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Estimating Water Demand Elasticity at the Intensive and Extensive Margin

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(Revised April 2018)

Working Paper 2016-06
http://faculty.bus.lsu.edu/papers/pap16_06.pdf

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Working Paper

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Abstract

I generate 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. Households that maintain dry landscapes are significantly less elastic that the general population. The extensive margin due to landscape accounts for 10% of total elasticity in the short run and this increases to 20-26% in the long run. As cities transition away from water-intensive landscapes aggregate demand becomes less elastic it will be more difficult to cope with future droughts by reducing water for residential irrigation.

JEL classification: Q21, Q25, Q54, L95
Keywords: water demand; extensive margin elasticity; satellite data; landscape conversion; water conservation

*Contact: Department of Economics, Louisiana State University; *dbrent@lsu.edu*. The author is grateful to Kerry Smith, Michael Hanemann, and Sheila Olmstead for advice and suggestions, as well as Hendrik Wolff, Joe Cook, and seminar participants at the Camp Resources and Arizona State University's Water Demand Workshop for helpful comments. Additionally the author is indebted to Doug Frost and Adam Miller from the City of Phoenix for sharing data and providing insights into water demand in Phoenix. Financial support was provided by Arizona State's Center for Environmental Economics & Sustainability Policy.

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. Recently California suffered 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 permanently strained water supplies. Despite the growing severity of water scarcity there are 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. In the context of water demand, 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 lack of research on the extensive margin elasticity 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 Southern California.

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. Earlier water demand research employs partial adjustment models that include lagged consumption in the demand equation, and find that long run elasticity exceeds short run elasticity in absolute value (Billings and Agthe, 1980; Carver and Boland, 1980; Dandy et al., 1997; Pint, 1999; Nauges and Thomas, 2003; Bell and Griffin, 2011). 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 limitation of the flow-adjustment models is that they estimate changes along the extensive margin implicitly through a parametric specification of demand. While explicit treatment of the capital stock has been studied in energy markets (Dubin and McFadden, 1984; Vaage, 2000; Goulder et al., 2009; Busse et al., 2013; Gillingham, 2014; Newell and Siikamäki, 2014; Allcott and Wozny, 2014) there is little research devoted to changes in the water capital stock.

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

This paper's primary objective is to incorporate changes in landscape choices over time into a model of water demand, which allows me to make three contributions to the water demand literature. First, I incorporate landscape decisions in a two-stage model to estimate the effect of price on consumption through the channel of landscape change. Second, I isolate the intensive margin elasticity by estimating conditional demand functions for households that maintain a fixed landscape over the course of the sample. Third, I examine the long-run effect of water rates on water-efficient landscape adoption, as well as the impact of landscape conversions on water demand. The primary barrier to addressing these objectives in the previous 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 primary result is that water rates affect landscape choices; higher prices increase the probability that households adopt water-efficient landscapes. Landscape choices also have a significant effect on water consumption. Combining results on the effect of price on landscape and the impact of landscape on demand generates estimates of the extensive margin elasticity of demand due to changes in landscape. In the two stage model for annual landscape choice and water demand, the extensive margin represents roughly 10% of the total demand elasticity. In the long run model of dry landscape adoption the share of the extensive margin increases to 20-26% of aggregate elasticity. Across all specification prices increase the probability of adopting water efficient landscapes. The results are robust to multiple model specifications and a boundary discontinuity analysis that restricts the sample to households near utility borders.

There are also lessons for water management policy based on the heterogeneity in water demand due to landscape. Households that maintain a dry landscape throughout the sample are significantly less price elastic than the general population. This has implications for how the aggregate elasticity will change as households in arid regions convert to dry landscapes. Neighbors' landscape choices are also positive and significant determinants in the conversion decision, although I caution a causal interpretation of this results due to the challenge in identifying peer effects (Manski, 1993, 2000). The empirical association between neighbors' landscape choices is consistent with anecdotal evidence of the importance of social peer effects that lead to the transition towards drought-resistant landscapes as social norms evolve. Landscape conversions have a large impact on demand; converting landscape from wet to dry decreases water consumption by roughly 20%. 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).[2]

While there are many complementary goods that comprise the extensive margin in water demand, I focus on landscape due its 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.[3] 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 (Nataraj and Hanemann, 2011; Klaiber et al., 2014; Ferraro and Price, 2013; Brent et al., 2015; Wichman et al., 2016). 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).[4] Water 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.[5] 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

[2]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.

[3]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).

[4]The alternative to mandatory restrictions is supply disruptions, which Buck et al. (2016) also show have large welfare consequences.

[5]Tchigriaeva et al. (2014) does address heterogeneity due to landscape, but does not incorporate changing landscape over time and Brelsford and Abbott (2018) examines response to turf rebates.

in demand.

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 River via the Central Arizona Project, with additional water sourced from the Verde and Salt Rivers via the Salt River Project. 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

[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] There is also 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).

September good indicators of the landscape during the summer season. Summer landscape has a high fixed costs of conversion, so a landscape conversion is typically a long-run decision.[8] Conversely, 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. Therefore some households' green summer lawns will appear dry in the winter even if they still have turf grass. Households may also refrain from watering their lawns in the summer, which will have the same satellite signature as a xeric landscape.

A key feature of water demand in the Phoenix metropolitan area is the Salt River Project (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 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. 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.[9] 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 images during the summer for each year. For each summer period I use two images to capture the average landscaping patterns, and to limit the impact of random weather events.[10] 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

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

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

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 comprised of turf lawn and referred to 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).[11] 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.3 of the Appendix describes the normalization procedure and presents results from the weather normalization regressions. Using the residuals from the weather normalization regressions I create quantiles over the 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.[12]

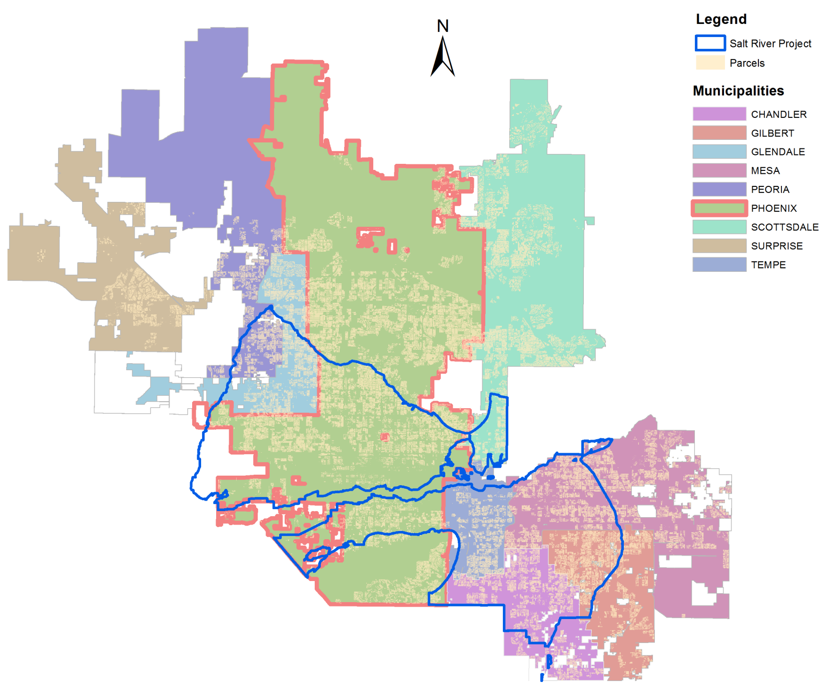
In addition to the landscape and weather data I obtain geo-referenced parcel characteristics from the Maricopa County Assessor, socioeconomic data and census boundaries from the U.S. Census, and water metering records from the City of Phoenix. These data sources produce two final datasets: a monthly panel of water metering records for 172,314 house-

[11] As of 4/6/2018 Stefanov et al. (2001) had 501 citations in Google Scholar.

