined by those that were continuously above the 80th percentile and below the 30th percentile of NDVI respectively. The Mix group is the remainder of the sample.

component of the extensive margin. I spatially merge the time series of NDVI, structural housing characteristics, selected census demographic variables, and weather variables to each single family residential parcel in the Metro area. In order to avoid the foreclosure problem for the Metro data, for which there are no water consumption records, I focus on the period 1998-2006 prior to the financial crisis that hit Phoenix particularly hard (see Figure A.1). I also drop all houses that were built after 1998 to maintain consistency with the CoP water data. Lastly I merge in historical water rates data for each of the eight municipalities as well as policies related to rebates for turf conversion. The resulting dataset is a panel with the parcel as the cross sectional unit and a year as the time series.

Similar to CoP each of the water utilities employs some form of increasing block pricing. Since the price a household faces depends on consumption I conduct an out of sample prediction for each household's water consumption from a regression of water on housing characteristics using the CoP sample. This assumes that the relationship between house size, pool ownership, and other characteristics is similar for CoP and the other municipalities. Using the estimated consumption and each municipality's rate structure I calculate the average and marginal price for each household. I also use the maximum volumetric price for each municipality, which is not a function of household consumption. The maximum price is paid by high users who have substantial outdoor water use making it a relevant metric for the cost of water in the landscape conversion decision. Table 1b shows the the averages for relevant variables by municipality.

Table 1: Summary Statistics

(a) Water Dataset - City of Phoenix

Landscape Group	Water Use	Lot	House Price	Year Built	Pool	Households
Mix	22.1	8,869	128,760	1972	0.34	140,642
Dry	15.5	7,739	125,936	1980	0.32	13,829
Wet	30.9	13,780	220,510	1958	0.42	17,847

(b) Landscape Dataset - Metro Area

City	Convert Rate	AP	MP	MxP	Rebate	Lot	House Price	Year Built	Households
Chandler	1.2	1.38	1.01	1.39	200	7,721	141,578	1986	31,610
Gilber	0.6	1.28	0.69	0.93	0	9,559	169,996	1992	23,069
Glendale	2.6	0.92	1.08	1.39	375	9,005	135,303	1981	36,960
Mesa	1.9	0.65	1.78	1.81	0	8,255	138,530	1985	9,739
Peoria	2.1	1.41	2.1	2.51	1,650	8,501	138,461	1989	21,573
Phoenix	3.1	1.09	1.8	1.8	0	9,276	135,912	1971	194,193
Scottsdale	1.2	0.73	1.71	1.78	625	14,114	280,250	1981	37,812
Surprise	0.3	1.99	1.61	1.61	0	8,056	160,489	1994	4,180
Tempe	2.6	0.84	0.71	0.87	150	8,312	125,658	1967	11,645
All	2.4	1.08	1.56	1.68	218	9,512	153,346	1977	370,781

Note: In panel (a) water use is in ccf/month, Lot is square feet, House price is in dollars, Pool is the fraction of households with a pool. In panel (b) Convert Rate is the percentage of households that converted in that city, AP is average price per ccf, MP is marginal price per ccf, MxP is the maximum price per ccf, and Rebate is the average maximum rebate for turf conversion in dollars. Variables present in both panels have the same units.

3 Estimation Strategy

Observing changes in the capital stock and water use over time enables demand estimation on the intensive and extensive margin. While there are many changes on the extensive margin with respect to water demand, I focus on landscape. Landscape is the primary discretionary use in urban water demand, making this analysis particularly relevant for policy. Additionally, reliable time series data for landscape proxies are readily available, allowing the analysis to be extended to different locations.[18] The framework can be applied to other goods (toilets, dishwashers, etc.) such as washing machines or toilets given data

[18] Even though Landsat data are available across the United States, Phoenix provides a particularly conducive study area for three reasons. First there are many clear days free of cloud cover, second parcels are relatively large, and lastly the differences in landscape are stark.

availability. In this context I define the intensive margin as changes in water consumption holding landscape constant; changes in the capital stock for other goods are incorporated into the intensive margin. For these reasons, elasticity estimates for the intensive margin should be considered upper bounds, while the extensive margin estimates are effective lower bounds.

To simplify the notation assume there are only two types of landscape: wet and dry (ignoring the mixed group for now).[19] Similar to Dubin and McFadden (1984) I disaggregate water demand into probability weighted averages conditional on landscape. In this setting average water consumption is represented as $E[w] = P_{dry}E[w|dry] + P_{wet}E[w|wet]$, where $E[w|dry]$ and $E[w|wet]$ are the conditional expectations of water consumption given a dry and wet landscape; and P_{dry}, P_{wet} are the probabilities of dry and wet landscapes.

$$\begin{aligned}\epsilon(E[w], p_w) = {} & \epsilon(E[w|dry], p_w)P_{dry}\left(\frac{E[w|dry]}{E[w]}\right) \\ & + \epsilon(E[w|wet], p_w)P_{wet}\left(\frac{E[w|wet]}{E[w]}\right) \\ & + \epsilon(P_{dry}, p_w)P_{wet}\left(\frac{E[w|dry] - E[w|wet])}{E[w]}\right)\end{aligned} \tag{1}$$

The elasticity of x with respect to y is $\epsilon(x, y)$, where w is the quantity of water and p_w is the price of water. The first two terms are the probability weighted averages of the conditional elasticities for dry and wet households respectively, and the last term captures the impact of price on landscape conversions. There are two key insights in equation (1). First, heterogeneity exists in the intensive margin elasticity based on the type of landscape, displayed as $\epsilon(E[w|dry], p_w)$ and $\epsilon(E[w|wet], p_w)$. Second, the extensive margin elasticity measures the impact of price on the proportion of households with dry landscapes, $\epsilon(P_{dry}, p_w)$, scaled by the change in consumption from converting from a wet to a dry landscape, $P_{wet}\frac{E[w|dry]-E[w|wet]}{E[w]}$. Estimating the separate elements of equation (1) requires a time series for landscape to identify changes in landscape as well as households that preserve a fixed landscape. Using the Wet and Dry groups I isolate changes in consumption for

[19] Note that these are not the same definitions as Wet and Dry, rather these are colloquial terms that designate two general landscaping regimes.

households that maintain one type of landscape throughout the sample, thus defining the intensive margin. The Mixed group consists of changes along the extensive margin that will be estimated in a discrete choice model of landscape conversion.

3.1 Intensive Margin

In order to capture the intensive margin elasticity and explore heterogeneity in demand parameters I estimate conditional demand functions defined as

$$\ln(w_{it}^{l}) = \alpha_i^l + \gamma_1^l ln(p_{it}) + \beta^l X_{it}' + \xi_{it}^l \tag{2}$$

Here w_{it} is water consumption for household i at time t, p_{it} is the price of water, X_{it} is vector weather controls, α_i is a household level fixed effect, and ξ_{it} is an idiosyncratic error term. The superscripts refer to the landscape groups, where $l = \{M, D, W\}$. The dependent variable is the log of monthly water consumption, with panel cluster-robust standard errors at the household level as defined by Woolridge (2002).[20] The parameters of interest are the values of γ^l for each landscape group, interpreted as elasticities in the log-log specification. In order to account for the change in incentives due to SRP the model is augmented with an interaction of the price variable with a dummy variable for households withing the SRP service area.

Before estimating the conditional demand functions I perform model specification based on the aggregate sample by estimating the water demand function presented in equation 2. The motivation for the model specification is that the City of Phoenix has an increasing block rate, and leading to several potential specifications for the relevant water price to consumers. There is an active debate in the economics literature whether consumers facing nonlinear budget constraints respond to the average or marginal price (Nataraj and Hanemann, 2011; Baerenklau et al., 2014; Klaiber et al., 2014; Ito, 2014; Wichman, 2014).[21] In reality price

[20] A cluster-robust version of the Hausman test for the random effects versus fixed effects (Mundlak, 1978; Chamberlain, 1982; Woolridge, 2002) for each model in Table A.3 rejects the null of no correlation, requiring the fixed effects model.

[21] Shin (1985) was one of the first to acknowledge that acquiring price information is costly in the presence of nonlinear rate structures, and that consumers may rationally choose to use average price instead of marginal price if the benefits to using marginal price do not outweigh the costs of learning the actual marginal price.

response is likely heterogeneous and certain rate structures may generate aggregate demand that is best modeled as either average or marginal price response.

In Phoenix the price signal primarily stems from the volumetric charge in the second block, and it is likely that even consumers in the first block respond to the price for the second block. The first block is set at 10 hundred cubit feet (CCF)[22] in the summer and the price in this block ranges from $0.09-0.39 over the sample; yielding a maximal variable cost in the first block of less than $4.00 per month. Looking at the data, almost 80% of monthly observations are in the high block and fewer than 0.6% of households never consume in the high block. Given the nature of the Phoenix rate structure it is probable that the high marginal price is more relevant for consumer demand than the actual marginal price. I run three specifications of the price in the water demand function: marginal price, average price, the high marginal price, where marginal and average price specifications are instrumented with the full rate structure (Nieswiadomy and Molina, 1989; Olmstead et al., 2007). Table in the Appendix A.3 presents the results from the water demand specification regressions, and supports the high marginal price specification, and the estimates are similar across all specifications. This is intuitive given the rate structure in Phoenix, and in the subsequent analysis I use lagged values of the high marginal price for the water demand analysis.[23]

3.2 Extensive Margin Elasticity

The extensive margin elasticity requires estimating two separate components: (1) the effect of prices on landscape conversion and (2) the impact of landscape conversions on water demand. The decision to replace turf grass with native desert plants is a major investment for a household. The benefits are a sequence of savings from lower water consumption as well as reduced labor costs if the xeriscape requires less maintenance, as is often the case. Costs of conversion consist primarily of the upfront fixed cost of the conversion; for example

[22] One CCF equals approximately 748 gallons.

