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Peer Effects in Residential Water Conservation: Evidence from Migration[†]

By BRYAN BOLLINGER, JESSE BURKHARDT, AND KENNETH T. GILLINGHAM*

Social interactions are widely understood to influence consumer decisions in many choice settings. This paper identifies causal peer effects in residential water conservation during the summer using variation from movers. We classify high-resolution remote sensing images to provide evidence that conversions of green landscaping to dry landscaping are a primary determinant of the reductions in water consumption. We also find suggestive evidence that without a price signal, peer effects are muted, indicating a possible complementarity between information and prices. These results inform water use policy in many areas of the world threatened by recurring drought conditions. (JEL D12, L95, Q25, Q54, Z13)

Social interactions have been shown to play a pivotal role in the diffusion of many new technologies and practices, and have undergirded classic economic models of technology diffusion (Griliches 1957, Bass 1969, Rogers 1995). The idea that individuals learn from their peers, neighbors, or friends to adopt behaviors or technologies has been explored in settings ranging from agriculture (Foster and Rosenzweig 1995, Conley and Udry 2010) to foreclosures (Towe and Lawley 2013) and schooling (Sacerdote 2001, Graham 2008). In the environmental realm, such “peer effects” have been shown in the adoption of solar photovoltaic panels (Bollinger and Gillingham 2012, Graziano and Gillingham 2015) and hybrid vehicles (Narayanan and Nair 2013, Heutel and Muehlegger 2015).

This paper is the first to identify causal peer effects in water consumption. Specifically, we use water billing and housing transaction data from over 300,000 households in Phoenix, Arizona to show that a household’s water consumption is influenced by the water consumption of nearby households in the previous year. Our identification strategy relies on quasi-experimental variation from movers

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into the homes surrounding an individual household. We show that a home's water consumption declines when a new household moves into the home, so housing turnover influences the nearby households' average water consumption. At the same time, housing turnover should not otherwise influence an individual household's water consumption after controlling for changes in the housing market and time-varying unobservables. Thus, we use housing turnover in nearby homes as an instrument for the lagged peer water consumption. We find that a one-gallon decrease in the mean summer water consumption of households within a 500-foot radius of a home reduces the summer water consumption of that home in the next year by 0.25 ccf.¹

To better understand this result, we use a machine learning approach on high-resolution remote sensing images to classify the greenness of a household's landscaping. Using these data, we find evidence that landscape greenness is a primary factor contributing to the peer effects in water consumption. This might be expected if households convert to dry landscaping after observing and/or discussing such a conversion by their neighbors. We further examine the nature of these peer effects by exploiting a natural experiment: some of the Phoenix region has access to extremely low-cost non-potable outdoor water for historical reasons. We find no evidence of peer effects in these areas, while we do find similar peer effects to those in our primary results using a matched set of households in the rest of Phoenix. These results provide suggestive evidence of a complementarity between economic incentives and peer effects that has not yet been noted in the literature.

This work contributes to several literatures. Most directly, it adds new, well-identified evidence to the large and growing literature on peer effects in the diffusion of consumer behaviors. In addition, it adds to the literature on how information transmission, in our case through social learning, can influence consumer decisions about energy and water use. Several papers explore how social norm-based messages aimed at energy conservation can reduce energy use (e.g., Allcott 2011; Allcott and Rogers 2014; Ayres, Raseman, and Shih 2013; Costa and Kahn 2013; Dolan and Metcalfe 2015; Gillingham and Tsvetanov 2018; Bollinger, Gillingham, and Gullo 2020) or how prosocial appeals influence energy use relative to economic incentives (e.g., Reiss and White 2008; Ito, Ida, and Tanaka 2018; Burkhardt, Gillingham, and Kopelle 2017).

Our paper is the first to begin to explore how the effect of social interactions can be directly influenced by economic incentives. Jessoe and Rapson (2014) show that households are three standard deviations more responsive to temporary price increases when provided with high frequency information on electricity usage, and Dolan and Metcalfe (2015) show that the effect of financial incentives can disappear when information on social norms is provided. In the context of residential water demand, Ferraro and Price (2013) show that social comparison messages are the most effective among the least price-sensitive households. However, in these studies, information transmission is exogenously manipulated. In contrast to these previous findings, we provide evidence suggesting that social interactions—a phenomenon

¹For simplicity, we define the "summer" in Phoenix as the six-month period from April to September, as this is the period when watering is needed the most.

involving *endogenous* information transmission—may be muted in the absence of a nonnegligible price signal.

Our findings can inform active discussions about water policy. Water districts make large upfront infrastructure investments and face continual planning challenges. For example, water is a constrained resource in Phoenix, which is among the fastest-growing and most arid cities in the United States. Between 1980 and 2010, the population of Phoenix increased by approximately 83 percent, leading to an increase in residential water use of 23 percent (US Census Bureau 2010b, Phoenix Water Services 2004–2012b). Yet, even with growing overall water demand in Phoenix, water demand per household has been declining over time, from nearly 230 ccf per year (one ccf is equal to 748 gallons) in 1990 to under 180 ccf in 2014, due to both improved appliance water efficiency and conversion to dry landscaping. This decline in per capita water usage is a positive development for concerns about water availability, but can pose challenges for municipalities that designed water systems for greater demand. For example, in some locations the city of Phoenix has to run clean water through sewer pipes that were overbuilt just to maintain adequate flow.

Thus, understanding the speed and pattern of the diffusion of water conservation activities, such as a transition from green to dry landscaping, is immediately valuable for water planning purposes. An understanding of such diffusion can also enable better targeting of policies. Neighborhoods that begin with some landscape transitions in a given year may be expected to experience contagion from these first transitions and observe a greater number of transitions in the future relative to other neighborhoods. Policymakers may be interested in one-time targeted information campaigns (Ferraro and Price 2013) or subsidies for dry landscaping for fast-growing areas that are straining the water system (Brelsford and De Bacco 2018), while such efforts may be of less interest for areas that have too much water system capacity.

The remainder of the paper is organized as follows. In the next section we describe our unique dataset, which combines water bills, remote sensing images, and housing transaction data. Section II presents the model and discusses our identification strategy. Section III describes the results and mechanisms underlying the peer effect. Section IV concludes.

I. Data

A. Data Sources

The foundation of our analysis is monthly water billing data for all single-family households served by Phoenix Water Services between 2004 and 2012 (308,529 households in the raw data) (Phoenix Water Services 2004–2012b). These contain the address of the land parcel and the total monthly water consumption for each household supplied by Phoenix Water Services. We complement the water billing data with remote sensing images to develop a measure of landscape greenness (Phoenix Water Services 2004–2012a). These images, taken once a year in the fall, have resolutions ranging from 0.3 to 0.8 feet. All years from 2004 to 2012

are available at high resolution except 2010, which is only available at a lower resolution. Figure 1 shows a map of Phoenix with the Phoenix Water Services territory, Salt River Project (SRP) territory, and the remote sensing subsample of 71,477 parcels. In SRP territory, households receive potable water from Phoenix Water Services, but can receive nearly free flood irrigation water from SRP, as we will discuss in Section IIIC.

Our next data source is the Maricopa County Assessor's Office, which provided data on housing sales and other physical housing characteristics including pool size, lot size, construction date, home size, and garage size (Maricopa County Assessor 2004–2012). Importantly, we observe the date on which the housing transactions occur and the address of the parcel, allowing us to match these data with the previous data.² Our final data source is the US Census, which provides data on a variety of demographic variables (US Census Bureau 2010a, 2010b).

B. Data Preparation

Peer Group Definition.—A first question in any study on social interactions is how to define the peer group. Defining the peer group membership too broadly could pick up sufficient heterogeneity in the group that it leads to spurious correlations.³ In our setting, we are interested in how peer effects influence water consumption. While water usage itself may not be visible to peers, landscaping is usually highly visible. This lends itself to a definition of the peer group based on spatial proximity to the household parcel. In a similar setting, Towe and Lawley (2013) define neighbors as the nearest 13 and nearest 25 neighbors by distance. Because there is variation in parcel sizes, we prefer a peer group definition based on geography, as is common in the literature (Topa 2001; Arzaghi and Henderson 2008; Bell and Song 2007; Manchanda, Xie, and Youn 2008; McShane, Bradlow, and Berger 2012; Narayanan and Nair 2013).