[12] 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).

holds in the City of Phoenix and a yearly panel of landscape choices for 370,781 households in the Phoenix metropolitan area 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. The City of Phoenix data will be referred to as the Phoenix (or PHX) data and the metropolitan area data will be referred to as the Metro data. The primary purpose of the Metro data is to introduce spatial variation in the long run changes to water rates when estimating the effect of prices on long run dry landscape adoption.

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.

2.2.1 City of Phoenix Water Dataset

Water consumption data are only available within the City of Phoenix, and therefore all water demand models are estimated exclusively within Phoenix data. Water consumption is observed though monthly metering records for single-family homes in the City of Phoenix Water Department's service area from 1998-2009. This rich dataset is a balanced panel containing nearly 25 million observations, with over 8 million observations during the summer demand period. Since this period corresponds with the collapse of the housing market, using data from *active* accounts ensures that dry landscapes in the Phoenix 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 Phoenix to the time series of water metering records and water rates.[13] The resulting dataset is a panel with two sources of time-varying data. Water 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.[14]

In the Phoenix 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 70th percentile or below the 30th percentile respectively.[15] 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 70th percentiles. It is possible 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 for annual landscape classifications, 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 roughly one third more water than the Mixed group and two thirds 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

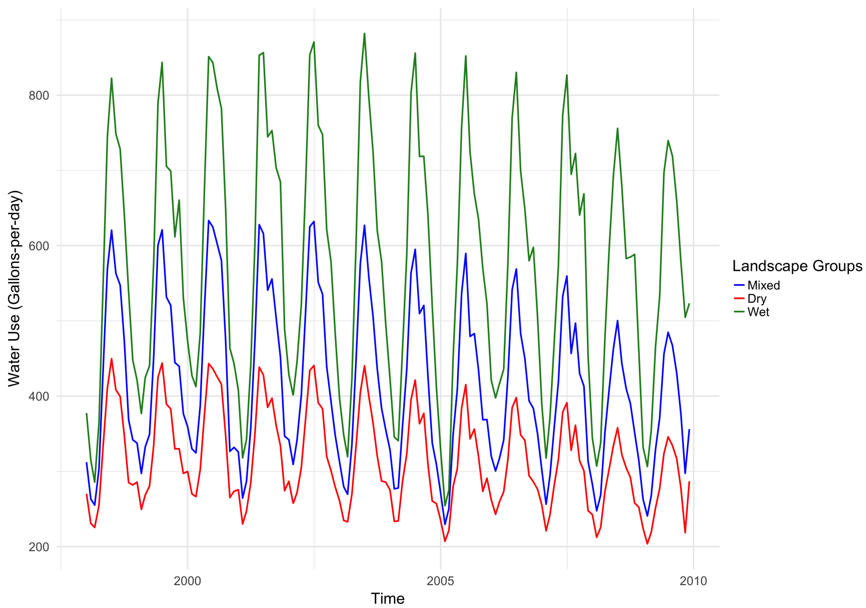
[13]According to a confidentiality agreement with the City of Phoenix I merge the NDVI values at the parcel level and then City officials attached it to an anonymous identifier representing a water account.

[14]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.

[15]The results from the classification diagnostics in the Appendix reveal that performance of NDVI for dry extends out from the tails to a greater degree than for wet. I also consider using non-symmetrical cutoffs for landscape classification in order to obtain a relatively balanced group for Wet and Dry. This is explored in the robustness and the results are robust to changing the NDVI classification thresholds.

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.[16] 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.

Figure 2: Water Consumption by Landscape Group



Note: Wet and Dry groups are determined by those that were continuously above the 70th percentile and below the 30th percentile of NDVI respectively. The Mix group is the remainder of the sample.

2.2.2 Landscape Conversion Dataset

In order to augment the Phoenix dataset and introduce cross-sectional variation in water rates, I incorporate data from the surrounding municipalities in the Phoenix metropolitan area (Metro) when modeling long run dry landscape adoption, which constitutes the central 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.

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

Similar to the Phoenix each of the water utilities employs some form of increasing block pricing. My primary specification of water rates is to use the highest marginal price in the rate structure. This avoids the need to observe consumption to determine the price. The maximum marginal price is also appropriate for determining the impact on landscape because most increasing block rates use the highest tier to target outdoor water use such as irrigation. Therefore, the maximum marginal price is a relevant metric for the cost of water in the landscape conversion decision. As a robustness check I also estimate the marginal and average price for each household outside of Phoenix using an out of sample prediction for each household's water consumption from a regression of water on housing characteristics, weather, and time fixed effects using the Phoenix sample. This assumes that the relationship between house size, pool ownership, and other characteristics is similar for Phoenix and the other municipalities. Using the estimated consumption and each municipality's rate structure I calculate the average and marginal price for each household. Table 1b shows the summary statistics 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	21.7	8,686	121,845	1972	0.34	132,673
Dry	17.3	8,119	122,742	1977	0.33	14,028
Wet	28.9	11,254	172,386	1965	0.39	25,614

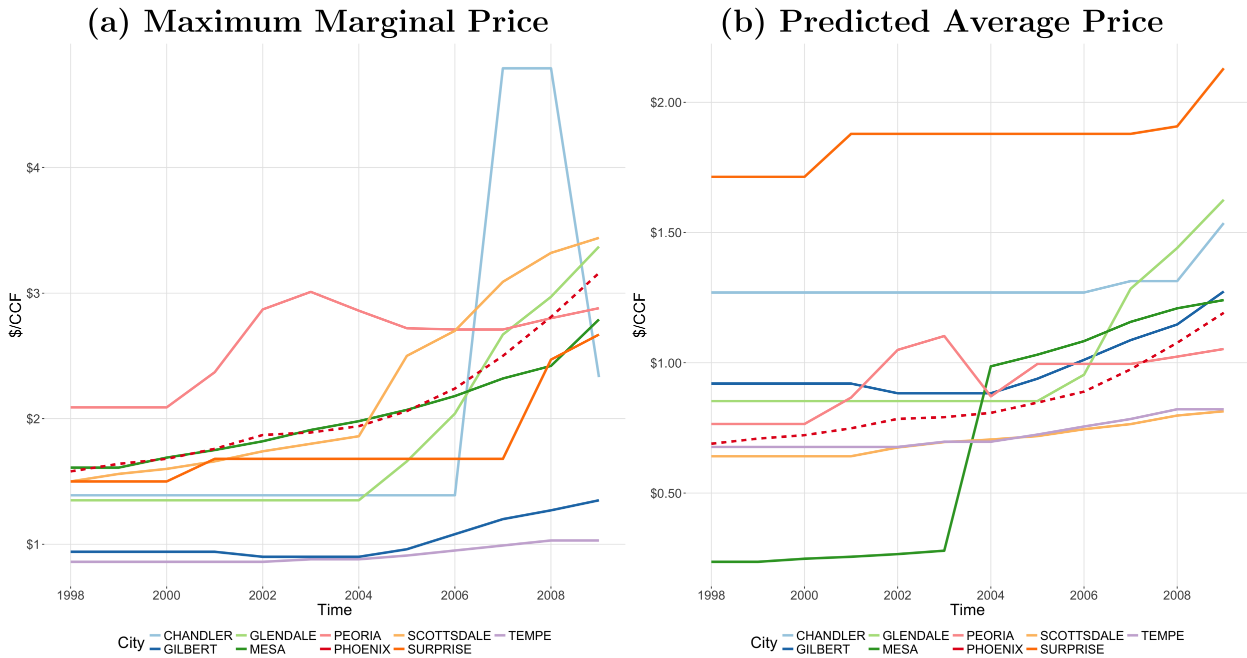
(b) Landscape Dataset - Metro Area

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.

The water rates for the various municipalities are shown in Figure 3. Panel (a) shows the maximum marginal price and Panel (b) shows the average price. For all municipalities other than Phoenix the average price is calculated using predicted water consumption as described above. Most utilities have experienced increases in the water rates, although the rate of increase over the sample is quite different across utilities. All prices are in 2008 dollars.

Figure 3: Water Rates



Note: Panel (a) shows the maximum marginal price in dollars per CCF for each year in each utility. Panel (b) shows the predicted average price in dollars per CCF for each year in each utility. Since each consumer may have a different average price the graph shows the average price averaged over all consumers. All prices are in 2008 dollars.