[23] Lagged values are used because since it is likely that consumers respond to prices increases only after they are reflected on their bills, which takes place with a one month lag. Prices are posted online before they take effects so a forward looking consumer may respond to prices before she receives a bill, though this is less likely for a small expenditure like water.

one set of estimates from Las Vegas range from \$1.37-1.93 per square foot (Sovocool et al., 2006).[24] I treat landscape conversion as an irreversible investment since it is unlikely that a household will re-install grass after an expensive investment in xeriscape due to the high fixed costs. This is similar to the decision to invest in residential energy efficiency (Hassett and Metcalf, 1995; Revelt and Train, 1998), development and land use (Butsic et al., 2011; Schatzki, 2003), technology adoption (Farzi et al., 1998), and factory exit decision (Biørn et al., 1998).

I model the timing of landscape conversion as the product of a household optimization problem such that a household chooses the time of conversion T to minimize:

$$V = \int_0^T [p_t \bar{W} + (m_t - b_t)]e^{-\rho t} dt + \int_T^\infty (1-\theta) p_t \bar{W} e^{-\rho t} dt + K_t e^{-\rho t} \tag{3}$$

where p_t is the price of water at time t, $\bar{W}$ is the water requirement for a green landscape, m_t is the maintenance cost (outside of water costs) of a green landscape relative to a dry landscape, and b_t is the dollar value of the relative benefits of a mesic landscape compared to xeric. There is a one-time cost of K_t to convert a landscape, taken to be the numeraire, and I assume a conversion achieves a proportional reduction in water consumption by a factor θ. The discount rate is ρ and is less than one. The first order condition to this optimization problem that dictates whether, and when, a household will convert is

$$\theta p_T \bar{W} + (m_T - b_T) - \rho K_T \geqslant 0 \tag{4}$$

If the water savings and non-water costs of a green landscape exceed the discounted capital cost then a household will convert. The term $(m_t - b_t)$ captures the non-water component of the landscape decision with b_t representing the visual appeal and recreational value of a grass lawn, whereas m_t consists of labor and material costs associated with landscape maintenance. The non-market benefits, b_t, distinguish the landscape conversion decision from a conventional model of residential investment in efficiency that exclusively focuses on

[24] The Sovocool et al. (2006) estimates are from 2001 and match up with those for the Phoenix area after accounting for inflation. In 2010 dollars the conversion costs are \$1.80-2.54, within the range of \$1.50-2.50 reported for the Phoenix area.

minimizing expenditure.[25]

Landscape is a highly visible feature of the house for which consumers have heterogeneous preferences. For many households the non-water benefits, b_t, outweigh the non-water maintenance costs m_t, since a green landscape is generally considered a desirable feature of a home as evidenced by Klaiber and Smith (2015) who find that green landscapes positively and significantly capitalize into housing prices. Furthermore, living in a neighborhood with predominantly green landscapes adds more value to a residential home than if the property itself has a green landscape. Neighborhoods with significant irrigation have lower nighttime temperatures, a valuable attribute in southwestern cities where the minimum summer temperature can be above 90 degrees Fahrenheit. Therefore, a household in a predominantly green neighborhood that converts their lawn to a xeric landscape free-rides on neighborhood-level amenities by avoiding the expense of maintaining their own green yard.

Another factor in landscape conversions that does not necessarily exist in other contexts is the role of social norms and attitudes. Neighbors' landscapes may alter the decision to convert one's landscape since there may be pressure to either maintain a predominantly green neighborhood, or to prove environmental credentials by adopting native desert vegetation (Hurd, 2006; Larson et al., 2009). As social norms evolve having a xeric landscape may become more socially acceptable and may even become a desirable signal of environmental stewardship. Regardless of the direction of the effect, neighbors' decisions play a role in the decision to convert from a wet to dry landscape, and are therefore included in the model.

Landscape conversions are coded through a series of NDVI values over time. After normalizing for weather, as described in section A.2 of the Appendix, I generate quantiles of NDVI to define either wet or dry landscape years. Since there is noise in the NDVI data I am conservative in defining a conversion as a sequence of at least two wet years followed by at least two dry years. I also relax the thresholds for dry to below the 40th percentile of

[25] For example, the fixed cost and reduction in energy costs are the primary factors for replacing windows, since consumers, irrespective of energy costs, are unlikely to be differentiate between weather proofed and old drafty windows.

NDVI and wet to above the 70th percentile, since the original specification underestimated conversions based on conversations about the estimated number of conversions with water managers from CoP.[26] Through this sequence I can not only observe whether a household converted from wet to dry, but also the year of conversion. The dependent variable, C_{it}, is equal to one if household i converts at time t, and is otherwise equal to zero. The price of water is observed, as are the landscape choices for each household and their neighbors. The fixed amount of water and the efficiency factor are not directly observed but are likely a function of observable household characteristic such as the size of the yard. Similarly the elements that make up $(m_t - b_t)$ are not observed but are likely captured by household fixed effects. Household level data for the fixed capital costs of landscape conversion and variable landscape maintenance costs for both wet and dry landscapes are not available. Therefore identification requires the assumption that water rates are not correlated with these unobserved costs over time.

The empirical model estimates the probability thathousehold i converts at time t

$$C_{it} = \alpha_i + \gamma_{2_{SR}} p_{it} + \phi r_{it} + \pi NC_{it} + x_{it}\beta + \epsilon_{it} \tag{5}$$

I parameterize ϵ_{it} in equation 5 as normally distributed leading to a panel data linear probability model. Logistic regressions with over 170,000 fixed effects are computationally difficult and suffer from the incidental parameters problem (Heckman, 1981; Lancaster, 2000).[27] The price variable, p_{it} is either the average price, marginal price, or maximum volumetric price that a household faces during the summer of year t. I also include r_{it}, a dummy if the water utility serving household i had a landscape rebate at time t, and NC_{it} the percentage of noncontiguous neighbors that converted their landscape in the previous year. Additional controls include a quadratic time trend and a dummy if the house was sold in year t are represented in x_{it}, and α_i is a household fixed effect that controls for idiosyncratic features of the house including static unobserved water utility policies. Robust standard

[26] The estimated number of conversions is rougly 3% in Phoenix so we are still underestimating the number of conversions with this specification.

[27] Logistic regressions without fixed effects are also estimated and produce similar results; these are available upon request.

errors are clustered at the census block to account for unobserved neighborhood-level serial correlation.

In order to under to analyze long run changes in prices on landscape choices I estimate equation 6, which represents the long-run version of the model that examines the probability of having a dry landscape by the end of the sample based on changes in prices, rebates, and neighbors decisions. This analysis accounts for all households, including those that start the sample with a dry landscape, and thus includes the effect of price on dry households remaining dry rather than switching to wet.

$$C_i = \alpha + \gamma_{2LR}\hat{p}_i + \phi\hat{r}_i + \pi \hat{NC}_i + \hat{x}_i\beta + \epsilon_i \tag{6}$$

This is no longer a panel model since the dependent variable is not time varying, rather it is a dummy that is equal to one if a household is dry at the end of the sample. Ending prices and rebates $(\hat{p}_i, \hat{r}_i)$ are subtracted from initial values. Cumulative neighbors' conversions $(\hat{NC}_i)$ and the number of times the house was sold during the sample replace the annual values of those variables and $\hat{x}_i$ also includes a variable indicating whether the household had a wet landscape at the beginning of the sample. Both the short run and long run landscape conversion models are estimated using the entire Metro dataset.

In order to complete the extensive margin elasticity calculation I estimate the impact of conversions on water demand. A simplistic approach is to multiply the marginal change in the conversion probability by the difference in average consumption between the Wet and Dry group. A problem with this methodology is that the Wet and Dry groups may have fundamental differences because, by definition, they do not convert during the sample. In order to estimate the impact of conversions on water demand I create a variable that designates whether household i experienced a conversion at time t defined by $\tilde{C}_{it}$, which is equal to one if household i converted prior to time t and zero otherwise.

Augmenting the water demand model with landscape conversions, $\tilde{C}_{it}$, estimates the impact of conversion on consumption. Incorporating conversions into water demand also provides a validation test for the conversion classification by linking it back to water metering data. Since the NDVI data is relatively coarse there is a concern that the landscape conversion model is actually picking up landscape decisions of neighboring parcels instead of the parcel itself.[28] To test for this potential problem I create a variable for how many neighbors have converted their landscape. $\tilde{NC}_{it}$ is the sum of non-contiguous neighbors' conversions. I run regressions across all the specifications for conversion classification The augmented water demand model is defined by:

$$\ln(w_{it}) = \alpha_i + \gamma_1 p_{it} + \beta X_{it} + \delta_1 \tilde{C}_{it} + \delta_2 \tilde{NC}_{it} + \xi_{it} \tag{7}$$

Since I only observe water consumption for CoP Equation 7 is estimated with the CoP data, and I assume that the savings due to landscape conversions is similar for the other municipalities in the Metro data.

4 Results

4.1 Conditional demand functions

The first three columns of Table 2 present the regression results from the conditional demand functions for the three landscape groups: Mixed, Dry, and Wet. Table 2a presents the results with price lagged one month, which I refer to as short run (SR) results and Table 2b shows the results for the same regressions except price is lagged one year, which I call the long-run (LR).[29] Since landscape remains constant for the Dry and Wet groups, households in these groups can only change indoor water use and the intensity of outdoor use so the coefficients on price represent intensive margin elasticity.

As seen in Table 1 there are significant differences in the characteristics of the households across the landscape groups. Therefore, there may be issues of sample selection in the conditional demand functions since the differences in elasticity estimates may be due to underlying differences, irrespective of landscape, between the three groups (Heckman, 1974). The conditional demand functions in the first three columns of Table 2 all contain

[28]This is unlikely because the immediate contiguous neighbors are removed when creating variables for neighbors landscapes precisely to address this concern.

[29]There is not a precise distinction between short run and long run, however, households clearly have more margins of adjustments in one year relative to one month.

household fixed effects that capture static unobserved heterogeneity that is idiosyncratic to the household. However, to address issues of sample selection for the time-varying unobservables across landscape groups I run several models that control for sample selection. I employ sample selection corrections employed by Lee (1983); Schmertmann (1994); Dahl (2002) that utilize functions of predicted probabilities from the selection equation in the conditional demand functions. The selection equation utilizes two significant time-varying variables: neighbors' conversions and a dummy whether the house was sold in the previous year.[30] As seen in Section 4.2 these are key indicators of landscape conversions and they are plausibly exogenous to water use. Neighbors' landscape is a particularly attractive variable to account for selection because it captures time-varying unobserved heterogeneity at the neighborhood level.