We geocode each address in our data and include all households within a 500-foot radius around each individual household as members of the peer group. This definition includes 25.3 neighbors on average. We also explore different radii in robustness checks. Of course, households can also be expected to have other social groups as well, such as those relating to family, friends, schools, and jobs. So we view our geographic measure as a minimal measure of the social group relevant to water and landscape decisions.

Seasonal Water Consumption Definition.—As the focus in this paper is on peer effects in water consumption that may come about through dry landscaping, we focus on water consumption during the hottest six months of the year when irrigation is used the most: April through September. As all of these months have a summer climate, we simplify by referring to these months as “summer months.” We refer to the remainder of the year as the “non-summer months.”

²Summary statistics for physical house characteristics are presented in Table A.1 in the online Appendix.

³Indeed, a careful definition of the peer group is central to identification in some studies (e.g., Bertrand, Luttmer, and Mullainathan 2000).

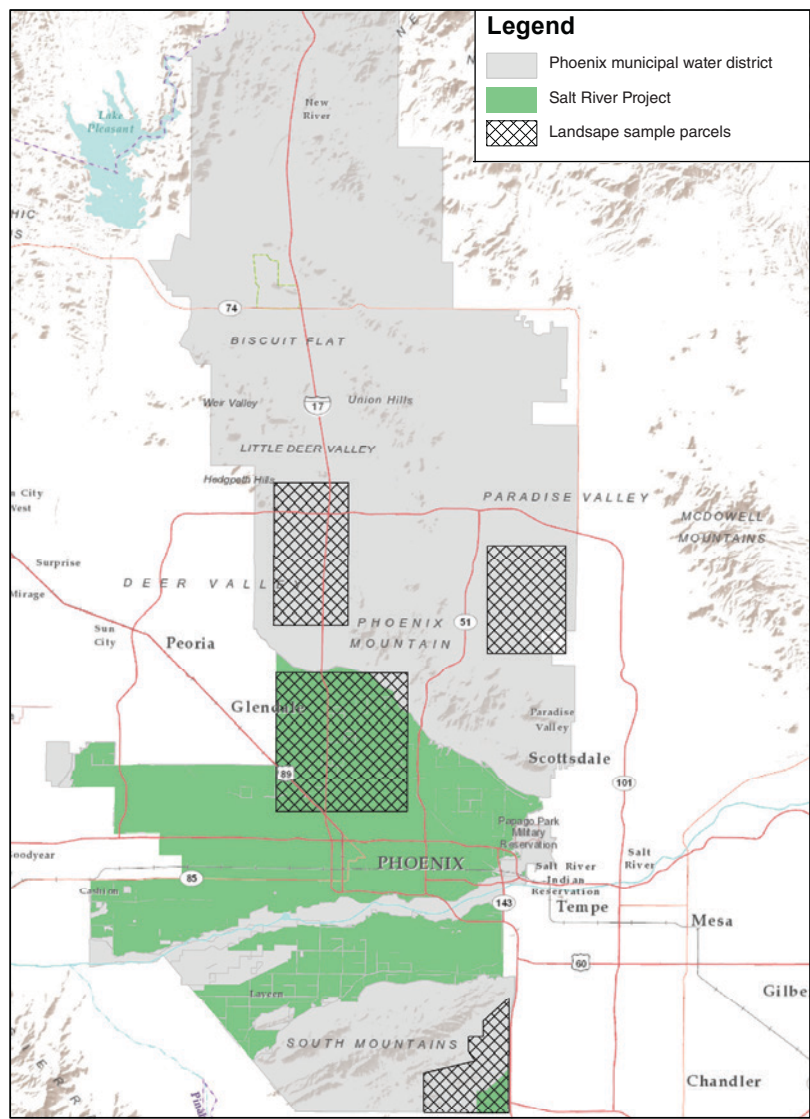


FIGURE 1. PHOENIX WATER DISTRICT BOUNDARY, ALONG WITH IDENTIFICATION OF AREAS UNDER THE SALT RIVER PROJECT AND LANDSCAPE SAMPLE PARCELS

Landscaping Data.—To convert the remote sensing images to measures of landscape greenness, we code each pixel as green landscaping or not. Each image has three color bands: red, green, and blue. There are standard software packages for developing vegetation indices, such as the Normalized Difference Vegetation Index, but our remote sensing images lack the infrared band needed for such standard packages. Therefore, we used a machine learning approach to train the computer to find green pixels through a series of iterations. The approach we used is a supervised maximum likelihood classification routine developed by the company Imagine Software, Inc. (described in more detail in online Appendix A.3). To verify



FIGURE 2. ILLUSTRATIVE REMOTE SENSING IMAGES DEMONSTRATING THE CLASSIFICATION OF GREEN SPACE

Notes: Panel A on the left shows what our remote sensing images look like, while panel B on the right shows how the machine learning algorithm codes the pixels of green space.

the algorithm, we compared the machine learning results to hand-coded results⁴ and found that the machine learning approach provided the same coding as the hand-coded pixels in 85–90 percent of the parcels. The mean greenness based on the machine learning and hand coding are not statistically different from one another using a simple *t*-test of differences in means.

Figure 2 provides an example of the output of the classification process. The photo on the left shows several randomly chosen parcels while the photo on the right shows the same parcels with the pixels the computer designates as green landscaping, including tree tops, grasses, and other vegetation, highlighted in green. As is seen in the photo, trees and bright green lawn are coded green. Dry grass is coded (correctly) as not green. It may be hard to see in the photo, but succulents (like cacti) are also not coded as green.

C. Summary Statistics

Table 1 presents summary statistics.⁵ The average house consumes 16.9 ccf (just under 13,000 gallons) of water per month during the summer months and only 12.3 ccf (about 9,000 gallons) of water per month during the non-summer months. As we are interested in the causal effect of peer water consumption on individual water consumption, we create a variable for the mean water consumption of all

⁴Specifically, a group of interns visually estimated the percentage of turf and greenery in 30,293 parcels and we consider the coding to be accurate if it is within 1–2 percentage points.

⁵Further details on the data cleaning process used to develop the final water and landscaping dataset are included in online Appendix A.

TABLE 1— SUMMARY STATISTICS

Variable	Mean	SD	Min.	Max.
<i>Panel A. Water consumption (N = 1,535,545; 260,307 households)</i>				
Summer water consumption (ccf/month)	16.9	11.3	0	100
Non-summer water consumption (ccf/month)	12.3	8.1	0	99.3
Peer summer water consumption in $t - 1$ (ccf/month)	16.7	6.2	0.5	82.6
$\mathbf{1}(\text{housing transaction})$	0.05	0.21	0	1
Fraction of peer houses sold in $t - 1$	0.05	0.05	0	0.8
$\mathbf{1}(\text{SRP-eligible})$	0.40	0.49	0	1
<i>Panel B. Landscape (N = 531,650; 71,477 households)</i>				
Lot size (ft ²)	9,706	570	1,537	299,200
Fraction of green landscape	0.37	0.10	0.19	0.68
$\mathbf{1}(\text{housing transaction})$	0.04	0.20	0	1
Fraction of peer households sold in $t - 1$	0.04	0.05	0	1
$\mathbf{1}(\text{SRP-eligible})$	0.38	0.49	0	1

Notes: An observation is a household-year. The peer group is defined as households within 500 feet of each house. Sample from preferred specification shown here. SRP refers to the Salt River Project. The dummy for housing sales for parcel i is zero because we drop all houses sold in t for our primary specification.

neighbors in the peer group (within 500 feet) in the summer months of the previous year. These summary statistics are very similar to those for the individual households, as would be expected. Roughly 5 percent of the homes in our sample observe a housing transaction in each year and, not surprisingly, the fraction of houses sold in the peer group (within 500 feet) is about 0.05. About 40 percent of our sample is served by SRP.

The landscape sample is a much smaller data sample. The landscaping data summary statistics indicate that the mean fraction of green landscaping is 0.37, with the mean taken over parcels. The summary statistics for the other variables are similar to those in the water data.

Figure 3 shows an important trend in our data: declines in annual water consumption per household over time in Phoenix. This decline may be due in part to reduced water usage from appliances but may also come about from conversion of green landscaping to dry landscaping.