3 Estimation Strategy

Observing changes in the capital stock and water use over time add richness to modeling water demand, and allows for demand estimation on the intensive and extensive margin. The framework can be applied to other goods such as washing machines or toilets given data 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).[17] Similar to Dubin and McFadden (1984) I disaggregate water demand elasticity 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 fractions of households with dry and wet

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

landscapes. The general notation for the elasticity of x with respect to y is $\epsilon(x, y)$ and p_w is the price of water.

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

The first two terms of equation 1 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 dry landscape adoption. 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 of landscape decisions to identify changes in landscape as well as households that preserve a fixed landscape. I estimate the model using two different methods described in detail below: 1) a two stage model of annual landscape choice and monthly water demand and 2) separate models for conditional demand and long run dry landscape adoption.

3.1 Short-Run Two Stage Model

The first approach to incorporating landscape into water demand is a two stage model. The first stage models the impact of price and other factors on landscape choice and the second stage estimates a water demand model augmented by the predicted probabilities for each type of landscape from the first stage. The first stage landscape choice model is defined as:

$$L_{it} = \gamma_1^l p_{it-12} + \beta X'_{it} + \xi_{it} \tag{2}$$

where $L_{it} \in \{mixed, dry, wet\}$ represents the three landscape choices, and p_{it-12} are the water prices from the previous year (12 months). The coefficient on price, γ_1^l, captures the effect of price on the probability for selecting a dry or wet landscape relative to the mixed class. I also include other variables in X'_{it} to predict landscape choice such as structural features of the house, neighborhood demographic variables, the number of neighbors with dry landscapes, and a dummy indicating if the house was sold in the year leading up to the summer demand period. The error term, ξ_{it}, is assumed to follow the type-I extreme value distribution leading to a multinomial logit model. From the landscape choice model I calculate the predicted probabilities for having a dry or wet landscape in a given year and use these in the second stage water demand model defined as:

$$\ln(w_{it}) = \alpha_i + \gamma_2^l ln(p_{it-1}) + \delta_{dry} P_{dry} + \delta_{wet} P_{wet} + \beta X'_{it} + \epsilon_{it} \quad (3)$$

where $\ln(w_{it})$ is the natural log of monthly household water consumption, $ln(p_{it-1})$ is the logged water price from the previous month. The predicted probabilities for dry and wet landscapes from the first stage landscape model are P_{dry} and P_{wet}, with mixed being the omitted class. Additional control variables in X'_{it} include weather variables and a time trend. The water demand model includes household fixed effects (α_i) and ϵ_{it} is a normally distributed idiosyncratic error term. To account for the two-stage process the standard errors in the water demand model are bootstrapped across both stages, re-sampling at the household level. In the two stage model the extensive margin is the effect of price on landscape in the first stage multiplied by the effect of landscape on water demand in the second stage. The elasticity parameter in the second stage accounts for the effect of price on water demand through all channels other than landscape.

3.2 Long-Run Landscape Adoption Model

The two stage model is appealing because it simply incorporates landscape choices into water demand, however, households are allowed to choose a different landscape each year. In reality changing landscape from turf lawn to xeriscape is a costly long-term investment. Therefore, another way to model landscape choice is to focus on dry landscape adoption in the long run. The long run model consists of three parts. First, I estimate conditional demand functions based on the time series of landscape choices for three types of households: consistently dry (Dry), consistent wet (Wet), and neither consistently wet nor dry (Mixed). Second, I estimate the long run effect of changes in prices on the probability of having a dry landscape. Lastly, I estimate how landscape conversions affect water consumption. It is important to note that the conditional demand regressions and the effect of landscape conversions on water demand (parts one and three) are conducted with the Phoenix data, whereas the impact of price on dry landscape adoption (part two) uses the Metro data.

The conditional demand functions are defined as

$$\ln(w^l_{it}) = \alpha^l_i + \gamma^l ln(p_{it-1}) + \beta^l X'_{it} + \epsilon^l_{it} \quad (4)$$

where w_{it} is water consumption for household i at time t, p_{it} is the price of water, X_{it} is a vector of 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 $l = \{Mixed, Dry, Wet\}$. The dependent variable is the log of monthly water consumption, and the parameters of interest are the values of γ^l for each landscape group, interpreted as elasticities in the log-log specification.

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 individual heterogeneity, irrespective of landscape, between the three groups (Heckman, 1974). The conditional demand functions presented in Table 3 all contain 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 use sample selection corrections employed by Dahl (2002) utilizing third order polynomials of predicted probabilities from the selection equation in the conditional demand functions. These models require strong functional form assumptions if there is no exclusions criteria: variables that show up in the selection equation but not if the conditional demand regressions. The selection equation utilizes two significant time-varying variables that are plausibly exogenous: neighbors' conversions and a dummy whether the house was sold in the previous year.[18] As seen in Table A.4 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. 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 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 one set of estimates from Las Vegas range from \$1.37-1.93 per square foot (Sovocool et al., 2006).[19] The landscape conversion model treats 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:

$$V = \int_0^T [p_t \bar{W} + (m_t - b_t)] e^{-\rho t} dt + \int_T^\infty (1-\theta) p_t \bar{W} e^{-\rho t} dt + K_t e^{-\rho t} \quad (5)$$

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

[19]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.

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

$$\theta p_T \bar{W} + (m_T - b_T) - \rho K_T \geqslant 0 \tag{6}$$

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.

In order to analyze long run changes in prices on landscape choices I estimate equation 7, which is a long-difference 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. I parameterize ϵ_i in equation 7 as normally distributed leading to a panel data linear probability model.

$$D_i = \alpha + \gamma_{LR}\hat{p}_i + \phi\hat{r}_i + \hat{x}_i\beta + \epsilon_i \tag{7}$$

This is no longer a panel model since the dependent variable is not time varying, rather D_i 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. The term $\hat{x}_i$ includes the long run difference in the fraction of neighbors' with dry landscapes, the number of times the house was sold during the sample, and an indicator for whether the household had a wet landscape at the beginning of the sample. The long run model requires cross sectional variation in the long run price changes and therefore is only estimated with for the Metro sample.

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.[20] 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. The augmented water demand model is defined by:

$$\ln(w_{it}) = \alpha_i + \gamma ln(p_{it-1}) + \beta X_{it} + \delta_1 \tilde{C_{it}} + \delta_2 \tilde{NC_{it}} + \epsilon_{it} \tag{8}$$

Since I only observe water consumption for City of Phoenix Equation 8 is estimated with the City of Phoenix data, and I assume that the savings due to landscape conversions is similar for the other municipalities in the Metro data.

3.3 Water Price Specification

Before estimating the water demand functions I perform model specification based on the aggregate sample by estimating the water demand function presented in equation 4. The motivation for the model specification is that the City of Phoenix has an increasing block rate, 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 response is likely heterogeneous and certain rate structures may generate aggregate demand that is best modeled as either average or marginal price response (Olmstead et al., 2007).

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 cubic 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

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

[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.

[22] One CCF equals approximately 748 gallons.

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 based on values of the log likelihood. 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] As discussed above, in the landscape adoption model using Metro data I use the maximum marginal price in the rate structure since I do not observe water consumption for households outside of the City of Phoenix. As a robustness check I run models where I generate out of sample predictions of water use based on the water demand model using City of Phoenix data, and then estimate the marginal and average price facing Metro households outside the City of Phoenix.

4 Results

The results are presented in three sections. The first set of results are the estimates from the two stage model than incorporates annual landscape choices. Second, I present the analysis that models landscape conversions, which has three components: conditional demand functions, the dry landscape adoption model, and the effect of conversions on demand. Third, I analyze heterogeneity and examine the robustness of the results by relaxing various assumptions.

4.1 Two Stage Model

The two stage model estimates the effect of price on landscape in the first stage, and then uses the predicted probabilities for dry and wet landscape in the second stage water demand model. The results of the two stage model are presented in Table 2. Panel (a) shows the first stage results of the multinomial logit regression presented as semi-elasticities.[24] The interpretation of the coefficients is the marginal effect on the probability of being in a specific landscape class for a percentage change in the independent variables. Presenting the results as semi-elasticities facilitates the calculation of the extensive margin elasticity. When considering the dry class the coefficient price$_{t-12}$ is positive and significant indicating that higher prices in the previous year increase the probability of having a dry landscape in the

[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.