Columns (4)-(6) of Table 2 display the results based on third order polynomial selection model of Dahl (2002). All regressions that include selection correction estimate the standard errors with bootstrap methods that re-sample at the household level to account for the two-stage estimation. The presence of the household fixed effects controls for a significant amount of selection that is not time-varying. Selection primarily increases the magnitude of the elasticity for the Mixed group in the long run specification. The results are robust to a variety of models, shown in Figure 3, that employ additional selection correction techniques as advocated by Bourguignon et al. (2007).

The SR results from the selection model, displayed in the last three columns of Table 2a, show that the Dry and Wet groups have lower point estimates for demand elasticities relative to the Mixed group. The elasticity for the Mixed Group is -0.3, while the elasticities for the Dry and Wet groups are -0.2 and -0.24 respectively. Wald tests reveal that the Dry and Mixed elasticities are statistically different at the 1% level and the differences in elasticity estimates between the Wet and Mixed groups are significant at the 5% level. Long run demand is categorically more elastic, and both Dry and Wet households are significantly less

[30]The results of the selection equation and results are described in more detail in Section A.6 of the Appendix.

elastic than the Mixed group at the 1% level. These differences are economically meaningful as well; relative to the Mixed group the Wet group is 24% less elastic in the SR and 40% less elastic in the LR, while the Dry group is 39% and 36% less elastic in the SR and LR respectively. An additional result from the conditional demand regressions is that the time trend varies across landscape groups. Table 2a shows that the Mixed and Dry groups reduce water use by roughly 1.5% per year while the Wet group only uses roughly 0.5% less each year. A similar result holds in the LR results, and in fact the time trend for the Wet group is insignificant in these models.

Since the SRP changes the incentives regarding water use across the landscape classes I estimate models that interact the SRP dummy with the price of water. Figure 3 summarizes the elasticities after incorporating heterogeneity due to SRP in both the SR and LR elasticities. The rows designate elasticities for the aggregate sample, the sample excluding households within SRP, and the SRP households. The aggregate results are from the base model and the No SRP and SRP results are based on the model that adds an interaction term between a dummy variable for SRP and price.[31] The columns report elasticity estimates using each of the three selection correction techniques performed in Bourguignon et al. (2007). Similar to Table 2 the LR elasticities are categorically larger in magnitude.

The impact of SRP is striking for the elasticity estimates. The Mixed and Dry groups within SRP are more price elastic, whereas the Wet group within SRP is less sensitive to price. This has implications for interpreting the aggregate intensive margin elasticity results. Excluding SRP, the point estimate for the Wet group's intensive margin elasticity is greater in absolute value than the Mixed group, though the difference is generally not statistically significant. This is likely due to the fact that studies find outdoor water use to be more elastic than indoor use due to its discretionary nature (Barrios García and Rodríguez Hernández, 2008; Martínez-Espiñeira and Nauges, 2004; Mansur and Olmstead, 2012). The SRP is unique to the Phoenix; nationally most households use municipal water for 100% of their

[31]The SRP elasticities are based on the linear combination of the base price elasticity and the price $\times$ SRP interaction term.

Table 2: Conditional Demand Regressions

(a) Short Run (t-1)

	(1) Mix	(2) Dry	(3) Wet	(4) Mix	(5) Dry	(6) Wet
ln(high marginal price)$_{t-1}$	-0.2807***	-0.2057***	-0.2342***	-0.3005***	-0.2032***	-0.2357***
	(0.0083)	(0.0266)	(0.0243)	(0.0084)	(0.0272)	(0.0244)
Time Trend	-0.0155***	-0.0147***	-0.0046***	-0.0150***	-0.0151***	-0.0046***
	(0.0004)	(0.0014)	(0.0013)	(0.0005)	(0.0015)	(0.0013)
Net ET	0.0016***	0.0040***	-0.0084***	-0.0004	0.0037***	-0.0084***
	(0.0003)	(0.0008)	(0.0008)	(0.0003)	(0.0008)	(0.0008)
Cooling Degree Days	0.0006***	0.0004***	0.0007***	0.0006***	0.0004***	0.0007***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PHDI	-0.0079***	-0.0057***	-0.0070***	-0.0080***	-0.0056***	-0.0069***
	(0.0001)	(0.0004)	(0.0003)	(0.0001)	(0.0004)	(0.0003)
Constant	2.5192***	2.3119***	2.4564***	10.7332	-131.5736	99.8989***
	(0.0051)	(0.0161)	(0.0149)	(7.3432)	(135.4380)	(24.9110)
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Selection Correction	No	No	No	Yes	Yes	Yes
Selection Method	None	None	None	Dahl	Dahl	Dahl
Households	140,638	13,829	17,847	139,580	13,671	17,795
Observations	4,929,535	481,894	627,236	5,964,060	581,062	762,591

(b) Long Run (t-12)

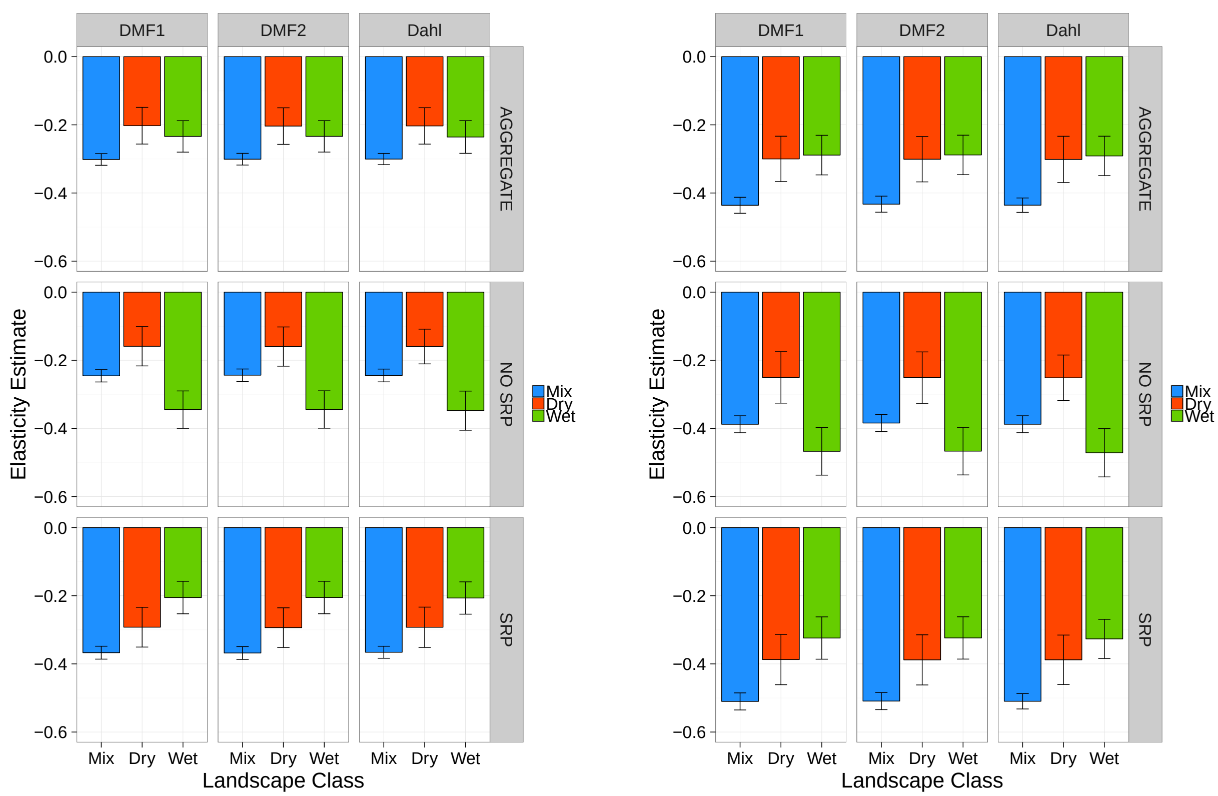
	(1) Mix	(2) Dry	(3) Wet	(4) Mix	(5) Dry	(6) Wet
ln(high marginal price)$_{t-12}$	-0.3648***	-0.2929***	-0.2857***	-0.4357***	-0.3016***	-0.2912***
	(0.0104)	(0.0333)	(0.0304)	(0.0108)	(0.0347)	(0.0295)
Time Trend	-0.0134***	-0.0122***	-0.0022	-0.0104***	-0.0120***	-0.0021
	(0.0005)	(0.0016)	(0.0014)	(0.0005)	(0.0017)	(0.0014)
Net ET	0.0269***	0.0205***	0.0313***	0.0262***	0.0204***	0.0313***
	(0.0002)	(0.0005)	(0.0005)	(0.0001)	(0.0005)	(0.0005)
Cooling Degree Days	0.0004***	0.0003***	0.0004***	0.0004***	0.0003***	0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PHDI	-0.0053***	-0.0042***	-0.0040***	-0.0060***	-0.0042***	-0.0040***
	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0003)	(0.0003)
Constant	2.6284***	2.3953***	2.5851***	12.0238*	-116.9635	114.3466***
	(0.0061)	(0.0194)	(0.0178)	(7.2530)	(138.8632)	(27.7507)
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Selection Correction	No	No	No	Yes	Yes	Yes
Selection Method	None	None	None	Dahl	Dahl	Dahl
Households	140,373	13,797	17,814	139,844	13,703	17,828
Observations	5,997,998	586,425	763,349	4,901,671	477,487	626,620

Note: Dependent variable is the natural log of monthly water consumption, and conditional demand functions subset the sample determined by NDVI over time. Selection correction is based on a flexible version of Dubin and McFadden (1984). Robust standard errors clustered at the household level are given in parentheses. For the selection regressions the standard errors are bootstrapped to account for the two-stage method. *** p<0.01, ** p<0.05, * p<0.1

water demand, including landscape irrigation. Thus, the aggregate result that the Wet group is less price elastic than the Mixed group is unlikely to generalize outside of the Phoenix metro area since it is driven by the SRP subsample whose irrigation costs are decouples from the price of municipal water. The main insight from the conditional demand results is that Dry households are less elastic the Mixed group, but Wet household that maintain a green landscape respond similarly to price to households that have mixed use landscape or change landscape. This suggests that prices can still effectively reduce demand for households that keep their lawns green.