II. Empirical Strategy

Peer effects are notoriously challenging to identify because the decisions by peers are often endogenous. Put simply, our empirical strategy takes each individual household and uses movers into homes surrounding that household to exogenously shift the average water consumption of all homes surrounding the household (i.e., the peer group). Our identification is facilitated by including a rich set of time-varying fixed effects and housing market characteristics as controls.

In this section, we first present evidence that water consumption (and landscaping) decisions are indeed influenced by movers to motivate our instrumental variables approach for estimating peer effects. Then we present our empirical specification and a discussion of potential identification concerns.

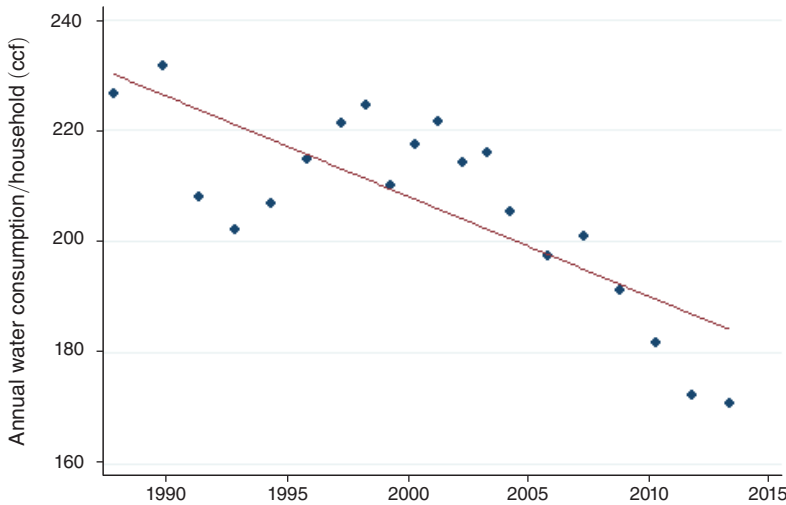


FIGURE 3. BINSCATTER PLOT OF THE ANNUAL WATER CONSUMPTION PER HOUSEHOLD SERVED BY PHOENIX WATER SERVICES ALONG WITH A LINEAR BEST-FIT TRENDLINE

A. Evidence on the Effect of Movers on Water Consumption

As our empirical strategy is based on movers influencing the water consumption of peer households, we first examine evidence of the effect of movers into a house on summer water consumption. For all houses that are sold, the mean summer water consumption in the year prior to a move is 15.37 ccf/month, while the mean summer water consumption during the year of a move is 13.41 ccf/month (a difference of 1.96 ccf/month with a t -statistic for a two-sided test of differences in means of 42). For the same group of houses, the mean non-summer water consumption in the year prior to a move is 11.15 ccf/month, while in the year of a move it is 11.35 ccf/month. These statistics from our data suggest that something dramatic is going on in summer water consumption in the year before and after a move.

To examine this more closely, we perform an event study analysis, taking the move as the event. We examine how summer water consumption for house i changes in the years proceeding and after a housing transaction, with the following specification:

$$(1) \quad \Delta cons_{it} = \sum_{\tau=-2}^{\tau=2} \beta_{\tau} \mathbf{1}(transaction_{i\tau}) + \gamma_{tb} + \epsilon_{iy},$$

where $\Delta cons_{it} = cons_{it} - cons_{it-1}$ and $cons_{it}$ is summer water consumption, and $\mathbf{1}(transaction_{i\tau})$ is a dummy for whether a housing transaction occurred (i.e., someone new moved into a house). The term γ_{tb} denotes census block \times year fixed effect to capture time-varying unobserved heterogeneity at the census block level. Figure 4 plots the β_{τ} coefficients over time (see online Appendix B.1 for the regression results).

The results in Figure 4 show that water consumption decreases the year of the sale and then continues to decrease in the two years after the sale, although by smaller

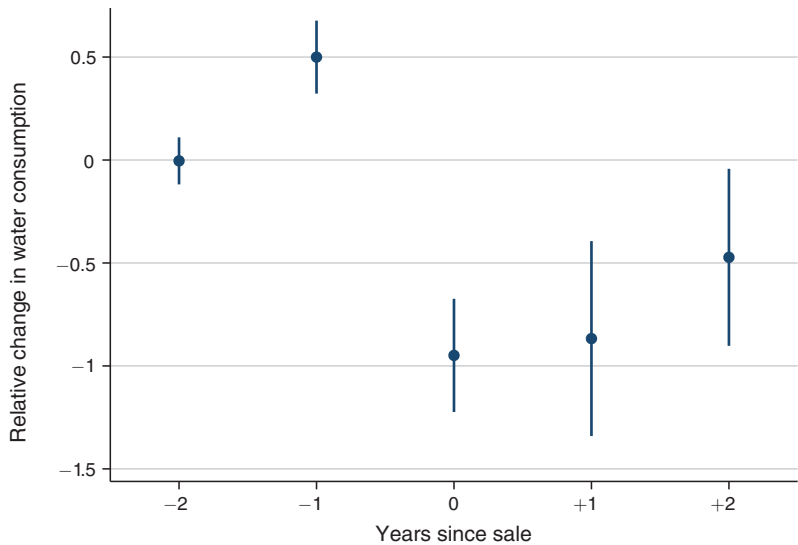


FIGURE 4. CHANGE IN WATER CONSUMPTION BY YEAR SINCE A HOUSING TRANSACTION OCCURS (YEAR 0 = YEAR OF TRANSACTION)

Notes: Only homes that have a transaction are included. All changes are relative to year -3 . See online Appendix Table A.3 for the full regression results.

amounts each time, as one would expect. The year prior to the housing transaction, water consumption increases slightly, which is consistent with the owner preparing the house for sale by making sure that plants are well-watered and healthy. In the year of the housing transaction, there is a major decrease in summer water consumption. This may be due in part to the new owner coming in and converting part of a lawn to dry landscaping.⁶ We also observe a further decrease in water consumption one year later and then again two years later, which may come about because some households wait a year or two to make the conversion to dry landscaping. By the second year, the change in water consumption from the previous year is much smaller. Taken together, this evidence indicates that having a new household move into a home tends to reduce water consumption and this effect persists.⁷

B. Empirical Specification for Peer Effects

Our empirical specification is a classic linear-in-means model in which the water consumption of household i in year t is given by

(2)
$$cons_{i,t} = \theta \overline{cons}_{i,t-1} + \delta H_{i,t} + \eta_i + \phi_{t,b} + \epsilon_{i,t},$$

⁶Indeed, when we perform a similar event study analysis using the landscaping data, we observe a decrease in greenness in the year of the housing transaction and the following two years (online Appendix B.2).

⁷We show the event study results for SRP and non-SRP houses separately in the online Appendix.

where $cons_{i,t}$ is the household's water consumption. If we denote household i 's peer group (e.g., houses within a 500-foot radius) as the set P_i , then $\overline{cons}_{i,t-1} = 1/|P_i| \sum_{i' \in P_i} cons_{i',t-1}$ is the average water consumption of the peers, not including household i .⁸ The variable $H_{i,t}$ is a vector that includes the average house price in the peer group in t , the change in the average house price in the peer group between t and $t - 1$, and the fraction of homes in the peer group that are new construction. The term η_i contains time-invariant household characteristics, which we model with a separate effect for each parcel \times owner combination; $\phi_{t,b}$ captures time-varying factors such as localized economic shocks, gentrification, vegetation shocks such as ash borer infestations, or major new development in a neighborhood, and we model this with census block \times year dummy variables.⁹

We instrument for $\overline{cons}_{i,t-1}$ using the fraction of homes in the peer group that have a housing transaction in year $t - 1$, as will be discussed in the next section. We estimate this model *only* on the sample of households that do not move in the current or previous summer (this includes moves during all of year t , and the summer of $t - 1$) to avoid any confounding from households moving themselves. Further, we estimate the model in first differences to difference out η_i , as this requires weaker identification assumptions than demeaning when using a lagged instrumental variable.¹⁰

C. Identification

There are three main categories of concerns in identifying peer effects in a linear-in-means specification (Manski 1993, Brock and Durlaf 2001, Moffitt 2001, Hartmann et al. 2008). The first is “simultaneity” (sometimes called “reflection”), which refers to the concern that just as peers may influence a household, the household may influence peers. Our research design addresses simultaneity by using recent, but not contemporaneous, decisions by peers.¹¹

The second is “self-selection” of peers (sometimes described as “homophily”), which can be an issue if consumers with similar preferences sort into neighborhoods. We address this concern with household fixed effects (e.g., each owner of a house has a separate fixed effect) to capture time-invariant preferences of the household and census block \times year fixed effects for time-varying factors at a fine level of geographic disaggregation. A census block is an extremely localized area, often covering only a single city block. In our sample, there are 12,485 census blocks, and each census block has on average 37 households.¹² These controls are particularly useful because there are frictions in the housing market, such that homebuyers may

⁸ In the incomplete information framework of Manski (1993), $\overline{cons}_{i,t}$ would be represented by $E[cons_{gt}]$, where g refers to the group.