[24]Note that the Dry and Wet columns in Panel (a) of Table 2 are the marginal effects from one multinomial logit regression model.

current year. Conversely, for the wet class higher prices last year decrease the probability of having a wet landscape. Note that all the coefficients need to be interpreted relative to the omitted class, which is mixed landscape. In these regressions dry is defined as having normalized NDVI in a given year below the 30th percentile and wet is defined as normalized NDVI exceeding the 70th percentile.

The second stage results, which augment a standard water demand model with the predicted probabilities from the first stage landscape model, are presented in panel (b) of Table 2. The effect of having a dry or wet landscape on water use are captured in the predicted probabilities for each class, P_{dry} and P_{wet}. Not surprisingly increasing the probability of having a dry landscape decreases consumption and the probability of having a wet landscape increases consumption. The coefficient on $\ln(\text{price})_{t-1}$ represents one measure of the intensive demand elasticity, since the second stage model controls for the effect of price on water demand through the channel of landscape choices.

Table 2: Two Stage Model

(a) 1st Stage: Landscape

	Dry	Wet
price_{t-12}	0.2428***	-0.2303***
	(0.0043)	(0.0038)
Home Size	-0.0076***	0.0283***
	(0.0019)	(0.0018)
Bedrooms	-0.0006	0.0035
	(0.0042)	(0.0042)
Year Built	3.8614***	-5.6218***
	(0.1290)	(0.1020)
Pool	0.0058***	-0.0094***
	(0.0006)	(0.0006)
House Price	-0.0038**	0.0109***
	(0.0018)	(0.0021)
% Renters	0.0157***	-0.0032***
	(0.0007)	(0.0006)
% College	-0.0021	0.0655***
	(0.0015)	(0.0017)
Same House	-0.0470***	0.0011
	(0.0025)	(0.0025)
Number of Dry Neighbors	0.3678***	-0.2071***
	(0.0013)	(0.0007)
House Sold	0.0010***	-0.0007***
	(0.0001)	(0.0001)
Time Trend	-0.0852***	0.0760***
	(0.0016)	(0.0014)
Households	171,081	171,081
Observations	7,441,832	7,441,832

(b) 2nd Stage: Water Demand

	First Stage
$\ln(\text{price})_{t-1}$	-0.2811***
	(0.0073)
P_{dry}	-0.0824***
	(0.0066)
P_{wet}	0.0701***
	(0.0081)
Time Trend	-0.0135***
	(0.0004)
Net ET	0.0048***
	(0.0002)
Cooling Degree Days	0.0006***
	(0.0000)
PHDI	-0.0078***
	(0.0001)
Household FEs	Yes
Households	171,073
Observations	5,479,234

Note: Panel (a) presents the semi-elasticities from the first stage landscape multinomial logit model for both dry and wet categories. The mixed category is the omitted category. The interpretation is the how a percentage change in the independent variables affects the probability of being either dry or wet. Standard errors in the first stage model are computed by the delta method. The parameters for the second stage water demand model are presented in panel (b). The dependent variable is the natural log of monthly water consumption; P_{dry} and P_{wet} are the probabilities for having dry or wet landscape in a given year estimated in the first stage. The second stage standard errors are calculated using the bootstrap method where re-sampling takes place at the household level. *** p<0.01, ** p<0.05, * p<0.1

4.2 Long Run Landscape Adoption

The long run landscape adoption results are presented in three steps. First, I show results from conditional demand regressions that isolate households that do not convert their landscape and maintain either wet or dry landscapes. Second, I present the results of a discrete choice model for the decision to convert landscape from wet to dry. Third, I show how wet to dry landscape conversions impact water demand.

4.2.1 Conditional Demand Results

Table 3 presents the regression results from the conditional demand functions for the three landscape groups: Mixed, Dry, and Wet. 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 water use so the coefficients on price represent intensive margin elasticity. The Dry group is comprised of households that are below the 30th percentile of normalized NDVI every year and the Wet group represent households that are above the 70th percentile of normalized NDVI every year.

The results of Table 3 show that the Dry and Wet groups have lower point estimates for demand elasticity 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 -0.25 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. These differences are economically meaningful as well. Relative to the Mixed group the Dry group is 40% less elastic, while the Wet group is 18% less elastic. The relatively inelastic demand for households in the Wet group is consistent with in early consumer theory of conditional demand and quasi-fixed goods (Pollak, 1969). The Dry group's relative inelasticity may stem from removing one margin of adjustment, namely outdoor water use; and because indoor use is less elastic than outdoor use. These results also reveal the degree of heterogeneity in water demand parameters due to landscape.

Table 3: Conditional Demand Regressions

	(1) Mix	(2) Dry	(3) Wet
$\ln(\text{price})_{t-1}$	-0.3004***	-0.2023***	-0.2529***
	(0.0089)	(0.0262)	(0.0193)
Time Trend	-0.0153***	-0.0152***	-0.0068***
	(0.0005)	(0.0014)	(0.0010)
Net ET	-0.0000	0.0036***	-0.0076***
	(0.0003)	(0.0009)	(0.0006)
Cooling Degree Days	0.0006***	0.0004***	0.0007***
	(0.0000)	(0.0000)	(0.0000)
PHDI	-0.0079***	-0.0056***	-0.0077***
	(0.0001)	(0.0004)	(0.0003)
Selection Method	DHL	DHL	DHL
Household FEs	Yes	Yes	Yes
Households	172,315	172,315	172,315
Observations	8,198,288	8,198,288	8,198,288

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 Dahl (2002) using a third order polynomial of predicted probabilities.. 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

4.2.2 Long Run Landscape Adoption Results

The second set of results present a long run model that analyzes household landscapes at the end of the sample using the last two years prior to the collapse of the housing market (2005 and 2006).[25] The dependent is an indicator equal to one if the household has a dry

[25] All models that use data from outside the City of Phoenix end at 2006 prior to the collapse of the housing market because we cannot distinguish purposely dry landscape from vacant lots. For the City of

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 choices, and the household's initial landscape. The long run model is only estimated on the Metro sample because there is no variation across households in the long run differences in prices within a utility. Since there may be unobserved differences across utilities other than prices and landscape rebates I use a boundary discontinuity design that limits the sample to 1000 feet from a utility border when estimating models for the whole metro area (Black, 1999; Ito, 2014).[26]

Table 4 shows the results of the long run dry landscape adoption model. I show three results based on three definitions of conversions that vary the normalized NDVI threshold for annual dry and wet landscape classifications. I relax the normalized NDVI thresholds for wet and dry to above the 60th percentile and below the 40th percentile to more accurately measure the number of conversions.[27] First, wet is defined as above the 60th percentile and dry as below the 40th percentile, which correspond to the results shown in Table 4. I also define wet as above the 70th percentile and dry as below the 30th percentile. Lastly, since the landscape groups are asymmetric (there are more households consistently wet than consistently dry) I maintain the wet threshold at the 70th percentile and relax the dry threshold to below the 40th percentile. Households are quite responsive in the long run, which is 8 years. Increasing the maximum price by one dollar increases the probability of having a dry landscape between 20-25% depending on the specification. Since this includes households that started with, and maintained, dry landscapes the price effect is do to both converting from wet to dry and maintaining a dry landscape.[28] Additionally, introducing a rebate for turf removal increases the probability of dry landscapes. The long run difference in the proportion of neighbors with dry landscapes increases the probability of having a dry landscape, as does the cumulative housing sales in a neighborhood. 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).

Phoenix we know when lots are abandoned to the presence of water billing records.

[26]Figure A.4 visualizes the boundary discontinuity approach and Table 9 shows estimates using a variety of distance bandwidths.