Figure 3: Conditional Demand Elasticity

(a) Short Run Demand Elasticity **(b) Long Run Demand Elasticity**



Note: The elasticity estimates are based on regressions shown Table 2 and an augmented regression that interacts price with an SRP dummy. The SRP subsample is the linear combination of the sample outside SRP and the SRP*price interaction term. The rows designate the sample and the columns represent the different selection correction methods. Price is lagged by 1 month for the short run specification and one year year for the long run specification. Standard errors are bootstrapped to account for the two-stage method. *** p<0.01, ** p<0.05, * p<0.1

4.2 Landscape conversion

As described in Section 2.2 each of the eight utilities has a different version of an increasing block rate so a single variable cannot capture the price of water. In the landscape conversion models I consistently show the results for three different price specifications: expected average price (AP), expected marginal price (MP) and the maximum volumetric price (MxP). Expected average price and marginal price are based off the household's rate structure and the out of sample prediction for expected water consumption using a model estimated with CoP water data. Additionally, there is uncertainty with respect to the appropriate time lag for the price variables. Since most conversions take place prior to the summer the relevant price is from previous summers, however, households may require exposure to multiple summers of expensive water bills to induce them to covert their landscape. I model each of the three prices (AP, MP, MxP) with last summer's price $(t-1)$, the last two summers' prices $(t-1, t-2)$, and the average of last two summers' prices $(t-\overline{1, t}-2)$. In each specification I model neighbors' landscape conversions in the same time dimension as price assuming that social and monetary factors impact the conversion decision in a similar temporal manner. Households that begin the sample with a dry landscape are removed since they cannot convert from wet to dry.[32] The models are estimated using a linear probability model with household fixed effects and standard errors clustered at the census block level.[33] The results, available in the Appendix, show that in all specifications higher prices increase the probability of converting from a wet to dry landscape. Prices from both $t-1$ and $t-2$ are statistically significant indicating that factors from the last two years are relevant in the conversion decision. The model that averages prices and neighbors' conversions from the past two years has a lower root mean squared error, and thus is the preferred model that I utilize moving forward.[34]

The base specification in panel (a) of Table 3 shows that increasing the price of water by \$1 raises the probability of adopting a xeric landscape by roughly 2%. This is a relatively small effect since the average price for the whole sample is \$1.08 and the mean price increase was \$0.24 over the course of the sample. However, landscape conversions are uncommon, only 2.4% of households convert during our sample, and generate large reductions in consumption

[32]Including those households does not change the sign or significance of the results, though the magnitude decreases for most parameters.

[33]The sign and significance for all models are consistent when estimated in a logistic regression.

[34]Since I utilize prices from two years prior this could also be referred to as a medium run model.

as seen below. Introducing utility rebates for landscape conversions does not increase the probability of conversion, and is even negative in one specification. The interpretation of the rebate result is that households do not respond to annual changes in the rebate due to the presence of household fixed effects in the regression. Increasing the average number of neighbors that converted significantly increases the probability of converting to from wet to dry, if all of a household's neighbors switched to a dry landscape the probability of the household converting would increase by 34%.[35] The positive coefficient on neighbors' conversions suggests that alleviation of social pressure from being an isolated xeric landscape in a green neighborhood, and/or evolution of social norms to favor water-efficient landscape, dominates the desire to free ride on a neighborhood-level amenity. While the association between neighbors' conversions and a household's conversion probability is intriguing, the estimates should not be considered causal peer effects due to the issues of endogeneity raised in Manski (1993, 2000).

The SR landscape conversion results show that variation in water prices over time affects landscape decisions, though the magnitude is quite small. The long run landscape conversion model examines household landscapes at the end of the sample using the last two years prior to the collapse of the housing market (2005 and 2006). The dependent is an indicator equal to one if the household has a dry landscape in the last two years of the sample. A linear probability model estimates the probability of being dry based on long-run changes in water prices, utility rebate policies, neighbors landscape choice, and the household's initial landscape. The results, presented in panel (b) of Table 3, are similar to the SR results; increases in water prices lead households to adopt dry landscapes and the magnitudes are larger in the long run. Additionally, introducing a rebate in the long run increases the probability of dry landscapes, whereas short run changes in rebate policies do not impact landscape decisions.

[35] The results are similar when using the average number of neighbors that have a dry landscape.

Table 3: Landscape Conversion

	Base			SRP Interaction		
	(1)	(2)	(3)	(4)	(5)	(6)
	AP	MP	MxP	AP	MP	MxP
	(a) Short Run Landscape Conversion					
Avg Price$_{\overline{t-1,t-2}}$	0.0187***			0.0171***		
	(0.0021)			(0.0022)		
Marginal Price$_{\overline{t-1,t-2}}$		0.0238***			0.0188***	
		(0.0021)			(0.0020)	
Max Price$_{\overline{t-1,t-2}}$			0.0224***			0.0189***
			(0.0020)			(0.0020)
Rebate	-0.0023***	-0.0006	-0.0010	-0.0001	0.0014	0.0013
	(0.0006)	(0.0006)	(0.0006)	(0.0009)	(0.0009)	(0.0009)
Avg Price*SRP$_{\overline{t-1,t-2}}$				0.0026***		
				(0.0010)		
Marginal Price*SRP$_{\overline{t-1,t-2}}$					0.0105***	
					(0.0014)	
Max Price*SRP$_{\overline{t-1,t-2}}$						0.0080***
						(0.0013)
Rebate*SRP				-0.0028***	-0.0029***	-0.0054***
				(0.0010)	(0.0010)	(0.0011)
Time trend	0.0133***	0.0115***	0.0116***	0.0133***	0.0113***	0.0115***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Time^2	-0.0015***	-0.0013***	-0.0013***	-0.0015***	-0.0013***	-0.0013***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Neighbor Conversions$_{\overline{t-1,t-2}}$	0.3488***	0.3486***	0.3488***	0.3475***	0.3435***	0.3446***
	(0.0173)	(0.0172)	(0.0172)	(0.0173)	(0.0173)	(0.0173)
House sold	0.0009***	0.0009***	0.0009***	0.0009***	0.0009***	0.0009***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Constant	-0.0352***	-0.0500***	-0.0499***	-0.0354***	-0.0523***	-0.0520***
	(0.0022)	(0.0030)	(0.0031)	(0.0022)	(0.0031)	(0.0032)
Observations	1,129,939	1,129,957	1,129,957	1,129,939	1,129,957	1,129,957
Households	191,325	191,328	191,328	191,325	191,328	191,328
RMSE	0.0730	0.0729	0.0729	0.0730	0.0729	0.0729
	(b) Long Run Landscape Conversion					
Avg Price	0.1324***			0.1378***		
	(0.0087)			(0.0107)		
Marginal Price		0.0583***			0.0112	
		(0.0115)			(0.0141)	
Max Price			0.0557***			0.0132
			(0.0123)			(0.0144)
Rebate	0.0779***	0.0403***	0.0265**	0.0514**	0.0096	0.0143
	(0.0133)	(0.0144)	(0.0132)	(0.0233)	(0.0238)	(0.0232)
Avg Price*SRP				-0.0104		
				(0.0122)		
Marginal Price*SRP					0.0972***	
					(0.0113)	
Max Price*SRP						0.1047***
						(0.0107)
Rebate*SRP				0.0449*	0.0500**	0.0166
				(0.0255)	(0.0254)	(0.0257)
Start Wet	-0.5539***	-0.5594***	-0.5584***	-0.5537***	-0.5655***	-0.5651***
	(0.0027)	(0.0027)	(0.0027)	(0.0026)	(0.0026)	(0.0026)
Neighbor Conversions	0.4461***	0.4663***	0.4741***	0.4461***	0.4025***	0.3946***
	(0.0242)	(0.0244)	(0.0245)	(0.0241)	(0.0238)	(0.0238)
# of Sales	0.0104***	0.0105***	0.0105***	0.0104***	0.0105***	0.0106***
	(0.0009)	(0.0009)	(0.0010)	(0.0009)	(0.0009)	(0.0009)
Constant	0.5663***	0.5852***	0.5828***	0.5663***	0.5896***	0.5850***
	(0.0039)	(0.0046)	(0.0049)	(0.0038)	(0.0046)	(0.0049)
Observations	370,772	370,781	370,781	370,772	370,781	370,781
Adjusted R^2	0.266	0.263	0.263	0.266	0.264	0.265
RMSE	0.427	0.428	0.428	0.427	0.427	0.427

Notes: The dependent variable in panel (a) is an indicator whether a household converts from a wet to dry landscape in year t, and in panel (b) is an indicator whether a household ends the sample with a dry landscape. Households that have a dry landscape at the start of the sample are removed from regressions in panel (a). Columns (4) -(6) add interactions of the price and rebate variable with a dummy for SRP. Robust standard errors clustered at the census block level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.3 Landscape conversions robustness

As a robustness check I conduct a boundary discontinuity analysis (Black, 1999; Ito, 2014) where I restrict the sample to households within a certain distance from a utility border. This reduces the concern that unobserved city-level variables are correlated with the landscape decision. Since the SR analysis has household fixed effects the boundary discontinuity analysis addresses potential time-varying city-level unobservables. I choose buffers ranging from 500 feet to 3000 feet from a utility border, and a visual description of the sample is provided in Table A.4 in the Appendix. The results are robust to the boundary discontinuity analysis; all the coefficients on price are positive and statistically significant at the 1% level. The short run results in the restricted samples are very similar in magnitude to the aggregate sample, indicating that the household fixed effects control for utility-specific unobservables. There are significant differences between the restricted samples and the aggregate samples for the long run results, with the boundary samples producing much larger estimates of the price parameter than the aggregate sample. This suggests that city-level unobservables may bias the price effect down in the long run samples.