⁹ We do not include water prices as a covariate because there is no usable variation in water prices.

¹⁰ If we demean the data to remove the fixed effects, then we have to assume that all current and future period values of the instrument are uncorrelated with the current period error term (i.e., strong exogeneity), while if we take first differences, we need only that additionally lagged values of the instruments are uncorrelated with the current period error (i.e., weak exogeneity) (Cameron and Trivedi 2005).

¹¹ This use of prior peer group decisions to overcome reflection follows several papers in the recent literature (e.g., Towe and Lawley 2013, Bollinger and Gillingham 2012).

¹² We could also use subdivision-by-year fixed effects, which are at a more highly aggregated level. There are 3,930 subdivisions, and each subdivision has on average 135 households.

be able to choose a given broad neighborhood, but are very rarely going to be able to choose the exact location of the purchase. For example, there could be some census blocks where everyone is more liberal and “green,” but housing market frictions make it very unlikely that the left side of a street is all environmentalists while the right side is all conservatives. As long as any time-varying sorting into or out of the neighborhood (e.g., due to an ash borer infestation or gentrification on that block) occurs at the census block level or a greater level of aggregation, then the block-by-year fixed effects nonparametrically control for such sorting.¹³

The third category of concerns is about “correlated unobservables,” which include the many other factors that may influence both the individual household and peers. For example, if there is an economic downturn facing all households in a neighborhood, their decisions may appear to be aligned, but this alignment is due to the conditions faced by the households rather than peer effects. Likewise, gentrification may influence whether households change their landscaping to potentially raise the resale value of the home. Our census block \times year and household fixed effects should address most correlated unobservables, but it is possible that some time-varying correlated unobservables work within the census block group.¹⁴ For example, there could be changes in local amenities, such as the revitalization of a local park, which mean green space is less (or more) important to a small number of houses than it was previously.

To address any correlated unobservables that work within a census block group, we instrument for lagged peer water consumption using the lagged fraction of movers in the peer group.¹⁵ For the instrument to be valid, we need the variation in this instrument to be plausibly exogenous. Because housing market frictions make sorting at the block level extremely difficult, the remaining variation in our instrument after including census block \times year fixed effects should be due to individual shocks, such as moves for family reasons or a job. As evidence of these housing market frictions, McCartney and Shah (2016) provide survey evidence indicating that realtors do not field housing requests at the block level, with the exception of new construction of the most expensive homes. Census data from 2014 indicate that roughly 50 percent of moves are for family or job reasons and we exploit this idiosyncratic variation that should be orthogonal to a neighbor’s water consumption.¹⁶

¹³Bayer, Ross, and Topa (2008) make a similar but stronger assumption, arguing that a neighborhood corresponds to a census block, but that the housing market works at an even higher level of aggregation—at the census tract level. Our approach allows for sorting at the census block level, but like Bayer, Ross, and Topa (2008), we rely on frictions in the housing market to rule out sorting within our level of geographic aggregation (i.e., within census block in our case or within census tract in the case of Bayer, Ross, and Topa 2008).

¹⁴Using rich fixed effects is a strategy employed by Bayer, Mangum, and Roberts (2016) to study housing investment decisions; Towe and Lawley (2013) to study foreclosure decisions in Maryland; and McCartney and Shah (2016) to study the decision to refinance. These papers also use lagged peer group variables. We use more granular fixed effects and controls: Bayer, Mangum, and Roberts (2016) use zip code fixed effects and other controls at larger geographic aggregation; Towe and Lawley (2013) include controls for housing prices as the census tract level and county fixed effects; and McCartney and Shah (2016) use census block fixed effects.

¹⁵Our goal is for an exogenous shifter of peer water consumption, consistent with Angrist (2014), who states that this is crucial for a well-identified peer effects study: “Research designs that manipulate peer characteristics in a manner unrelated to individual characteristics provide the most compelling evidence on the nature of social spillovers.”

¹⁶See Ihrke (2014).

Of course, differences in annual home sales in Phoenix may be driven by factors such as urbanization, gentrification, housing prices, and new construction. While most of these factors would be expected to be largely picked up by census block \times year fixed effects, we also include peer-group measures of housing prices, changes in housing prices, and new construction in our vector $H_{i,t}$. These additional controls directly address the possibility of a bias from sorting of households due to gentrification or the construction of new dwellings at this finer level of geography.¹⁷

For there to be a remaining threat to the validity of our instrument, one must believe that people disproportionally move to or from a small radius around a household in a particular year—relative to the rest of that census block—for factors that *both* directly influence the individual household's water consumption and are not already captured by our controls for gentrification, new home construction, household fixed effects, and census block-by-year fixed effects.¹⁸

A final identification concern in our setting relates to the definition of the peer group as “all homes within a 500-foot radius around each individual household.” This geographic definition allows the radius to cross census block boundaries; indeed, in just under half of the observations, the peer group does cross the boundaries. This could be a concern because the census block \times year fixed effects may not entirely capture the correlated unobservables that cross boundaries. To address this potential concern, we run a robustness check redefining the peer group by excluding all peers that are in a different census block than the household.

III. Results

A. Peer Effects in Water Consumption

We begin by estimating our primary specification examining peer effects in water consumption (equation (2)). Table 2 presents ordinary least squares (OLS) estimates in columns 1 and 2, and instrumental variables (IV) estimates in columns 3 and 4. Columns 1 and 3 include household and subdivision-by-year fixed effects while columns 2 and 4 include household and census block-by-year fixed effects. Subdivisions are much larger than census blocks, with 135 households in a subdivision on average, rather than 37 in a census block. All specifications include the controls for housing prices and new construction and drop households who moved that year. The IV estimations instrument for the lagged average water consumption of the peers using the lagged fraction of homes in the peer group that have a housing transaction. As one would expect from the evidence in our event study, the instrument is strong, with an F -statistic of over 800 in both columns 3 and 4 (see online Appendix C for full first-stage results).

¹⁷Graham (2018) describes the bias that may result if sorting occurs on correlated unobservables that remain even after the extensive use of control variables. In this discussion he also points out that fortunately “sorting into neighborhoods is mediated by the housing market, for which we observe a price.”

¹⁸The common assumption that this does not hold is stated formally in Graham (2018) as the conditions for no sorting or matching on unobservables conditional on predetermined attributes. Graham (2018) further states that such approaches “... have a meaningful role to play in neighborhood-effects research.”

TABLE 2—PEER EFFECTS IN SUMMER WATER CONSUMPTION

	OLS (1)	OLS (2)	IV (3)	IV (4)
Mean peer consumption in $t - 1$	0.19 (0.01)	0.33 (0.01)	0.14 (0.06)	0.25 (0.06)
Housing market controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Subdivision \times year dummies	Yes	No	Yes	No
Census block \times year dummies	No	Yes	No	Yes
First stage F -statistic	N/A	N/A	796	880
R^2	0.04	0.08	0.04	0.08
Observations	1,537,435	1,535,545	1,537,435	1,535,545

Notes: The dependent variable in each specification is summer water consumption in t (in ccf/month). An observation is a household parcel-year. The peer group is defined as all houses within a 500-foot radius of the household and on average, there are 25.3 houses within a 500-foot radius of any household in our study. The “mean peer consumption in $t - 1$ ” refers to the average peer summer water consumption. Columns 1 and 2 present OLS peer effect results. Columns 3 and 4 instrument for peer consumption using the fraction of parcels with housing transactions within 500 feet in the previous year. All models are estimated in first differences to difference out the household fixed effects. Housing market controls include the average sales price of homes in the peer group, the change in the price of homes in the peer group, and the fraction of parcels in the peer group that had new construction. Standard errors are clustered at the census block level.