[27]The actual number of conversions is estimated to be roughly 20% based on analysis of aerial imagery conducted by the City of Phoenix Water Department. Using the 60/40 thresholds 3.5% of households convert and using the 70/30 only 1% of the households convert. There are two primary reasons for the distinction between the my estimates of conversions and the City of Phoenix's estimates. First, the City of Phoenix classifies any household that transitions from primarily turf grass as a conversion, even if they have some green landscape that may represent a high NDVI measure. Second, the City of Phoenix classifications do not track individual households over time but rely on repeated cross sections at different points in time.

[28]A model that excludes initially dry households yields similar qualitative results.

Table 4: Landscape Conversion

	(1) 60/40	(2) 70/30	(3) 70/40
Δ Max Price	0.2012***	0.2466***	0.2291***
	(0.0211)	(0.0246)	(0.0234)
Δ Rebate	0.0003	-0.0079	0.0015
	(0.0219)	(0.0251)	(0.0245)
Start Wet	-0.5051***	-0.3521***	-0.4723***
	(0.0057)	(0.0062)	(0.0060)
Δ Dry Neighbors	0.3043***	0.1394***	0.2236***
	(0.0194)	(0.0206)	(0.0207)
$\sum$ Sales	0.0080***	0.0082***	0.0105***
	(0.0019)	(0.0020)	(0.0020)
Observations	86,901	86,901	86,901

Notes: The dependent variable in columns is an indicator equal to one if a household ends the sample with a dry landscape, defined as two consecutive annual low NDVI observations. The regressions use the Phoenix Metropolitan sample present boundary discontinuity results that limit the sample to within 1000 feet of a utility border. The difference variables (Δ) represent the differences from the last two years of the sample minus the first two years of the sample. Start Wet is a dummy equal to one if the household started the sample with two consecutive wet NDVI observations. The columns represent the NDVI percentile thresholds for an annual wet and dry classification, which are used to create the dependent variable (ending dry), Start Wet, and Dry Neighbors. Robust standard errors clustered at the census block level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.2.3 Landscape Conversions and Water Demand

The last component of the landscape conversion analysis estimates the change in water consumption due to landscape conversions. Table 5 presents the results of the water demand regression presented in equation 8 that includes the effect of conversions and neighbors' conversions on water demand. Similar to Table 4 the columns show different NDVI thresholds for annual landscape classification. All the results show that conversions have a negative impact on water consumption magnitude that is not only statistically, but also economically, significant at roughly 18-20% of monthly water demand. Neighbors' conversions cause a statistically significant reduction in demand, but the magnitude is roughly one tenth 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. It should be noted that the effect of a landscape conversion on water demand is only estimated with data from the Phoenix sample.

I calculate the long run arc elasticity of demand for the extensive by simulating the effect of a 10% price increase on the probability of dry landscape adoption, and multiplying this by the percentage change in consumption associated with a conversion ($\Delta q = \Delta p \times \gamma_{LR} \times \delta_1 \times E[w|wet]$). This captures the change in consumption due to price induced changes in landscape. The long run extensive margin ranges from -.06 to -.09 depending on the landscape classification thresholds used. I compare this to the intensive margin elasticity

Table 5: **Water Demand and Landscape Conversions**

	(1) 60/40	(2) 70/30	(3) 70/40
Conversions	-0.1773***	-0.2035***	-0.1898***
	(0.0055)	(0.0103)	(0.0070)
Neighbor Conversions	-0.0176***	-0.0274***	-0.0225***
	(0.0009)	(0.0021)	(0.0012)
Additional Controls	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes
Households	172,311	172,311	172,311
Observations	6,038,951	6,038,951	6,038,951

Note: Dependent variable is the natural log of monthly water consumption, and the sample is all household in the City of Phoenix. The columns refer to the thresholds of normalized NDVI defining the wet and dry annual landscape classifications when coding landscape conversions. The regression includes all controls shown in the first three columns of Table 3. Robust standard errors clustered at the household level are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1

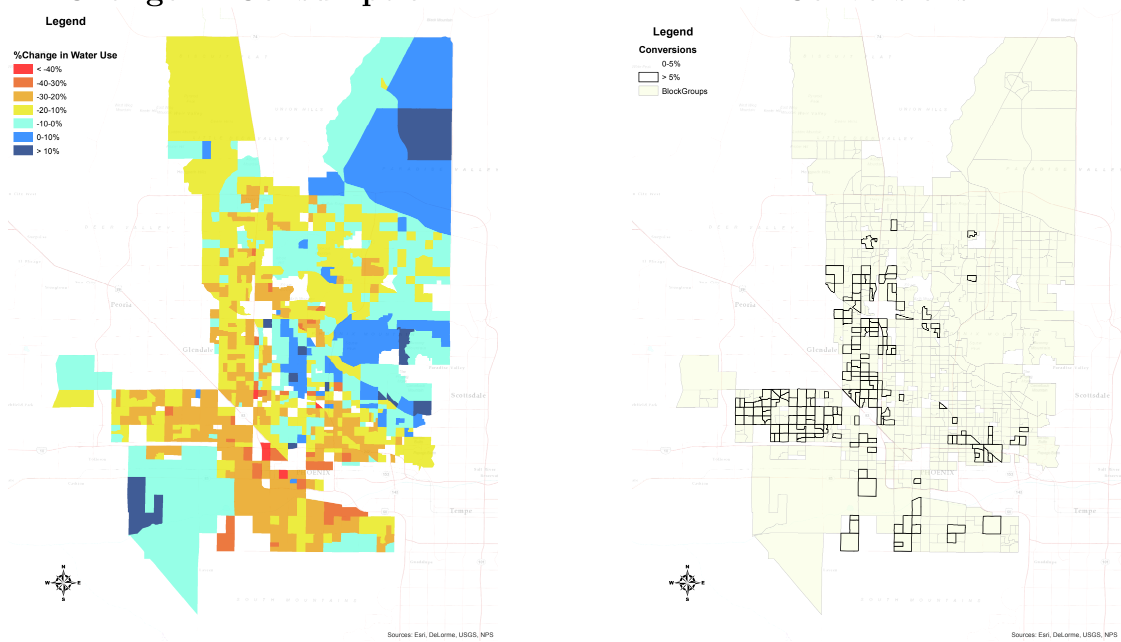
for households with green landscapes from the conditional demand regressions to show the relative importance of the extensive margin in the long run. This assumes that total elasticity is the sum of the intensive margin for the wet group plus the extensive margin due to landscape. In the long run the extensive margin accounts 20-26% of the total elasticity depending on the landscape classification thresholds. Comparing this to the short run results from the two stage model shows that the relative importance of the extensive margin is roughly twice as large in the long run.

Lastly, in order visualize the importance of landscape conversions in Phoenix's long-run changes in water demand I map 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.[29] 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.

[29]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.

4.3 Heterogeneity & Robustness

The next set of results is devoted to analyzing heterogeneity due to the SRP and the robustness of the results. 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. Table 6 shows the two stage results where the price variables are interacted with the SRP dummy. In the first stage SRP households are significantly less responsive to prices in terms of their landscape choices, but the magnitude is quite small. In the second stage SRP households are actually more elastic to prices outside the landscape mechanism. For the conditional demand results, presented in Table 7, SRP households in the Mix and Dry groups are both more elastic relative to the general sample, but the Wet group is less elastic. The Wet group is likely less elastic because they pay a depressed price for irrigation water. The effect of the SRP on the long run impact of prices on dry landscape adoption is shown in Table 8. In all models the SRP dampens the effect of price on landscape, although the joint effect is still positive and significant at either the 5% or 10% level. SRP households are also less responsive to the introduction of turf rebates.