Table 4: Landscape Conversion Boundary Discontinuity Regressions

(a) Short Run

	All	500ft	1000ft	1500ft	2000ft	2500ft	3000ft
Avg Price$_{\overline{t-1,t-2}}$	0.0187***	0.0223***	0.0159***	0.0159***	0.0176***	0.0159***	0.0172***
	(0.0021)	(0.0070)	(0.0039)	(0.0029)	(0.0027)	(0.0024)	(0.0023)
Marginal Price$_{\overline{t-1,t-2}}$	0.0238***	0.0236***	0.0211***	0.0244***	0.0271***	0.0259***	0.0267***
	(0.0021)	(0.0061)	(0.0038)	(0.0031)	(0.0028)	(0.0026)	(0.0024)
Max Price$_{\overline{t-1,t-2}}$	0.0224***	0.0220***	0.0194***	0.0221***	0.0244***	0.0232***	0.0241***
	(0.0020)	(0.0058)	(0.0036)	(0.0029)	(0.0027)	(0.0025)	(0.0023)
Observations	1,129,957	112,814	240,195	363,368	461,025	565,353	644,523
Households	191,328	19,143	40,728	61,588	78,168	95,866	109,286

(b) Long Run

	All	500ft	1000ft	1500ft	2000ft	2500ft	3000ft
Avg Price	0.1324***	0.1990***	0.1117***	0.0815***	0.0771***	0.0891***	0.1033***
	(0.0087)	(0.0222)	(0.0159)	(0.0129)	(0.0111)	(0.0100)	(0.0095)
Marginal Price	0.0583***	0.2685***	0.2155***	0.1976***	0.1586***	0.1430***	0.1293***
	(0.0115)	(0.0243)	(0.0188)	(0.0161)	(0.0146)	(0.0135)	(0.0128)
Max Price	0.0557***	0.2803***	0.2265***	0.2032***	0.1710***	0.1592***	0.1496***
	(0.0123)	(0.0242)	(0.0190)	(0.0180)	(0.0167)	(0.0153)	(0.0145)
Observations	370,781	42,478	86,901	126,119	159,057	191,084	213,985

Note: *** p<0.01, ** p<0.05, * p<0.1

4.4 Landscape conversions and water demand

To complete the extensive margin elasticity calculation I estimate the change in water consumption from landscape conversions. Table 5 presents the results of the water demand regression presented in equation 7 that includes the effect of conversions and neighbors' conversions on water demand. As a robustness check I relax the threshold for above the 60^{th} percentile for wet observations and below the 50^{th} for dry observations in columns (2) and (4) and the results do change substantively. Conversions have a negative impact on water consumption across all specifications and the magnitude is not only statistically, but also economically, significant at roughly 20% of monthly water demand. Similarly, neighbors' conversions cause a statistically significant reduction in demand, but the magnitude is less than one-twentieth of that for an actual household conversion. This is likely due to the fact that the probability of converting increases when a household's neighbors convert; therefore neighbors conversions may act as a proxy for partial conversions that are not picked up by the NDVI data. The results provide evidence from the water metering records that the satellite data are able to capture landscape conversions. Intuitively, households within the SRP save less municipal water from a landscape conversion since some of the water to maintain a wet landscape likely comes from SRP irrigation. SRP households save 6-7 percentage points less water from a conversion, which brings down the aggregate savings from conversion from 25% to 20%. However, the results shows that landscape conversions within the SRP still reduce water use by 18%, indicating that the aggregate results are still useful for inference.

4.5 Extensive Margin Elasticity

The results presented in Tables 2a and 5 contain the parameters necessary to calculate the extensive margin elasticity. I focus on the extensive margin elasticity for households that begin the sample with a green landscape. This elasticity is represented as the third term in equation 1, $\epsilon(P_{dry}, p_w)P_{wet}\left(\frac{E[w|dry]-E[w|wet])}{E[w]}\right)$. I calculate the arc elasticity of demand for extensive margin elasticity by simulating the effect of a 10% price increase on the probability of conversion, and multiplying this by the percentage change in consumption associated with

Table 5: Water Demand and Landscape Conversions

	Base		SRP Interaction	
	(1) 70^{th}	(2) 60^{th}	(3) 70^{th}	(4) 60^{th}
Conversion	-0.2082***	-0.2182***	-0.2466***	-0.2623***
	(0.0069)	(0.0061)	(0.0120)	(0.0111)
Neighbor Conversions	-0.0079***	-0.0036***	-0.0105***	-0.0050***
	(0.0011)	(0.0010)	(0.0021)	(0.0019)
Conversion*SRP			0.0649***	0.0725***
			(0.0146)	(0.0133)
Neighbor Conversions*SRP			0.0026	0.0007
			(0.0025)	(0.0023)
Household FEs	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes
Households	172,314	172,314	172,314	172,314
Observations	6,038,665	6,038,665	6,038,665	6,038,665

Note: Dependent variable is the natural log of monthly water consumption, and the sample is all household in the City of Phoenix. Robust standard errors clustered at the household level are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1

a conversion ($\Delta q = \Delta p \times \gamma_2 \times \delta_1$). In order to assess the importance of landscape conversions in aggregate water demand the extensive margin elasticity is then compared to the intensive margin elasticity for the Wet group derived from the conditional demand functions. The elasticities based on a variety of specifications are presented in Table 6.

In the short run the extensive margin is not a substantial component of demand elasticity, ranging from 2-3% of total elasticity. This increases modestly in the long run where the extensive margin ranges from 6-10% of total elasticity for the aggregate sample.[36] Utilizing the long run estimates from the boundary discontinuity analysis, which produce the highest estimates of the impact of prices on conversions, generates larger estimates for the role of the extensive margin ranging between 14-26%. These should be considered an upper bound, but may not be representative of the entire metropolitan area. This definition of the extensive margin exclusively accounts for changes in landscape and thus represents a lower bound of the true extensive margin that includes investments in non-landscape water efficiency.

The relatively small role of extensive margin elasticity with respect to landscape does

[36]It should be noted that the time dimensions are different for the intensive and extensive margin. The long run in the conditional demand regressions is one year, which corresponds to the short run in landscape conversions. The long run in the landscape conversions is changes over the full eight years of the Metro sample.

Table 6: Intensive & Extensive Margin Elasticity

Price	Sample	Time Horizon	Int. Elasticity	Ext. Elasticity	Total Elasticity	% Extensive
AP	Aggregate	SR	-0.236	-0.004	-0.243	2%
MP	Aggregate	SR	-0.236	-0.008	-0.246	3%
MxP	Aggregate	SR	-0.236	-0.008	-0.246	3%
AP	Aggregate	LR	-0.291	-0.031	-0.334	10%
MP	Aggregate	LR	-0.291	-0.020	-0.323	6%
MxP	Aggregate	LR	-0.291	-0.020	-0.323	7%
AP	Buffer500	LR	-0.291	-0.047	-0.349	14%
MP	Buffer500	LR	-0.291	-0.092	-0.391	24%
MxP	Buffer500	LR	-0.291	-0.103	-0.402	26%

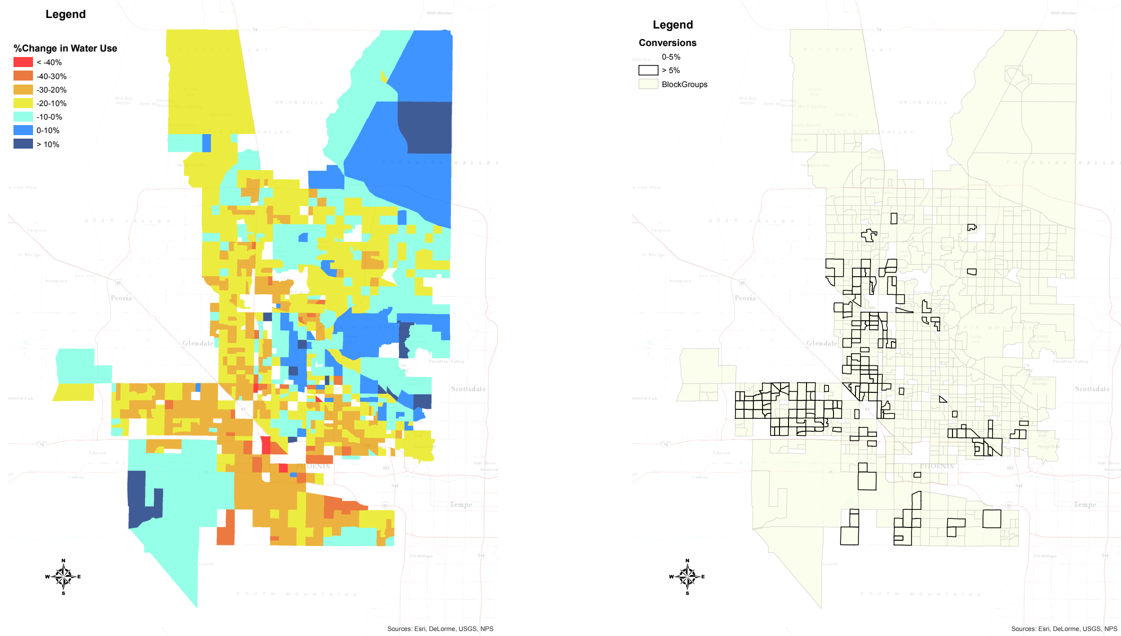
Note: The SR and LR elasticity estimates are the price parameters in Table 2. Extensive margin elasticity is the arc elasticity for a 10% price increase where the change in quantity is defined by $\Delta q = \Delta p * \gamma_2 * \delta_1$. The time horizon is defined by either (t-1) or (t-12) on the intensive margin and from the SR and LR model respectively for the extensive model.

not imply that landscape conversions are inconsequential for long run water demand. It is the small role of price on landscape conversions that drives the elasticity result; the impact of conversions on demand is quite large at over 20%. In order to put the landscape conversions in Phoenix into context I map out consumption from the last two years in the sample relative to the first two years in panel (a) of Figure 4, which represents long-run changes in demand. Consumption is averaged over all households at the Census block group level to preserve anonymity.[37] The map visualizes the spatial heterogeneity of changes in consumption over time. Panel (b) of Figure 4 shows block groups where at least 5% of the houses in the sample converted their landscape. The effect of landscape conversions on changes in long-run demand is striking in Figure 4. Central and northeastern Phoenix had very few conversions and consumption in those areas remained relatively constant, or even slightly higher than 10 years prior. Conversely, western Phoenix experienced many conversions and those areas reduced consumption by 20-30% over the course of the sample. Observing the distribution of homes with water-intensive landscape also provides a baseline for potential water reductions in the future. If the majority of households convert dry landscapes traditional water conservation mechanisms, including raising water rates, may not produce the same reductions in demand relative to periods when green landscapes were common.