Our preferred specification is in column 4, which shows that if the average peer summer water consumption in the previous year decreases by 1 ccf/month, the individual household will decrease summer water use by 0.25 ccf/month (about 187 gallons/month). Recall that the average monthly summer consumption in our data is 16.9 ccf or 12,642 gallons.¹⁹ Our event study provides some further context for this result, by showing that after a move, a household on average reduces water consumption by 1.2 ccf/month in the first year, following by an additional decrease in the second and third years. The sum of the decrease over the three years is approximately 2 ccf/month (about 12 percent of the average monthly summer consumption). For the sake of comparison, if all peers reduced their water consumption by 2 ccf/month, then our results indicate that the individual household’s water consumption over the six-month summer period would decrease by 2,244 gallons. Extrapolated to even 1 percent of the households in Phoenix, this implies a decrease in water use of nearly 7 million gallons over the summer months. For further comparison, if we use the -0.33 water demand elasticity from Olmstead, Hanemann, and Stavins (2007), a 2 ccf/month decrease in water consumption would require an increase in water prices by over 35 percent to achieve a similar reduction in water consumption.

One question that may arise in interpreting these results is whether we are actually estimating demand-side peer effects. It is possible that there are also supply-side factors that influence the decision to change water use through landscaping decisions. For example, it is possible that landscaping firms undertake focused localized marketing campaigns, such as door-to-door canvassing, that only affect the homes

¹⁹For reference, a typical load of laundry uses 30 gallons of water.

nearby a completed dry landscaping conversion. To provide evidence on whether firm marketing activities may help explain our results, we performed an informal phone survey of landscapers in Phoenix. We did a Google search for “Phoenix landscaper” and called the top 20 landscapers that had a rating of more than three stars. Seven of the landscapers took our call. We learned that none of the companies actively market around an individual installation or use door-to-door canvassing. Four out of the seven firms put signs in the yards of homes during the duration of the landscape conversion, but all remove the signs after the job is completed (see online Appendix D for further details on this informal survey). Thus, the signs would not be present a year after the landscape conversion, which means that they should not be a channel explaining our results unless there was a longer-term persistent effect from the short-term display of the signs. We also consider yard signs as another potential contributor of demand-side peer effects, because firms use them to attempt to leverage demand-side peer effects to increase sales by providing information that lowers search costs. Taken together, we view our informal survey findings as evidence that supply-side factors are unlikely to be an explanation for our primary results.

Another interpretation question relates to whether movers affect existing residents’ water use through channels other than their own water use. One could imagine movers influencing their neighbors through other types of peer effects (e.g., based on education levels or income levels), in which case the peer effects we capture may be a composite of several types of peer effects. To examine if this is the case, we acquired a cross section of household-level data on demographics from Acxiom for the landscape subsample in our data (Acxiom 2010). This allows us to examine the demographic characteristics of movers relative to their new peers. We find that on average there is no statistically significant difference between movers and the new peers for the mean of key demographics, such as education, income, housing price, and political affiliation (see online Appendix Table A.2). While only suggestive, this evidence is consistent with peer effects occurring due to reductions in water usage by peers, rather than other channels.

Placebo Tests and Robustness Checks.—To provide further evidence that our results are well-identified, we run a set of placebo tests. In our first and most important placebo test, we switch the ordering of the timing. In our specifications above, we examined the effect of summer water consumption by peer group households in the previous year ($t - 1$) on summer water consumption by the individual household this year (t). In our placebo test, we examine the effect of water consumption by summer peer group households today (t) on summer water consumption by the individual household during the previous year ($t - 1$). The only reason that we should find statistically significant results from the effect of peer decisions in t on the household decision in $t - 1$ is if there are correlated trends that are influencing both the peers and the individual household. Indeed, it would be physically impossible for such a relationship to be due to peer effects. Thus, if we find a statistically significant effect in our placebo test, that would raise questions about whether there are other unobservable trends influencing our results, rather than actual peer effects.

TABLE 3—PLACEBO TESTS

	OLS (1)	OLS (2)	IV (3)	IV (4)
Mean peer consumption in t	0.20 (0.01)	0.34 (0.01)	0.02 (0.06)	0.01 (0.09)
Housing market controls	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Subdivision \times year dummies	Yes	No	Yes	No
Census block \times year dummies	No	Yes	No	Yes
First stage F -statistic	N/A	N/A	191	109
R^2	0.04	0.08	0.04	0.08
Observations	1,500,611	1,498,693	1,500,611	1,498,693

Notes: The dependent variable in each specification is summer water consumption in $t - 1$ (in ccf/month). An observation is a household parcel-year. The peer group is defined as all houses within a 500-foot radius of the household and on average, there are 25.3 houses within a 500-foot radius of any household in our study. The “mean peer consumption in t ” refers to the average peer summer water consumption in year t . Columns 1 and 2 present OLS peer effect results. Columns 3 and 4 instrument for peer consumption using the fraction of parcels with housing transactions within 500 feet in the year t . All models are estimated in first differences to difference out the household fixed effects. Housing market controls include the average sales price of homes in the peer group, the change in the price of homes in the peer group, and the fraction of parcels in the peer group that had new construction. Standard errors are clustered at the census block level.

Table 3 presents the results of our first placebo test. Just as in Table 2, the first two columns present the OLS results, while the second two present the IV results. The first two columns indicate a small but statistically significant relationship between peer group water consumption in t and the household’s water consumption in $t - 1$. This immediately raises concerns about the identification of peer effects in the OLS specifications, even with the rich set of fixed effects. We view this result as indicating that there is an endogeneity issue, likely due to trends that affect both peer group water consumption and the household’s water consumption. On the other hand, the IV results are noisy but are quite close to zero and show no statistically significant relationship (see Table A.6 for the first-stage results). While this result alone cannot rule out all possible identification concerns, it shows that there is no evidence of unobservable trends confounding identification, further supporting the validity of our primary results. It also highlights the importance of an instrumental variables strategy in identifying peer effects in our setting.²⁰

To provide more evidence regarding the validity of our instrument, we run an additional placebo-type test relating to the concern that households may be sorting in a way that might be due to highly localized shocks. If the variation in our instrument—the fraction of households that move in the peer group—is due to highly localized trends that lead to sorting on preferences, we would expect new moves to be clustered. Thus, we use the full sample (including houses that are sold) and regress a dummy for whether the individual house is sold in year t on the fraction of households that moved in the peer group in the previous year, as well as household fixed effects and census block-by-year dummies. We find a small and

²⁰ We perform further placebo tests by examining the effect of peer group water consumption in t on the household’s water consumption in $t - 2$ and $t - 3$. In both cases, the peer water consumption coefficient is not statistically significant, further confirming our approach.

TABLE 4—ROBUSTNESS CHECKS

	Time trends		Include sold homes	
	(1)	(2)	(3)	(4)
Mean peer consumption in $t - 1$	0.14 (0.06)	0.25 (0.06)	0.14 (0.06)	0.25 (0.06)
Housing market controls	Yes	Yes	Yes	Yes
Housing transaction dummy	No	No	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Subdivision \times year dummies	Yes	No	Yes	No
Census block \times year dummies	No	Yes	No	Yes
Zip-code-specific time trends	Yes	Yes	No	No
First stage F -statistic	1,150	1,342	788	893
R^2	0.03	0.08	0.04	0.08
Observations	1,537,435	1,535,545	1,624,823	1,623,031

Notes: The dependent variable in each specification is summer water consumption in t (in ccf/month). All specifications instrument for peer consumption using the fraction of parcels with housing transactions within 500 feet in the previous year. The specifications that include sold homes include a dummy for whether the parcel had a transaction in the last year. An observation is a household parcel-year. All variable definitions are the same as in Table 2. All models are estimated in first differences to difference out the household fixed effects. Columns 3 and 4 include homes that were sold in the current and previous summer months. Housing market controls include the average sales price of homes in the peer group, the change in the price of homes in the peer group, and the fraction of parcels in the peer group that had new construction. Standard errors are clustered at the census block level.

statistically insignificant coefficient, which indicates that, after including our controls, the moving process (entry or exit from the neighborhood) does not appear to show clustering (see online Appendix Table A.8). We view this as further suggestive evidence that localized trends leading to sorting is unlikely to be a confounding factor in our empirical design.