Table 6: Two Stage Model with SRP Interaction

(a) 1st Stage: Landscape

	Dry	Wet
price_{t-12}	0.2450***	-0.2482***
	(0.0044)	(0.0038)
price_{t-12}*SRP	-0.0029***	0.0248***
	(0.0008)	(0.0009)
Additional Controls	Yes	Yes
Households	171,081	171,081
Observations	7,441,832	7,441,832

(b) 2nd Stage: Water Demand

	First Stage
$\ln(\text{price})_{t-1}$	-0.2492***
	(0.0080)
$\ln(\text{price})_{t-1}$*SRP	-0.0694***
	(0.0065)
P_{dry}	-0.0723***
	(0.0066)
P_{wet}	0.0706***
	(0.0084)
Household FEs	Yes
Additional Controls	Yes
Households	171,073
Observations	5,479,234

Note: Panel (a) presents the semi-elasticities from the first stage landscape multinomial logit model for both dry and wet categories. The mixed category is the omitted category. The interpretation is the how a percentage change in the independent variables affects the probability of being either dry or wet. Standard errors in the first stage model are computed by the delta method. The parameters for the second stage water demand model are presented in panel (b). The dependent variable is the natural log of monthly water consumption; p(Dry) and p(Wet) are the probabilities for having dry or wet landscape in a given year estimated in the first stage. The second stage standard errors are calculated using the bootstrap method where re-sampling takes place at the household level. Both models include all parameters that are shown in Table 2. Those parameters are omitted for space concerns and are available upon request *** p<0.01, ** p<0.05, * p<0.1

Table 7: Conditional Demand Regressions with SRP Interaction

	(1) Mix	(2) Dry	(3) Wet
$\ln(\text{price})_{t-1}$	-0.2412***	-0.1587***	-0.3439***
	(0.0100)	(0.0264)	(0.0223)
$\ln(\text{price})_{t-1}$*SRP	-0.1305***	-0.1331***	0.1247***
	(0.0067)	(0.0232)	(0.0187)
Selection Method	DHL	DHL	DHL
Household FEs	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes
Households	172,315	172,315	172,315
Observations	8,198,288	8,198,288	8,198,288

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). The models include all parameters that are shown in Table 3. Those parameters are omitted for space concerns and are available upon request. The standard errors are bootstrapped to account for the two-stage method. *** p<0.01, ** p<0.05, * p<0.1

The next set of results examines the robustness of the results. First, I replicate the two stage model after changing the NDVI percentile thresholds for wet and dry classifications to above the 80th and below the 20th percentiles, as well as above the 80th and below the 30th. The results are qualitatively similar and are presented in the Appendix in Tables A.5 and A.6. I repeat this same exercise with the conditional demand functions, presented in Tables A.7

Table 8: Dry Landscape Adoption with SRP Interaction

	(1)	(2)	(3)
	60/40	70/30	70/40
Δ Max Price	0.2725***	0.3391***	0.3068***
	(0.0224)	(0.0262)	(0.0246)
Δ Max Price*SRP	-0.2301***	-0.2970***	-0.2538***
	(0.0230)	(0.0271)	(0.0255)
Δ Rebate	0.1107***	0.1128***	0.1358***
	(0.0358)	(0.0428)	(0.0392)
Δ Rebate*SRP	-0.1929***	-0.2090***	-0.2339***
	(0.0382)	(0.0446)	(0.0421)
Observations	86,901	86,901	86,901

Notes: The dependent variable in columns (1)-(2) is an indicator whether a household converts from a wet to dry landscape in year t, and in column (3) 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 columns (2). Columns (2)-(3) that use the Phoenix Metropolitan sample present boundary discontinuity results that limit the sample to within 1000 feet of a utility border. The models include all parameters that are shown in Table 4. Those parameters are omitted for space concerns and are available upon request. Robust standard errors clustered at the census block level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

and A.8, and similarly find that the results are robust to changing the landscape classification thresholds. Next, I present a variety of thresholds for the boundary discontinuity bandwidths for the long run dry landscape adoption model. The results, presented in Table 9, show that long run differences in price always has a positive and significant effect on dry landscape adoption. The effect becomes larger as the bandwidth becomes smaller, which suggests that differences across municipality boundaries may bias the effect towards zero. Lastly, I present the long run dry landscape adoption model using predicted average and marginal prices instead of the maximum marginal price. The results, presented in Tables A.9 and A.10 show qualitatively similar results. The magnitudes are slightly different, but this reflects the different magnitudes of the price variables, as shown in Table 1.

Table 9: Boundary Bandwidths for Landscape Conversion Models

	All	3000ft	2500ft	2000ft	1500ft	1000ft	500ft
Δ Max Price	0.0583***	0.1542***	0.1650***	0.1840***	0.2133***	0.2466***	0.3592***
	(0.0132)	(0.0156)	(0.0168)	(0.0186)	(0.0212)	(0.0246)	(0.0323)
Δ Rebate	0.0135	0.0293*	0.0206	0.0011	0.0011	-0.0079	0.0019
	(0.0148)	(0.0150)	(0.0156)	(0.0171)	(0.0198)	(0.0251)	(0.0344)
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	370,781	213,985	191,084	159,057	126,119	86,901	42,478

Notes: The dependent variable is an indicator whether a household converts from a wet to dry landscape in year t. The columns show different different bandwidths for the boundary discontinuity analysis using observations from all of the Phoenix Metropolitan area. Column (1) (All) shows the results for the full sample. Households that have a dry landscape at the start of the sample are removed. The models include all parameters that are shown in Table 4. Those parameters are omitted for space concerns and are available upon request. Robust standard errors clustered at the census block level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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. 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 than the general population.

I find that higher water rates increase the probability of adopting a water-efficient landscape in both the short run and the long run. This is robust across a range of price and landscape specifications as well as controlling for utility specific unobservables with a boundary discontinuity analysis. Landscape conversions have a significant impact on demand; reducing consumption by roughly 20%. Changes along the extensive margin constitute only 10% of aggregate demand elasticity in the short run, and this rises to 20-26% 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 (Klaiber et al., 2017). 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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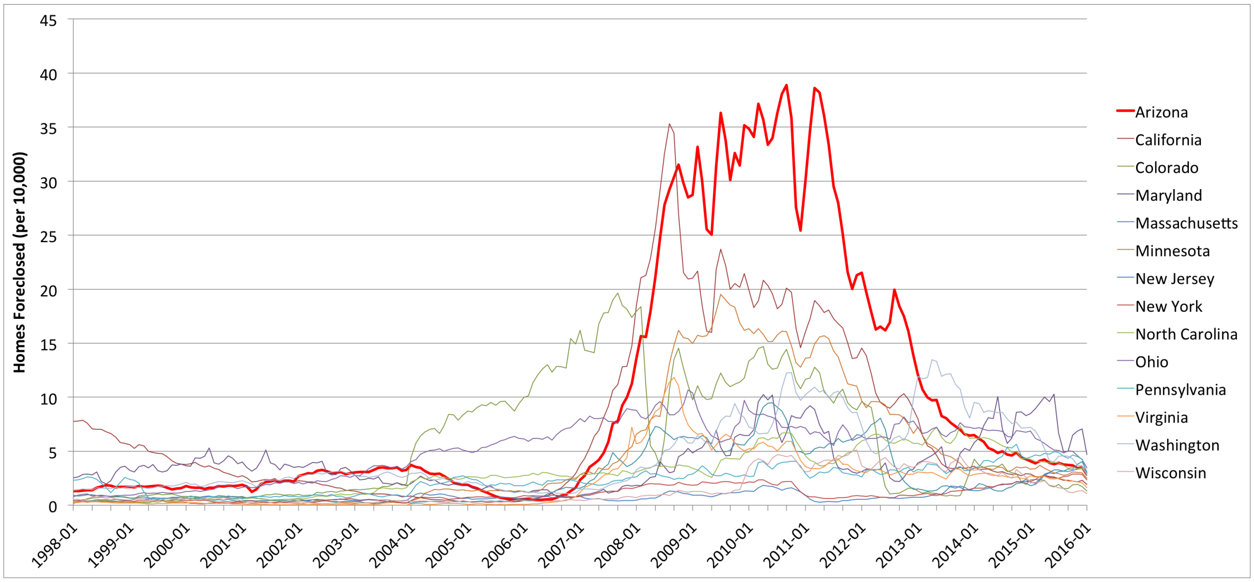
A Appendix