[37]For confidentiality concerns I drop all census block groups with fewer than 20 houses from the map.

Figure 4: Landscape Conversions & Water Consumption over Time

Change in Consumption **Conversions**



Note: The shaded coloring is the percentage change in household water consumption, averaged at the census block level, from 2008-2009 to 1998-1999. Census blocks with less than 20 houses in the sample are removed for confidentiality concerns. The outlined blocks are where more that 5% of the households within that block experienced landscape conversions.

5 Conclusion

This paper examines the role of landscape choice in water demand by merging a time series of satellite data with monthly water metering records. Jointly observing water demand and changes in complementary goods over time enables estimation of demand elasticity on the intensive and extensive margin. Prior research treats the extensive margin implicitly by examining the difference in short and long run demand with the assumption that changes in the extensive margin can only occur in the long run. As concerns of water scarcity increase it is critical to develop a deeper understanding of demand, particularly the role of complementary goods, as seen in energy economics (Gillingham, 2012; Goulder et al., 2009). I examine the heterogeneity in water demand due to an important complementary good by conditioning on landscape decisions over time. Key differences exist between households across the landscape spectrum. Households that maintain a dry landscape are less elastic in the short and long run

In a discrete choice model I find that higher water rates increase the probability of converting from water intensive vegetation to a xeric landscape. This is robust across a range of price specifications and controlling for utility specific unobservables with household fixed effects and a boundary discontinuity analysis. Landscape conversions have a significant impact on demand; reducing consumption by roughly 20%. Changes along the extensive margin constitute only 2-3% of aggregate demand elasticity in the short run, and this rises to 6-24% in the long run. There appears to be a strong social component to the landscape choice, as neighbors' conversions are a strong predictor of a household's decision to switch to a water saving landscape. As social norms evolve, and consumers sort to live near like-minded people or collocate along correlated unobserved heterogeneity, the pattern of conversion clusters is likely to continue. There are important implications for clusters of conversions in a desert city as xeric landscapes nonlinearly exacerbate the urban heat island. Establishing xeric landscapes may lead to a tradeoff between water and energy conservation as hotter neighborhoods use more energy for cooling. This highlights the notion that a green landscape provides both direct benefits and indirect benefits in arid regions.

Analyzing long-run changes in demand reveals that households maintaining a green landscape have a relatively constant trend in consumption over time, while areas that convert appear to be driving large scale reductions in demand. If, as expected, the transition of landscaping practices in the Phoenix metropolitan area leads to increases in xeric landscape there will be important implications for water demand. There will be smaller peaks in summer demand and, since dry households are less price elastic, aggregate demand elasticity will also decrease. Thus, conversions to dry landscapes smooth seasonal water consumption, but also reduce the potential savings from price increases and outdoor water restrictions during droughts. Grass and other types of water intensive landscapes act as an additional source of supply that can be drawn down during times of drought through reductions in irrigation. As cities in arid climates transition from towards more xerix landscapes they lose the ability to quickly reduce consumption during a drought. Understanding the stock of existing landscape, and the drivers of conversion, has enormous consequences for long and medium run planning by quantifying the potential savings from outdoor use.

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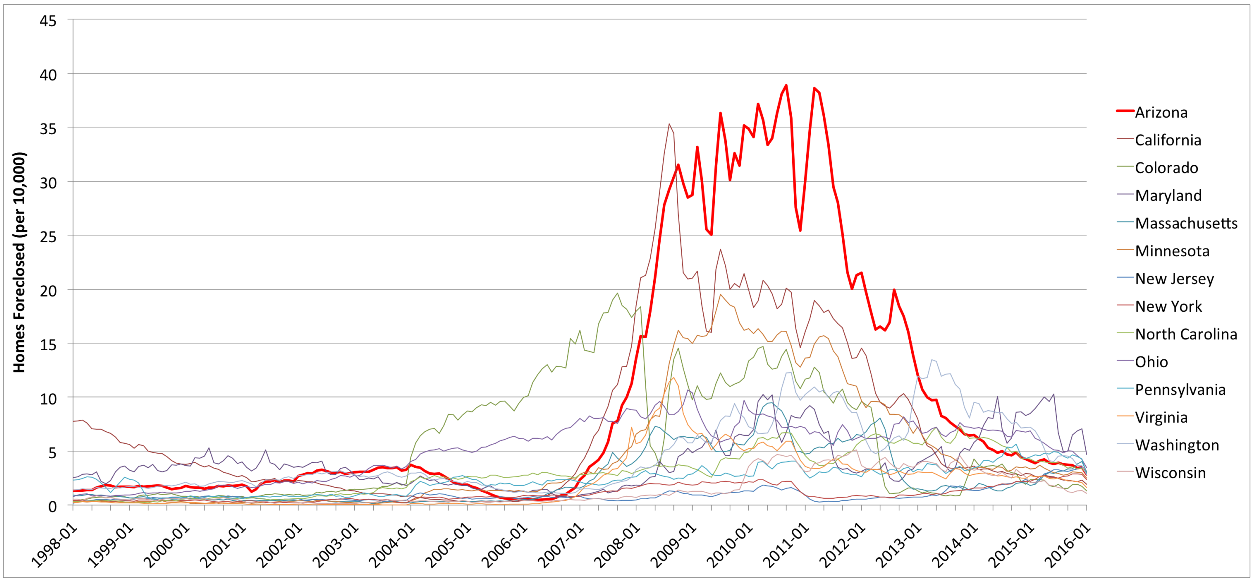
A Appendix

A.1 Foreclosure Data

Figure A.1: Foreclosure Rates



Note: Foreclosure data are from Zillow Research, available at
http://files.zillowstatic.com/research/public/State/State_HomesSoldAsForeclosures-Ratio_AllHomes.csv.

A.2 Processing Landsat Data

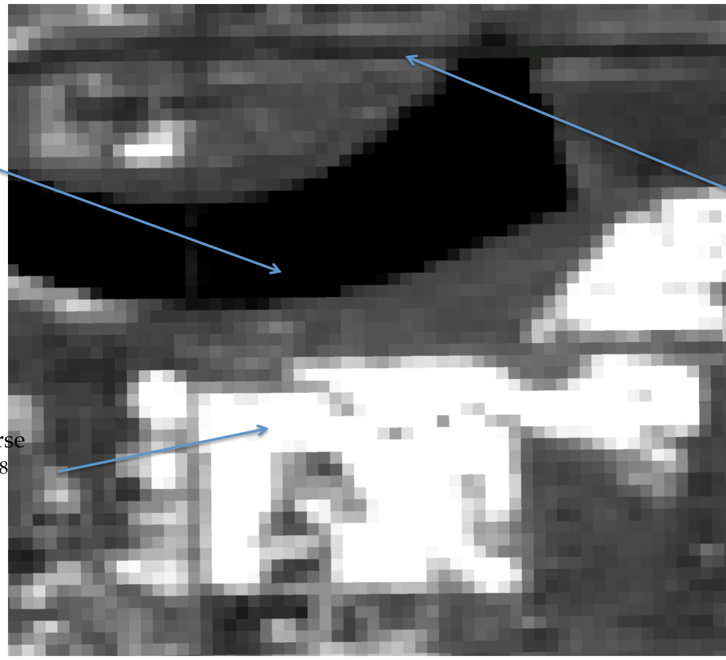
The Landsat data is publicly available in a raw form and requires processing in order to apply the data for analysis. Processing is particularly important when comparing two or more images over time or across space. I follow the steps presented in Myint et al. (2008) to process the Landsat data in Erdas Imagine. The first step is to find valid scenes via the USGS Glovis system. I only select images with less than 10% cloud cover and an overall quality score of at least 9 out of 10. I try to select at least two scenes for each year in between the months of June and August, though some scenes are also taken from May and September. Combining data from two scenes helps to alleviate idiosyncratic shocks due to weather. I end up with 25 scenes between the years of 1998 and 2009. I repeat the following steps for each of the 25 scenes.

Since the Landsat data is stored in separate bands I import the data and stack all the layers on top of each other. Next, I subset the image to limit the geographic area to Phoenix metro. Each Landsat scene is 185km x 117km so limiting the image to the study area greatly increases computational speed and the digital space required for storage. Each image is registered to a base image in order to reduce locational errors using 14 ground control points and ensuring root mean squared errors of less than 0.1. This process ensures that all the images align properly and that a parcel has the same geo-reference in each image over time. In order to account for differences in atmospheric reflectance and solar radiation I apply the Cos(t) method of radiometric correction of Chavez (1996). Once theses steps are complete the images are suitable to be compared over time and I calculate the Normalized Difference Vegetation Index (NDVI).