Table 4 illustrates the robustness of our results to a variety of further checks. In columns 1 and 2, we present the same IV specifications as columns 3 and 4 of Table 2, only we add zip-code-specific time trends as further controls to address potentially localized unobserved trends in water consumption. The coefficients are nearly identical to those in Table 2. Columns 3 and 4 are also the same IV specifications only instead of dropping all parcels that had a recent sale, we include the parcels that were sold in the previous year and a half (including the previous summer months) and control for whether there was a transaction with a dummy. Again, the coefficients of interest are identical. These results underscore the robustness of our results to both unobserved trends and the modeling decision we made to exclude parcels that observed a transaction.

In the online Appendix, we provide additional robustness checks. We examine specifications that use different definitions of the peer group (Table A.9). We also find no substantial difference in estimated peer effects for larger radii through 700 feet. However, the peer effects become statistically insignificant around 1,000 feet. Next, we limit the peer groups to peers that are both within 500 feet *and* in the same census block as the household (Table A.10). The reason for this robustness check is that the radius around a household can extend beyond the boundary into another census block, so the census block \times year fixed effects may not control for sorting

and time-varying unobservables. Using this definition of the peer group that does not cross census block boundaries provides similar results but with slightly larger coefficients, as might be expected when a narrower definition of the peer group is used.

We also explore a set of robustness specifications that are based on a downward “switch” in water consumption rather than the level of water consumption. Notably, the results are qualitatively similar if we use downward “switches” in water consumption (Table A.12). We also examine evidence for an asymmetric effect in a specification that is based on an upward “switch” in water consumption, and we find no evidence of peer effects in increases in water consumption (Table A.14). This finding suggests that the peer effects are strongest for consumer decisions that reduce, rather than increase, water consumption, providing further insight into the mechanisms generating our peer effect results. Finally, we drop all homes that were sold during the sample time period in case the peer effect might be due to the slight increase in water consumption the year before homes are sold. We again find similar results, with just a slightly smaller peer effect coefficient (Table A.15).

Finally, we show that our primary peer effect estimate is robust to including additional lags of peer consumption. The results of including peer consumption in $t - 1$ and $t - 2$ using OLS and IV are presented in online Appendix Table A.11. We find that adding peer consumption $t - 2$ does not appreciably change the findings for $t - 1$. As expected, the effect of peer use in $t - 2$ is also statistically significant, but the magnitude of the effect is much less than the effect in $t - 1$.²¹

B. Are the Peer Effects Due to Dry Landscaping?

Our primary results provide strong support for peer effects in water consumption, which is the outcome policymakers care about most. In this section, we examine whether conversion of green landscapes to dry landscaping appears to be a primary driver of these results.

We first examine whether there is evidence of a peer effect in the non-summer months. If outdoor water use is a primary driver of the peer effects in water consumption, we would expect to see little or no effect in the non-summer months. Column 1 of Table 5 presents the same specification as our preferred specification in column 4 of Table 2, only replacing the summer water consumption variables with water consumption variables for the non-summer months. We see that the coefficient on the lagged peer water consumption in the non-summer months is close to zero and not significant.²² The evidence of effect in the summer months and not the non-summer months suggests that outdoor water consumption, which is needed much more in the summer months, is a primary driver of the peer effects in water consumption.

²¹ In column 2, we instrument the peer consumption variables with the fraction of houses sold in the peer group in $t - 1$ and $t - 2$. In column 4, we instrument peer consumption in $t - 2$ with the fraction of houses sold in the peer group in $t - 2$.

²² This finding is robust to our exact specification and even holds for the “switches” specification we examined for robustness.

TABLE 5—IS DRY LANDSCAPING A DRIVER OF PEER EFFECTS IN WATER CONSUMPTION?

	Non-summer months (1)	Landscape subsample (2)	Landscape added (3)
Mean peer consumption in $t - 1$	0.02 (0.18)	0.37 (0.19)	0.16 (0.15)
Landscape greenness			0.62 (0.13)
Housing market controls	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes
Census block \times year dummies	Yes	Yes	Yes
First stage F -statistic	1,177	1,165	1,049
R^2	0.23	0.09	0.09
Observations	1,545,060	395,048	395,048

Notes: Column 1 uses water consumption in the non-summer months for both the dependent variable and the peer group variable. Column 3 is identical to column 4 in Table 2, only with the new covariate, which is household i 's landscape greenness. Column 2 uses the sample from column 3 but does not include landscape greenness. All specifications instrument for peer consumption using the fraction of parcels with housing transactions within 500 feet in the previous year. An observation is a household parcel-year. All models are estimated in first differences to difference out the household fixed effects. Housing market controls include the average sales price of homes in the peer group, the change in the price of homes in the peer group, and the fraction of parcels in the peer group that had new construction. Standard errors are clustered at the census block level.

We next examine whether the peer effect still holds after controlling for the household's landscape greenness. The idea behind this specification is to isolate the household's outdoor water use from indoor water use. In column 2 of Table 5, we use the landscaping data subsample and run our primary IV specification to confirm that our main result still holds in the subsample.²³ In column 3, we also control for the household's landscape greenness. We find that the effect of landscape greenness is large and significant, as would be expected in Phoenix, where most outdoor plants need substantial watering. The coefficient suggests that increasing landscape greenness by one percentage point increases monthly summer water consumption by 0.62 ccf (463 gallons). Notably, the coefficient on peer consumption is much smaller and is insignificant. This suggests that after controlling for a home's landscape greenness, which determines outdoor water use, we find very little evidence of any remaining peer effects (from non-outdoor use).²⁴

Finally, we use the landscape data to examine the trend in landscaping for households that observed a major decrease in summer water consumption between one year and the next (defined as a decrease of at least 2.8 ccf/month that persists at

²³ See Table A.17 in the online Appendix for details on the differences in the landscape subsample and broader water sample.

²⁴ As a further robustness check, we ran our primary peer effects specification using the landscaping data after correcting for nonclassical measurement error in the remote sensing data. The results are reported in Table A.16 in Section E.3 of the online Appendix. The results provide further evidence that the peer effect in water consumption is primarily driven by landscaping changes.

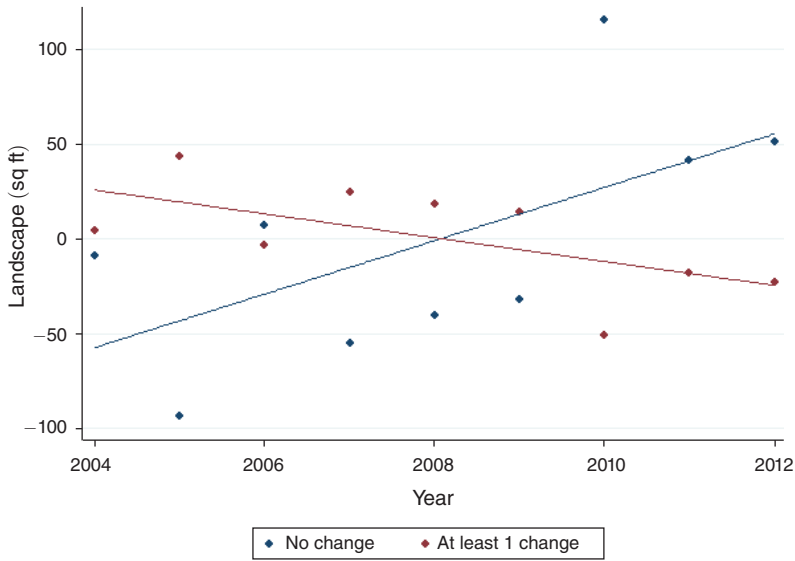


FIGURE 5. TRENDS IN LANDSCAPE OVER TIME USING LANDSCAPE SUBSAMPLE

Notes: Figure 5 is stratified by whether the parcel exhibits at least one switch in water consumption, where a switch is defined as a decrease of at least 2.8 ccf/month that persists for at least one additional year. To address remote sensing measurement error and allow for comparisons across years, we first regressed the raw data of square footage of green landscaping on a house dummy and year dummy. Each point is a residual, so the mean is normalized to zero. The two lines are best linear fits to the data.

least one more year) and households that did not.²⁵ Figure 5 shows the trends in the greenness of landscaping over time by these two groups. The mean in the figure is normalized to zero, so the figure can be interpreted as showing relative changes in landscaping over time for the two groups. There is a clear upward trend in greenness residuals for households that did not observe a major decrease in water consumption, and a downward trend in greenness for households that did. This is consistent with the evidence given above and serves as final descriptive evidence that dry landscaping is a primary contributor to the switches in water consumption.²⁶ It is also useful to note that after a new household moves into a parcel, the landscape greenness declines as well, consistent with movers converting to dry landscaping, which provided the motivation for our instrument (see online Appendix B.2).