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

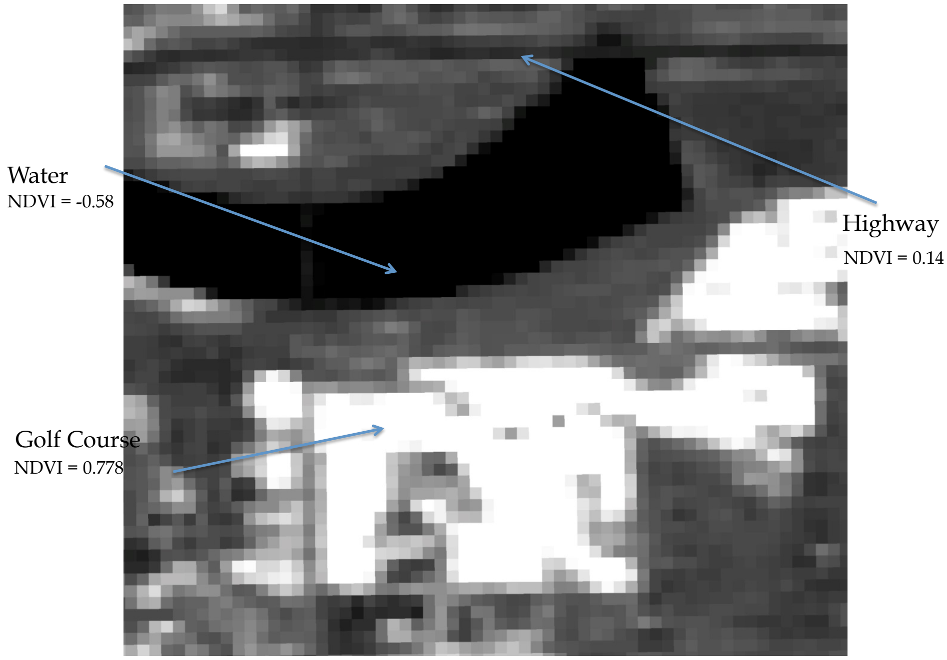
The Landsat data is publicly available in a raw form and requires processing in order to apply the data for analysis. Processing is particularly important when comparing two or more images over time or across space. I follow the steps presented in Myint et al. (2008) to process the Landsat data in Erdas 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.[30] 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-

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



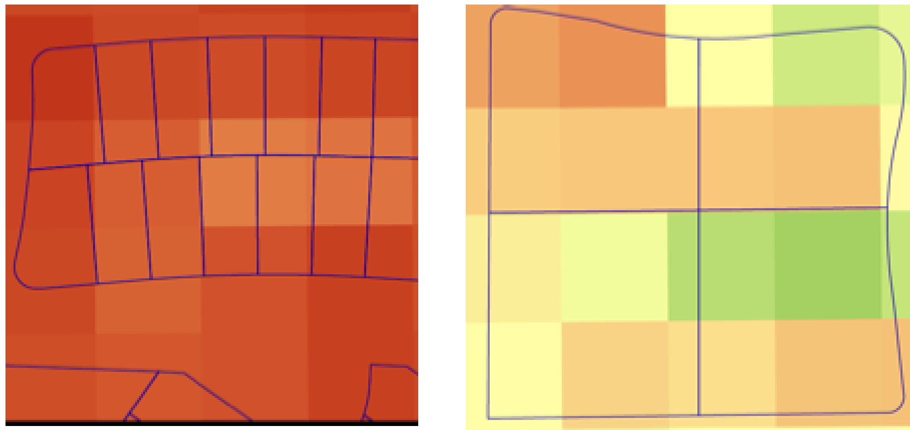
Note: This is a sample area just northwest of Arizona State University, whose land use features are known.

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
% Correct				
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).

$$\ln(w_{it}) = \alpha_i + \gamma ln(p_{it}) + \beta X'_{it} + \xi_{it} \tag{9}$$

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).[31]

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)

[31] 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.[32] 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.

[32] 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

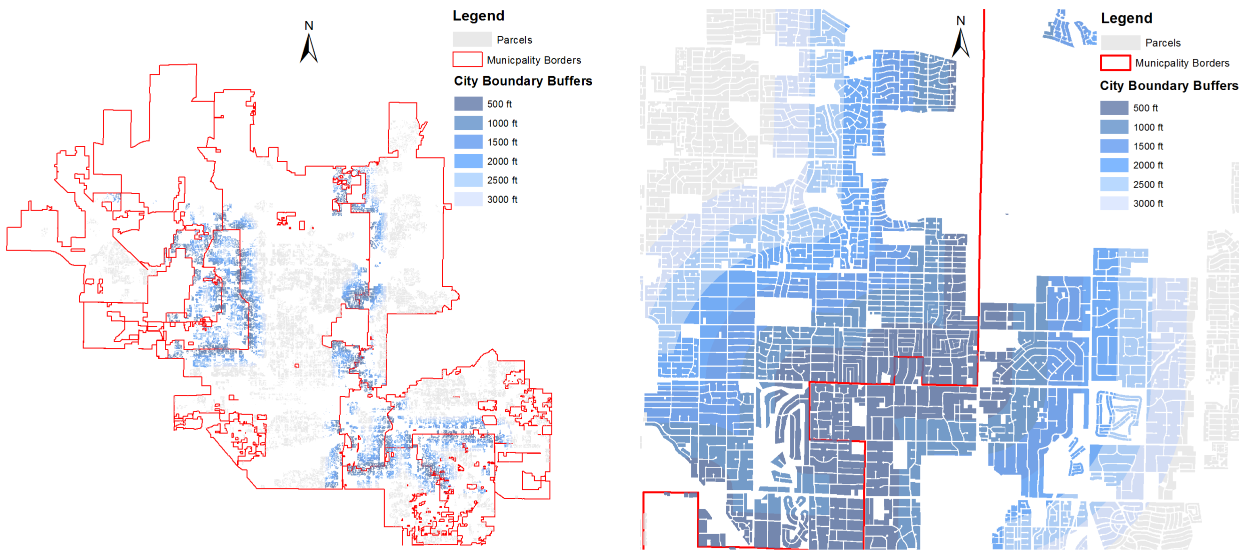
Dry		
Lot Size	-0.0109***	(0.000410)
Rooms	-0.0192***	(0.00134)
Year Built	0.0193***	(0.000137)
Pool	0.0954***	(0.00324)
Sale Price	-0.0719***	(0.00259)
% Renters	0.981***	(0.00804)
% College	0.00878***	(0.000139)
Same House	-0.530***	(0.00991)
Dry Neighbors	4.176***	(0.00691)
House Sold	-0.0440***	(0.00511)
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 Boundary Discontinuity

Figure A.4: Boundary Discontinuity Maps

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



Note: Panel (a) shows the municipality 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.

B Robustness to Landscape Thresholds

Table A.5: Two Stage Model - 80/20 Thresholds

(a) 1st Stage: Landscape

	Dry	Wet
price_{t-12}	0.1851***	-0.1688***
	(0.0040)	(0.0031)
Home Size	-0.0056***	0.0293***
	(0.0019)	(0.0015)
Bedrooms	0.0004	0.0051
	(0.0038)	(0.0036)
Year Built	3.5089***	-5.2918***
	(0.1233)	(0.0866)
Pool	0.0044***	-0.0073***
	(0.0005)	(0.0005)
House Price	-0.0042**	0.0096***
	(0.0018)	(0.0017)
% Renters	0.0147***	-0.0003
	(0.0006)	(0.0005)
% College	0.0090***	0.0666***
	(0.0014)	(0.0015)
Same House	-0.0459***	-0.0047**
	(0.0022)	(0.0022)
Number of Dry Neighbors	0.3405***	-0.1171***
	(0.0016)	(0.0005)
House Sold	0.0007***	-0.0005***
	(0.0001)	(0.0001)
Time Trend	-0.0634***	0.0522***
	(0.0014)	(0.0012)
Households	171,081	171,081
Observations	7,441,832	7,441,832

(b) 2nd Stage: Water Demand

	First Stage
$\ln(\text{price})_{t-1}$	-0.2806***
	(0.0074)
P_{dry}	-0.1159***
	(0.0048)
P_{wet}	0.1010***
	(0.0071)
Time Trend	-0.0136***
	(0.0004)
Net ET	0.0048***
	(0.0002)
Cooling Degree Days	0.0006***
	(0.0000)
PHDI	-0.0078***
	(0.0001)
Household FEs	Yes
Households	171,073
Observations	5,479,234