The Landsat satellite captures reflected and emitted energy in six bands of the electromagnetic spectrum as well as one thermal band. Landsat TM5 takes an image of the same location every 16 days with 30-meter resolution, but is often obstructed by clouds, rendering the image unusable. In the remote sensing literature there is a debate over the best index to measure vegetative cover see among others (Gitelson, 2013; Huete et al., 1997; Viña et al., 2011). NDVI is widely used and is appropriate as an introduction to incorporating remote sensing data into water demand. NDVI is the calculated from the visible and near-infrared bands in the Landsat data.[38] Healthy green vegetation absorbs visible light and reflects infrared light so the difference performs well in identifying healthy vegetation. The formula used to calculate the index is $NDVI = (NIR - VIS)/(NIR + VIS)$, where NIR is the near infrared band and VIS is the visible red band. This formula results in an index ranging from -1 to 1 with higher values representing more robust vegetation. Figure A.2 shows an area just northwest of Arizona State University to give an example of how different values of NDVI correspond to land use features.

The NDVI data are then merged with parcel boundaries in Geographic Information Sys-

[38] More information on NDVI is available at http://earthobservatory.nasa.gov/Features/MeasuringVegetation/measuring_vegetation_2.php.



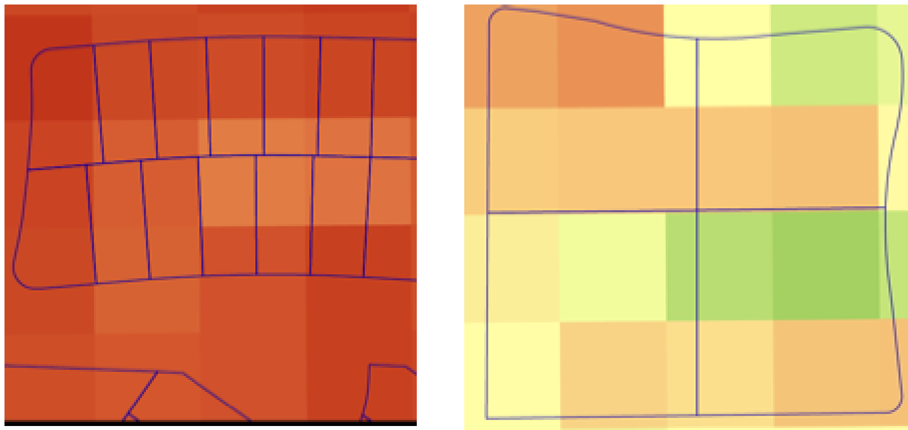
Note: This is a sample area just northwest of Arizona State University, whose land use features are known.

tem software. Each pixel of the Landsat data is 30m x 30m and is often larger, or matches imperfectly, with the parcel boundaries. The size of each Landsat pixel is $900m^2$, which is slightly larger than the average lot size of $861m^2$. An example of the problems that can arise from merging NDVI at the parcel level are displayed in Figure A.3. It is clear that smaller parcels create challenges for spatially merging NDVI data. To reduce the noise in the spatial merge I downscale each NDVI pixel to nice 10m x 10m pixels and take the spatially weighted average of the pixels within the parcel. The final results is a panel dataset at the parcel level that contains the time series variation of NDVI for each of the 25 Landsat scenes.

A.3 Weather Normalization

While the processing steps described above alleviates concerns due fluctuations over time in how the satellite captures images, I also need to account for the impact of natural variations in weather on NDVI. Irrespective of human watering practices NDVI will vary based on the weather conditions in the area. In order to minimize these variations and focus on the water-added component of landscape I normalize the NDVI for weather. Since the images are taken at different times of the month I match daily weather data based on the image date. From this I construct variables representing weather conditions for each of the four weeks prior to the image. Since Phoenix is very dry and often will not have rained within four weeks in the

Figure A.3: Merging Parcels and NDVI



Note: The color gradient for the images is the same, but is purely for illustrative purposes. Each pixel is $900m^2$ and is actually composed of nine $100m^2$ homogeneous pixels that improve the spatially weighted average of parcel-level NDVI.

summer I generate a variable for the number of days since the last precipitation event. Next I regress NDVI on these weather variables and keep the residuals as weather-normalized values of NDVI.

Table A.1 presents the results of the weather normalizations with lags of up to four weeks. I select residuals from the regression in column (4) as my preferred measure, though robustness checks using other normalizations produce very similar results. The results in Table A.1 are mostly intuitive with the cumulative effect of higher soil temperatures and evapotranspiration leading to lower values of NDVI. Net precipitation increases NDVI and the longer dry periods decrease NDVI. Overall weather explains between 10-14% of NDVI suggesting that most of the variation is spatial, due to different landscaping practices across the city. The regressions maintain the spatial variation because analyzing the residuals shows that the standard deviation in normalized NDVI within a given year is very similar to the standard deviation of the raw data.

Table A.1: Weather Normalization Regression

	(1) 1 Week	(2) 2 Weeks	(3) 3 Weeks	(4) 4 Weeks
Max Soil Temp (Week 1)	-0.00350***	-0.00945***	-0.00981***	-0.00610***
	(0.00000672)	(0.0000208)	(0.0000212)	(0.0000390)
Max Soil Temp (Week 2)		0.00624***	0.00279***	-0.0000182
		(0.0000202)	(0.0000276)	(0.0000450)
Max Soil Temp (Week 3)			0.00551***	0.00896***
			(0.0000238)	(0.0000378)
Max Soil Temp (Week 4)				-0.00583***
				(0.0000299)
Total Rain (Week 1)	0.0141***	0.0151***	0.0136***	0.0162***
	(0.0000452)	(0.0000548)	(0.0000567)	(0.000153)
Total Rain (Week 2)		-0.000958***	-0.00157***	0.000276***
		(0.0000113)	(0.0000202)	(0.0000516)
Total Rain (Week 3)			-0.000205***	-0.000465***
			(0.00000728)	(0.00000969)
Total Rain (Week 4)				0.000670***
				(0.0000117)
Evapotranspiration (Week 1)	0.00341***	0.0113***	0.0157***	0.0105***
	(0.0000634)	(0.0000675)	(0.0000776)	(0.0000860)
Evapotranspiration (Week 2)		-0.00983***	-0.00359***	0.00127***
		(0.0000473)	(0.0000583)	(0.0000626)
Evapotranspiration (Week 3)			0.00359***	-0.0125***
			(0.0000628)	(0.0000955)
Evapotranspiration (Week 4)				0.0158***
				(0.000115)
Days since Rain	-0.0000831***	0.0000197***	-0.0000982***	-0.000137***
	(0.00000107)	(0.00000118)	(0.00000129)	(0.00000184)
Constant	0.241***	0.219***	0.0528***	0.0727***
	(0.000992)	(0.00108)	(0.00142)	(0.00259)
Fourrier Control	Yes	Yes	Yes	Yes
Observations	13610445	13610445	13610445	13610445

Notes: Dependent variable is parcel-level NDVI for a given scene. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

A.4 Landscape Classification Diagnostics

In order to test the feasibility of using NDVI to classify different landscape varieties I compare the quantiles of NDVI to data from a widely cited remote sensing paper. Stefanov et al. (2001) classifies 11 different types of land use for Phoenix using 1998 data, including mesic and xeric residential. I merge the parcels with 1998 NDVI with the classification from Stefanov et al. (2001) keeping all parcels identified as either mesic or xeric. Table A.2 presents the percentage of parcels that were correctly identified as either mesic or xeric using various quantiles of NDVI. The columns show the thresholds for NDVI quantiles to make a classification. Parcels with NDVI above the higher threshold are classified as wet in a given year and parcels with NDVI less than the low threshold are defined as dry. Therefore decreasing the high threshold and increasing the low threshold relaxes the conditions to observe a conversion. NDVI does a relatively better job classifying dry landscapes and for that reason I use an asymmetric threshold for defining landscape groups For example in the conditional demand models I designate a the Wet group by households that have NDVI above the 80th quantile every year, and the Dry group by households that have below the 30th quantile every year. The results in Table A.2 contribute to establishing a relatively less stringent threshold for the Dry group.

Table A.2: Landscape Diagnostics

NDVI Quantiles	90/10	80/20	70/30	60/40
<u>% Correct</u>				
Wet	77%	71%	67%	64%
Dry	94%	90%	88%	85%

Notes: The columns designate the quantile of NDVI to compare with wet and dry landscapes. The higher quantile is used to determine wet parcels and the lower quantile designates dry parcels. The percentage correct takes the data from Stefanov et al. (2001) as the true value. We only compare single family residential households that were classified as xeric or mesic.

A.5 Water Demand Specification

Before estimating the conditional demand functions I perform model specification based on the full sample pooled over all landscapes by estimating the water demand function presented in equation (2).

$$\ln(w_{it}) = \alpha_i + \gamma ln(p_{it}) + \beta X'_{it} + \xi_{it} \tag{8}$$

Here w_{it} is water consumption for household i at time t, $p_{w,it}$ is the price of water, X_{it} is vector weather controls, α_i is a household level fixed effect, and ξ_{it} is an idiosyncratic error term. The dependent variable is the log of monthly water consumption, with panel cluster-robust standard errors at the household level as defined by Woolridge (2002).[39]

I run three specifications of the price in the water demand function: marginal price, average price, the high marginal price. Due to the increasing block rate structure of water rates the marginal and average price that a consumer faces depends on how much water she chooses to consume, creating a simultaneity problem when estimating demand functions (Hanemann, 1984; Hewitt and Hanemann, 1995; Nieswiadomy and Molina, 1989). A common approach to deal with the endogeneity is to use the full rate structure (fixed cost, low block price, and high block price) as instruments since the variables are correlated with actual marginal price and exogenous to the household (Nieswiadomy and Molina, 1989; Olmstead et al., 2007). In all specifications the dependent variable is the natural log of monthly household water consumption, as there is strong evidence that water demand is distributed log normally. I also run all three price specifications using one month lagged prices in case consumers change current consumption in response to the previous bill.