²⁵ 2.8 ccf is one-half of the average difference in monthly water consumption between the summer months and the non-summer months.

²⁶ We also regressed the change in landscape greenness on switches in water consumption (and controls such as lot size and year fixed effects and interactions of the two) and find a statistically significant coefficient of 66.5, which indicates that a switch in water consumption is associated with a decrease in irrigated landscaping of 66.5 square feet. This is remarkably close to an estimate by the city of Mesa, Arizona, of 59 square feet for a reduction of 2.8 ccf/month.

C. Role of Economic Incentives

We use the Salt River Project's provision of heavily discounted irrigation water for outdoor use as an opportunity to explore whether the price signal for outdoor water influences the strength of the peer effect. Roughly 43 percent of households in the City of Phoenix Water District are within the boundaries of the SRP. SRP-eligible households pay about \$5 per month (which has not changed in recent years) for occasional access to non-potable irrigation water that can be used by households that have constructed berms to direct the water. This is a small fraction of the cost of municipal water. For this setting to be a useful natural experiment, the boundaries of SRP must be plausibly exogenous and we must be confident that there is not sorting into the SRP territory based on water use.

The boundaries of SRP are based on historic water rights boundaries that tend to follow the path of canals built in the late 1800s, which themselves follow the paths of ancient canals built by the Hohokam Indians. These paths were designed to bring Salt River water to irrigated farmland and were based on convenience and historic land rights determined by where settlers created ranches in the 1800s. The areas covered by SRP are of the same general topography, quality, and climate as the rest of the Phoenix basin.²⁷ Also, it is important to note that today's residential development in Phoenix is not influenced by the SRP boundaries. The SRP boundaries cross neighborhoods and it would be difficult to know from looking at a house whether it is covered by SRP without close inspection of the yard and spigots. The distributions of municipal water consumption and landscaping for SRP and non-SRP households are also very similar.²⁸ SRP irrigation water is also not guaranteed and is not useful for all landscapes, making it unlikely that households sort based on SRP eligibility rather than more important factors, such as schools, housing quality, and proximity to jobs and amenities.²⁹

For our analysis, we matched each SRP-eligible household with a non-eligible household to develop a control group for the SRP-eligible households out of the larger pool of non-eligible households. We explore several matching approaches, but in our preferred specification, we match each SRP household with a non-SRP household using a nearest neighbor approach. We match based on key observables that might influence water consumption: summer water consumption in $t - 1$, the lot size, the average house sale price, median household income for the census tract, the

²⁷For more on the history of SRP, see Salt River Project (2017).

²⁸We find that annually, non-SRP houses use approximately 7 ccf (6.6 percent) more municipal water than on-project houses on average, but this difference is not statistically significant once lot size is controlled for. More broadly, the distributions of water consumption for SRP households and non-SRP households look nearly identical. The distributions of landscaping greenness are also similar, with non-SRP houses having nearly the same landscaping greenness.

²⁹SRP water is provided to households based on plot size and is distributed in 45-minute increments. Houses within subdivisions are scheduled to receive water as a group. SRP turns on the water to subdivisions and houses that have been scheduled for service. Houses that are scheduled are required to use the water they have requested. The service comes once a month in the winter months (October–March) and twice a month in the summer. There is a “dry up period” for maintenance, which occurs one month out of every year. Subdivisions are affected by the “dry up period”—December, January, or February. Residents could conceivably get SRP water without being scheduled if one of their neighbors had been scheduled to receive water and they left their tap open, but this would be considered water theft.

TABLE 6—TABLE OF BALANCE FOR MATCHED HOUSEHOLDS

	SRP-eligible (1)	Matched non-SRP (2)	Diff (3)	<i>t</i> -stat (4)
Median household income (1,000s \$)	45.7	46.1	0.4	6.8
Lot size (1,000s ft ²)	8.0	8.1	0.19	11.0
Average house sale price (1,000s \$)	143.6	153.1	9.5	31.1
Water consumption (ccf)	15.59	15.99	0.40	10.74
House size (1,000s ft ²)	1.56	1.60	0.04	16.99
Number of bath fixtures	6.05	6.14	0.08	10.13
1(has pool)	0.19	0.18	−0.01	−3.75

Notes: Column 1 reports means for SRP households in the water consumption data with standard deviations in parentheses. Column 2 reports means for the matched non-SRP households, using nearest neighbor matching, in the water consumption data. Column 3 reports the difference in means, while column 4 shows the *t*-statistic for a two-sided test of differences in means. Median household income refers to the median household income at the census tract level. There are 133,496 on SRP-eligible houses in the sample and 131,355 matched with frequency weights non-SRP houses in the sample.

house square footage, the number of bathroom fixtures, and a dummy for whether the household has a pool.³⁰

In Table 6, we show the balance of observables between the SRP households and the matched non-SRP households (see online Appendix Table A.18 for table of balance comparing SRP households to all unmatched households). The table illustrates that the match is overall very good. While the two groups of houses are not identical, the differences in the observables are small. Several are statistically significant, which is not surprising due to the fact that we are matching on so many different variables. In additional robustness checks, we find that regardless of how we match, our results continue to hold. While one can never fully rule out unobservables, this reasonable success in matching and the circumstances of our setting suggest that we are comparing similar households, some of which are eligible for nearly free water for outdoor use and others that are not.

Our hypothesis is that households that receive heavily discounted outdoor water will appear less susceptible to peer effects in their municipal water consumption. This is because SRP households receive essentially free water several days a month during the summer and at least one day a month during the winter. This means that their marginal price for outdoor water use on these days is basically zero. On all other days, non-SRP and SRP houses pay the same marginal price for outdoor water. Thus, on average, the marginal price (and average price) for SRP houses is lower than for non-SRP houses.

There are a few limitations to this analysis. One important limitation is that we are exploiting a natural experiment and using a matching approach rather than actually randomly varying SRP assignment in an RCT, so we cannot fully rule out sorting on unobservables. Another major limitation of this analysis is that we do not observe SRP-provided outdoor water consumption; however, it is important to note that this consumption is limited both in quantity and in the times it is available (which are not always predictable). Thus, to keep green plants alive, SRP-eligible households

³⁰In online Appendix G, we find similar results from matching based on other combinations of variables and using the Mahalanobis distance matching procedure (Rubin 1980).

TABLE 7—EFFECT OF RECEIVING DISCOUNTED SRP WATER

	SRP-eligible (1)	Matched non-SRP (2)
Mean peer consumption in $t - 1$	0.16 (0.10)	0.42 (0.11)
Housing market controls	Yes	Yes
Household fixed effects	Yes	Yes
Census block \times year dummies	Yes	Yes
First stage F -statistic	3,026	1,956
R^2	0.15	0.09
Observations	604,023	689,099

Notes: The dependent variable in each specification is summer water consumption in t . An observation is a household parcel-year. The peer group is defined as all houses within a 500-foot radius of the household. The “mean peer consumption in $t - 1$ ” refers to the average peer summer water consumption in period $t - 1$. All specifications instrument for peer consumption using the fraction of parcels with housing transactions within 500 feet in the previous year. The “matched non-SRP” estimations in columns 3 and 4 include only the subsample of matched homes, identified using a nearest neighbor matching routine. All models are estimated in first differences to difference out the household fixed effects. Housing market controls include the average sales price of homes in the peer group, the change in the price of homes in the peer group, and the fraction of parcels in the peer group that had new construction. Standard errors clustered at the census block level.

almost always use a combination of municipal water and SRP-provided water. We observe this in our data, as municipal water consumption is higher in the summer than in the non-summer months for SRP households (17.9 ccf versus 12.4 ccf), just as it is for non-SRP households. Thus, examining how SRP-eligible households respond differently than non-SRP households in their municipal water consumption can provide at least suggestive evidence on the role of economic incentives on peer effects in municipal water use.