Note: Panel (a) presents the semi-elasticities from the first stage landscape multinomial logit model for both dry and wet categories. The mixed category is the omitted category. The interpretation is the how a percentage change in the independent variables affects the probability of being either dry or wet. Standard errors in the first stage model are computed by the delta method. The parameters for the second stage water demand model are presented in panel (b). The dependent variable is the natural log of monthly water consumption; p(Dry) and p(Wet) are the probabilities for having dry or wet landscape in a given year estimated in the first stage. The second stage standard errors are calculated using the bootstrap method where re-sampling takes place at the household level. *** p<0.01, ** p<0.05, * p<0.1

Table A.6: Two Stage Model - 80/30 Thresholds

(a) 1st Stage: Landscape

	Dry	Wet
price_{t-12}	0.0901***	-0.0908***
	(0.0011)	(0.0010)
Home Size	-0.0065***	0.0247***
	(0.0022)	(0.0013)
Bedrooms	-0.0083*	0.0098***
	(0.0043)	(0.0032)
Year Built	3.5617***	-4.9440***
	(0.1489)	(0.0850)
Pool	0.0031***	-0.0030***
	(0.0005)	(0.0005)
House Price	-0.0068***	0.0050***
	(0.0025)	(0.0009)
% Renters	0.0108***	-0.0014***
	(0.0007)	(0.0005)
% College	0.0191***	0.0529***
	(0.0017)	(0.0013)
Same House	-0.0179***	0.0055**
	(0.0022)	(0.0023)
Number of Dry Neighbors	0.2251***	-0.0409***
	(0.0023)	(0.0004)
House Sold	-0.0001**	-0.0003***
	(0.0001)	(0.0000)
Time Trend	-0.0280***	0.0258***
	(0.0004)	(0.0003)
Households	171,081	171,081
Observations	7,441,832	7,441,832

(b) 2nd Stage: Water Demand

	First Stage
$\ln(\text{price})_{t-1}$	-0.2796***
	(0.0073)
P_{dry}	-0.2191***
	(0.0067)
P_{wet}	0.1422***
	(0.0089)
Time Trend	-0.0136***
	(0.0004)
Net ET	0.0049***
	(0.0002)
Cooling Degree Days	0.0006***
	(0.0000)
PHDI	-0.0077***
	(0.0001)
Household FEs	Yes
Households	171,073
Observations	5,479,234

Note: Panel (a) presents the semi-elasticities from the first stage landscape multinomial logit model for both dry and wet categories. The mixed category is the omitted category. The interpretation is the how a percentage change in the independent variables affects the probability of being either dry or wet. Standard errors in the first stage model are computed by the delta method. The parameters for the second stage water demand model are presented in panel (b). The dependent variable is the natural log of monthly water consumption; p(Dry) and p(Wet) are the probabilities for having dry or wet landscape in a given year estimated in the first stage. The second stage standard errors are calculated using the bootstrap method where re-sampling takes place at the household level. *** p<0.01, ** p<0.05, * p<0.1

Table A.7: Conditional Demand Regressions - 80/20 Thresholds

	(1) Mix	(2) Dry	(3) Wet
$\ln(\text{price})_{t-1}$	-0.2959***	-0.1883***	-0.2386***
	(0.0083)	(0.0426)	(0.0260)
Time Trend	-0.0150***	-0.0134***	-0.0045***
	(0.0004)	(0.0022)	(0.0013)
Net ET	-0.0002	0.0046***	-0.0083***
	(0.0003)	(0.0012)	(0.0007)
Cooling Degree Days	0.0006***	0.0004***	0.0007***
	(0.0000)	(0.0000)	(0.0000)
PHDI	-0.0079***	-0.0059***	-0.0069***
	(0.0001)	(0.0005)	(0.0003)
Selection Method	DHL	DHL	DHL
Household FEs	Yes	Yes	Yes
Households	172,315	172,315	172,315
Observations	8,198,288	8,198,288	8,198,288

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 Dahl (2002) using a third order polynomial of predicted probabilities.. 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

Table A.8: Conditional Demand Regressions - 80/30 Thresholds

	(1) Mix	(2) Dry	(3) Wet
$\ln(\text{price})_{t-1}$	-0.3003***	-0.2012***	-0.2383***
	(0.0087)	(0.0263)	(0.0261)
Time Trend	-0.0150***	-0.0152***	-0.0045***
	(0.0004)	(0.0014)	(0.0013)
Net ET	-0.0004	0.0036***	-0.0083***
	(0.0003)	(0.0009)	(0.0007)
Cooling Degree Days	0.0006***	0.0004***	0.0007***
	(0.0000)	(0.0000)	(0.0000)
PHDI	-0.0080***	-0.0056***	-0.0069***
	(0.0001)	(0.0004)	(0.0003)
Selection Method	DHL	DHL	DHL
Household FEs	Yes	Yes	Yes
Households	172,315	172,315	172,315
Observations	8,198,288	8,198,288	8,198,288

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 Dahl (2002) using a third order polynomial of predicted probabilities.. 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

C Robustness to Landscape Thresholds

Table A.9: Landscape Conversion - Predicted Average Price

	(1)	(2)	(3)
	60/40	70/30	70/40
Δ Avg Price	0.0865***	0.1099***	0.1009***
	(0.0159)	(0.0183)	(0.0180)
Δ Rebate	-0.0305	-0.0432*	-0.0324
	(0.0219)	(0.0251)	(0.0246)
Start Wet	-0.5106***	-0.3578***	-0.4775***
	(0.0058)	(0.0063)	(0.0060)
Δ Dry Neighbors	0.3348***	0.1751***	0.2569***
	(0.0173)	(0.0180)	(0.0186)
$\sum$ Sales	0.0073***	0.0074***	0.0097***
	(0.0020)	(0.0020)	(0.0021)
Observations	86,900	86,900	86,900

Notes: The dependent variable in columns is an indicator equal to one if a household ends the sample with a dry landscape, defined as two consecutive annual low NDVI observations. The regressions use the Phoenix Metropolitan sample present boundary discontinuity results that limit the sample to within 1000 feet of a utility border. The difference variables (Δ) represent the differences from the last two years of the sample minus the first two years of the sample. Start Wet is a dummy equal to one if the household started the sample with two consecutive wet NDVI observations. The columns represent the NDVI percentile thresholds for an annual wet and dry classification, which are used to create the dependent variable (ending dry), Start Wet, and Dry Neighbors. Robust standard errors clustered at the census block level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.10: Landscape Conversion - Predicted Marginal Price

	(1)	(2)	(3)
	60/40	70/30	70/40
Δ Marginal Price	0.1684***	0.2095***	0.1957***
	(0.0209)	(0.0241)	(0.0232)
Δ Rebate	0.0201	0.0182	0.0263
	(0.0234)	(0.0267)	(0.0263)
Start Wet	-0.5090***	-0.3569***	-0.4767***
	(0.0058)	(0.0062)	(0.0060)
Δ Dry Neighbors	0.3094***	0.1457***	0.2279***
	(0.0185)	(0.0193)	(0.0198)
$\sum$ Sales	0.0075***	0.0077***	0.0100***
	(0.0019)	(0.0020)	(0.0020)
Observations	86,901	86,901	86,901

Notes: The dependent variable in columns is an indicator equal to one if a household ends the sample with a dry landscape, defined as two consecutive annual low NDVI observations. The regressions use the Phoenix Metropolitan sample present boundary discontinuity results that limit the sample to within 1000 feet of a utility border. The difference variables (Δ) represent the differences from the last two years of the sample minus the first two years of the sample. Start Wet is a dummy equal to one if the household started the sample with two consecutive wet NDVI observations. The columns represent the NDVI percentile thresholds for an annual wet and dry classification, which are used to create the dependent variable (ending dry), Start Wet, and Dry Neighbors. Robust standard errors clustered at the census block level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1