Table A.3 presents the results from the water demand specification regressions. A 2SLS model is used to estimate demand for columns (1), (3), (4), and (6), and Columns (2)

[39] A cluster-robust version of the Hausman test for the random effects versus fixed effects (Mundlak, 1978; Chamberlain, 1982; Woolridge, 2002) for each model in Table A.3 rejects the null of no correlation, requiring the fixed effects model.

and (5) estimates a feasible generalized least squares model. Net evapotranspiratin (ET) is the consumptive water requirement for turf grass minus the observed precipitation in millimeters per square foot. Cooling degree days are the monthly sum of daily differences between maximum temperature and 65 degrees Fahrenheit. PHDI is the Palmer Hydrological Drought Index that serves as a proxy for medium to long-run drought conditions with lower values signifying more severe droughts. Comparing the results across specifications, the estimates for price elasticity range from -0.24 to -0.31 for the contemporaneous price, which is in the range of conventional estimates (Espey et al., 1997; Dalhuisen et al., 2003). The models that use lagged coefficients produce less elastic estimates that range from -0.20 to -0.27. Examining the log likelihood shows that the high marginal price specification produces the best model fit using both contemporaneous and lagged price. Similar to recent evidence, average price outperforms marginal price, however, in this setting almost all the price signal comes from the second tier price.[40] For rest of the analysis I utilize the high marginal price specification for demand for three reasons. The high marginal price produces the best model fit, avoids the need for instruments, and is justified by both the rate structure as well as observed consumption patterns. The high marginal price also produces the best model fit in the conditional demand functions for each landscape class.

[40] This setting is not appropriate for general tests of average versus marginal price response as in Ito (2014) because there is not exogenous variation in the difference between average and marginal price. Rather the model specification is intended to determine the most appropriate model for water demand in the City of Phoenix.

Table A.3: Specification for Water Demand

	(1)	(2)	(3)	(4)	(5)	(6)
ln(marginal price)	-0.3144***					
	(0.0102)					
ln(high marginal price)		-0.2861***				
		(0.0073)				
ln(average price)			-0.2402***			
			(0.0080)			
ln(marginal price)$_{t-1}$				-0.2606***		
				(0.0097)		
ln(high marginal price)$_{t-1}$					-0.2694***	
					(0.0075)	
ln(average price)$_{t-1}$						-0.1978***
						(0.0079)
Time Trend	-0.0126***	-0.0119***	-0.0130***	-0.0177***	-0.0143***	-0.0180***
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Net ET	0.0333***	0.0251***	0.0325***	-0.0081***	0.0007***	-0.0068***
	(0.0003)	(0.0001)	(0.0003)	(0.0004)	(0.0002)	(0.0004)
Cooling Degree Days	0.0004***	0.0004***	0.0004***	0.0008***	0.0006***	0.0007***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PHDI	-0.0058***	-0.0056***	-0.0056***	-0.0086***	-0.0076***	-0.0085***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-8776185	-6159229	-7675346	-5892473	-4633272	-5223253
Households	172,314	172,316	172,034	172,313	172,314	172,010
Observations	8,054,287	8,054,289	7,944,154	6,038,664	6,038,665	5,959,748

Note: Dependent variable is the natural log of monthly household water consumption. For columns (1), (3), (4), and (6) price is instrumented with the full rate structure to deal with simultaneity with consumption. Household fixed effects are used in and robust standard errors clustered at the household level are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1

A.6 Selection Equation

Table A.4: Selection Equation Results

Dry		
Lot Size	-0.0109***	(0.000410)
Rooms	-0.0192***	(0.00134)
Year Built	0.0193***	(0.000137)
Pool	0.0954***	(0.00324)
Sale Price	-0.0719***	(0.00259)
% Renters	0.981***	(0.00804)
% College	0.00878***	(0.000139)
Same House	-0.530***	(0.00991)
Dry Neighbors	4.176***	(0.00691)
House Sold	-0.0440***	(0.00511)
Constant	-42.99***	(0.271)
Wet		
Lot Size	0.0417***	(0.000204)
Rooms	0.0237***	(0.00142)
Year Built	-0.0464***	(0.000131)
Pool	-0.141***	(0.00368)
Sale Price	0.0533***	(0.00113)
% Renters	-0.128***	(0.00859)
% College	0.0348***	(0.000124)
Same House	0.248***	(0.0125)
Dry Neighbors	-8.849***	(0.0137)
House Sold	-0.0475***	(0.00602)
Constant	89.10***	(0.254)
Observations	8,153,144	

Note: The dependent variable is the landscape group, either Mixed, Dry, or Wet, with Mixed being the omitted category. Standard errors are clustered at the household level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

A.7 Landscape Conversion Timing

Table A.5: Short Run - Timing

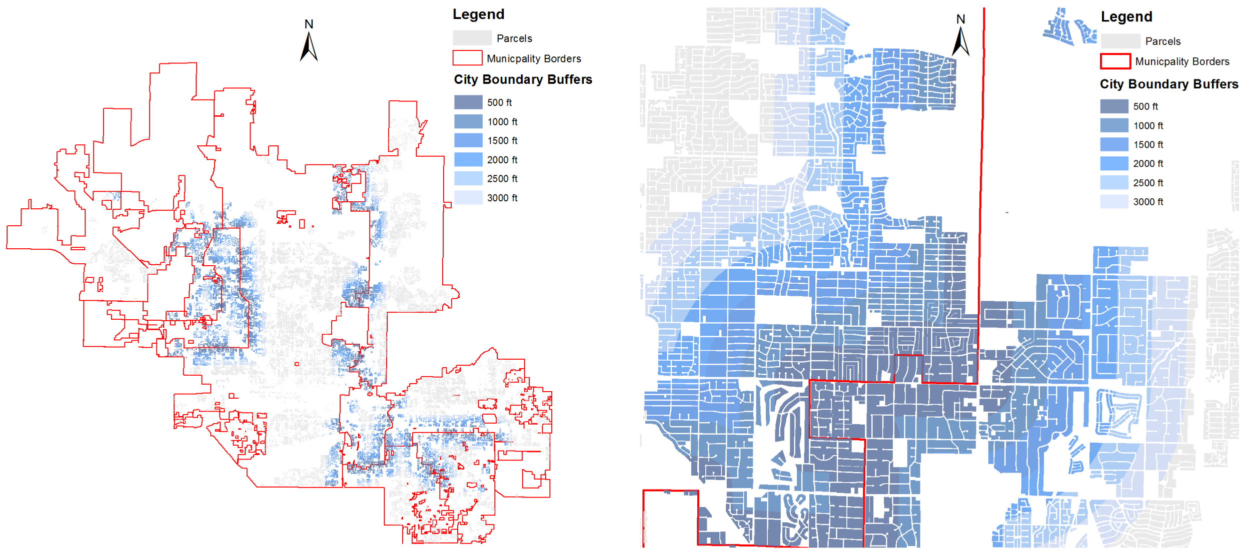
	t-1			t-1 & t-2			Mean(t-1, t-2)		
	(1) AP	(2) MP	(3) MxP	(4) AP	(5) MP	(6) MxP	(7) AP	(8) MP	(9) MxP
Avg Price$_{t-1}$	0.0145***			0.0095***					
	(0.0013)			(0.0012)					
Marginal Price$_{t-1}$		0.0190***			-0.0063***				
		(0.0019)			(0.0022)				
Max Price$_{t-1}$			0.0201***			-0.0155***			
			(0.0020)			(0.0035)			
Avg Price$_{t-2}$				0.0133***					
				(0.0019)					
Marginal Price$_{t-2}$					0.0302***				
					(0.0025)				
Max Price$_{t-2}$						0.0358***			
						(0.0032)			
Avg Price$_{\overline{t-1,t-2}}$							0.0187***		
							(0.0021)		
Marginal Price$_{\overline{t-1,t-2}}$								0.0238***	
								(0.0021)	
Max Price$_{\overline{t-1,t-2}}$									0.0224***
									(0.0020)
Rebate	-0.0023***	-0.0015***	-0.0016***	0.0005	0.0017***	0.0014**	-0.0023***	-0.0006	-0.0010
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Time trend	0.0131***	0.0112***	0.0112***	0.0287***	0.0271***	0.0281***	0.0133***	0.0115***	0.0116***
	(0.0003)	(0.0003)	(0.0003)	(0.0006)	(0.0006)	(0.0006)	(0.0003)	(0.0003)	(0.0003)
Time^2	-0.0014***	-0.0012***	-0.0012***	-0.0032***	-0.0030***	-0.0032***	-0.0015***	-0.0013***	-0.0013***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Neighbor Conversions$_{t-1}$	0.1451***	0.1440***	0.1439***	0.1366***	0.1379***	0.1383***			
	(0.0116)	(0.0116)	(0.0116)	(0.0112)	(0.0112)	(0.0112)			
House sold	0.0009***	0.0009***	0.0009***	0.0011***	0.0011***	0.0011***	0.0009***	0.0009***	0.0009***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Neighbor Conversions$_{t-2}$				0.2130***	0.2115***	0.2106***			
				(0.0135)	(0.0134)	(0.0134)			
Neighbor Conversions$_{\overline{t-1,t-2}}$							0.3488***	0.3486***	0.3488***
							(0.0173)	(0.0172)	(0.0172)
Constant	-0.0313***	-0.0431***	-0.0464***	-0.0731***	-0.0831***	-0.0812***	-0.0352***	-0.0500***	-0.0499***
	(0.0015)	(0.0027)	(0.0031)	(0.0030)	(0.0036)	(0.0038)	(0.0022)	(0.0030)	(0.0031)
Observations	1,129,939	1,129,957	1,129,957	938,614	938,629	938,629	1,129,939	1,129,957	1,129,957
Households	191,325	191,328	191,328	190,654	190,657	190,657	191,325	191,328	191,328
RMSE	0.0730	0.0730	0.0730	0.0745	0.0745	0.0745	0.0730	0.0729	0.0729

Notes: The dependent variable is a dummy equal to one if the household coverts at time t. The first three columns show models with prices lagged one year, columns (4)-(6) include prices lagged one year and two years, and the last three columns shows average prices over the past two years. Robust standard errors clustered at the census block level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

A.8 Boundary Discontinuity

Figure A.4: Boundary Discontinuity Maps

(a) Aggregate Sample **(b) Selected Location**



Note: Panel (a) shows the munipality borders and parcels in the full sample along with color coded buffers of 500 - 3000 feet for houses within a certain distance from a municipality border. Panel (b) shows a selected border (between Phoenix and Scottsdale) in greater detail.