Table 7 presents the results of our matching analysis. Each column runs our preferred IV specification from column 4 in Table 2. Column 1 presents the results using only the sample of SRP-eligible households, while column 2 presents the results using the matched sample of households. The coefficient in column 1 suggests no statistically significant peer effects for the SRP-eligible households, while the coefficient for the matched non-SRP households in column 2 is significant and larger than our primary results using the entire sample. Importantly, the peer consumption coefficient in column 1 is smaller (although not significant) than coefficients for the matched non-SRP households, despite a similar sample size in each of the regressions.³¹

While there are limitations to this analysis, these results provide the first evidence we are aware of that suggests economic incentives to reduce outdoor water use are important for the operation of peer effects in water consumption. In neighborhoods where green landscaping is more costly due to a lack of heavily discounted

³¹ Note that it is possible that SRP-eligible households exhibit peer effects in the SRP irrigation water, although the fact that municipal water is necessary to keep plants alive during the times when SRP water is unavailable makes this unlikely.

irrigation water, neighbors may be more likely to discuss xeriscaping (landscaping with slow-growing, drought-tolerant plants) as a money-saving tool. Economic incentives could also influence the peer effects because households are more susceptible to peer effects when they are looking to save money on their water bill, and it is possible that households are responding to the average price of water provision, which could amplify the effect. Neighbors may also be more likely to discuss and share information about dry landscaping when there is an obvious monetary benefit. It is likely that a combination of these reasons can explain our result.

Implications for Policy and Targeted Interventions.—Our primary results provide strong evidence that water consumption decisions made by peers influence a household's water consumption. We provided further evidence that conversions to dry landscaping appear to be a primary driver for the observed peer effects and that economic incentives appear to influence the strength of the peer effects. There are several possible channels for the peer effects we find, including information channels (e.g., social learning that reduces search costs), social norm channels, and combinations of these. For example, word-of-mouth could provide information that helps households learn the value of dry landscaping and could be facilitated by a changing social norm.

From a water district policymaker perspective, it is useful to just know that there are causal peer effects. Regardless of whether peer effects stem entirely from word-of-mouth or a social norm channel, such causal peer effects can lead to the diffusion of lower outdoor water consumption that occurs in a spatial pattern that has ramifications for water provision. Of course, knowing the exact channel may be useful for the design of the optimal policy to facilitate such spatial spillovers. For instance, if the key channel driving the peer effects is an informational channel, providing information may be more cost effective than simply subsidizing dry landscaping. Either way, subsidies for dry landscaping could still provide a benefit.

A key takeaway from our results is that policies to promote dry landscaping may have broader effects than might be expected. Consider a dry landscaping subsidy that leads a household to reduce water consumption by 1 ccf/month. Our primary result suggests that all of the peers would together reduce consumption by 0.25 ccf/month—a sizable spillover.³² So if a dry landscaping subsidy leads a single household to reduce water consumption by 4.6 ccf/month (i.e., the difference between the average summer consumption and non-summer consumption), then all of that household's peers would reduce water consumption by 1.15 ccf/month, or 864.6 gallons/month. This may even be an underestimate of the spillover; our robustness checks show that if the peer group is defined more broadly to include additional households, we still find an effect on the additional households.

These findings can be put into context by comparing them to the effects of other approaches. For instance, Ferraro and Price (2013) find that information provision

³² Put differently, the spillover from the single household making a conversion on one of their peers is a 1 percent water consumption decrease on average (i.e., 0.25 divided by 25.3, which is the average number of houses in a peer group).

reduces water consumption among treated houses by 1 percent relative to control houses, while the reduction for social comparisons is 4.8 percent. Our results imply that if there is a reduction of 4.8 percent for an individual household, the spillover to neighboring peers would reduce their water consumption on the order of 1.2 percent, which is remarkably close to the effect of the Ferraro and Price (2013) information provision intervention.

Of course, these estimates deserve several caveats. Most notably, because we are using an IV estimator, our results should be interpreted as a local average treatment effect and may not apply to the broader population. Similarly, they are an estimate of the average effect, but as we saw in the section above, economic incentives appear to matter. Policymakers may not want to target a dry landscaping program to SRP households, as our results suggest no peer effects in municipal water use for those households. It is also possible that targeting households that have greater economic incentives may lead to even larger peer effects. Another caveat is that our study provides the magnitude of causal peer effects in equilibrium over our sample period. Brock and Durlaf (2001) show that multiple locally stable equilibria may exist when the social interaction effects are sufficiently large and decision-making is noncooperative. In addition, if firms or consumers respond differently in a different empirical setting, the estimated effects would be different. However, Phoenix is not only a large desert city itself, but it also has similar water concerns and a similar diffusion of dry landscaping as many other desert cities, such as San Diego, Las Vegas, Tucson, Albuquerque, etc.

IV. Conclusion

In this paper, we estimate causal peer effects in residential water consumption using a unique IV strategy that leverages consumer migration into the peer group. Specifically, we study reductions in summer water usage consistent with (often observable) dry landscape transitions. To identify the effects of interest, we exploit within-household and within-census block-by-year variation after controlling for housing prices and new construction. Our key identifying assumption is that the remaining variation in peer housing transactions serves as an exogenous shock to the individual's peer group. We further perform a series of placebo tests and robustness checks that uniformly support the contention that our IV strategy allows us to identify causal effects.

Our primary result is that a 1 ccf/month decrease in the average water consumption in neighboring households within 500 feet of a given household reduces the given household's water consumption by 0.25 ccf/month. We then use machine learning techniques on high-resolution remote sensing data to develop a robust measure of landscape greenness. Using this measure and several other diagnostics, we provide evidence that suggests a close relationship between outdoor water use, dry landscape adoption, and water consumption. This evidence supports dry landscape adoption as a primary factor that generates our water peer effects results.

One suggestive new finding of this study is that economic incentives appear to complement the effect of social interactions. By exploiting a natural experiment

offered by the existence of the Salt River Project's provision of heavily discounted irrigation water and a matching approach, we provide suggestive evidence that the peer effect in municipal water is close to zero and not statistically significant for households eligible for the discounted water. While not dispositive, this finding suggests of the power of economic incentives on the influence of peers.

Our study is relevant because access to water is a major issue in many locations around the world. While the municipal sector uses less water than the agricultural sector in Arizona, municipal water use was approximately 1.47 million acre feet in 2017, which is more than the annual consumption in New York City and approximately 6 percent of the total volume of Lake Powell at full capacity.³³ Thus, municipal water use in Arizona is not trivial. Moreover, droughts and water scarcity can have serious implications. For example, the California droughts of 2012 and 2015 led to combined economic losses of approximately \$5.2 billion, and only a few years earlier, droughts in the Southwest and Midwest led to losses of \$20 billion.³⁴ The US Environmental Protection Agency predicts up to a 40 percent decrease in snow runoff and soil moisture in parts of the Western United States by 2050, further exacerbating concerns about droughts.³⁵

Our results have clear policy implications. The presence of peer effects suggests that policies influencing outdoor water use may have sizable indirect effects. Our results further suggest that targeted policies may be more effective than a uniform policy. For example, the intervention could avoid SRP households and focus on households in areas with a greater economic incentive to reduce water use. Of course, policymakers may be most interested in such targeted policies when there is a strain on parts of the water system from increasing demand or reduced supply. Thus, optimal policy design will inherently involve a consideration of both water district constraints and the potential indirect effects in the target audience.

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³³ Municipal water use was 21 percent of total water use in Arizona in 2017, with agricultural water use making up most of the remainder. See <http://www.arizonawaterfacts.com/water-your-facts>.

³⁴ See Daniels (2015).

³⁵ See EPA (2017).

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