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To Andrea, ever the raindrop on my helmet, without you I could not have made it. I know you worked as hard as I did to get here. To Titus, you changed me in a way nothing before you had and brought me a new level of motivation. To Addison, you are my joy. To Mom, you built the foundation upon which my life is constructed. To Dad, you provided me the wisdom to pursue all that matters in my life. To Alex, Jed, Eric, and Jay, your growth has made me proud to call you my brothers. To Olivia, Claire, and Annalise, in you I gained best friends. To Joel, Marlo, and Kendal, thank you for your patience, I look forward to more time together. To Weici, Jimmy, and Zexuan, my triumph is your triumph. To Michael, JP, Mark, Sun, and Matt, thanks for the memories, I treasure our friendship.

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Abstract

Chapter one presents a novel approach for analyzing spatially differentiated impacts of a variety of large, geographically anchored entertainment attractions, including professional sports venues, convention centers, destination retail, and mega-events. Public investments in such projects are often justified based on the potential to stimulate economic growth. The literature, however, fails to substantiate the existence of net aggregate benefits which are typically evaluated at the MSA level. I extend the literature by developing a spatial panel estimation approach which considers differential impacts across geographic locations as well as industry types. I demonstrate the method by investigating the relocation of the National Basketball Association Seattle team (Supersonics) to Oklahoma City (OKC Thunder). The franchise impacts are measured in terms of establishment-level sales using a unique micro dataset, the National Establishment Times series (NETs). The results highlight spatially differentiated impacts across the metro area: the franchise relocation attracted retail sales to the downtown area of OKC but may have decreased sales outside of downtown.

Chapter two designs and implements a field experiment in Norman, Oklahoma to analyze the effect of norm-based messages on residential water use. The analysis finds evidence that the conservation message and the peer comparison messages encourage water conservation. The estimated response to receiving a social comparison message is a 5 to 8.7% reduction in monthly water consumption. I find notable heterogeneity in response to social messages. Customers who consume more water than the median water utility user respond more to social messages than those who use less

than median. The findings suggest that social messages can be a cost effective option for municipalities looking to reduce residential water use through non-pecuniary mechanisms.

Chapter three investigates approaches for estimating water demand and responses to water rate changes. Water utility pricing generally involves different rates for different levels of consumption. Such block rate structures complicate demand estimation. I challenge the long standing implicit assumption that a city's demand can be represented by a single city-wide (or region-wide) demand curve in the presence of rate block pricing schemes. We employ the longest and most detailed panel dataset of household level water consumption, weather records, and housing characteristics available in empirical studies. This allows us to estimate demand curves for separate user groups in an increasing block rate scheme. We analyze two water utility rate changes implemented in Norman, Oklahoma and find downward sloping demand curves in all but one case. I estimate price elasticity to be between -0.13 and -0.53. Our estimates suggest that, in general, the more water a customer consumes, the more price sensitive she is.

Chapter 1: Location, Location, Location: Estimating the Economic Impact of Sports Venues and Other Attractions

This paper develops a generalizable approach for evaluating the economic impacts of entertainment attractions, including professional sports team, sporting venues, convention centers, destination retail, and mega-events. Proponents of public investment in such major attractions tout the potential stimulus effects. Popular press outlets are peppered with claims of large economic impacts associated with major attractions. “Fans and national media often spend the weekend at the city [during all-star weekend] and spur economic activity at surrounding restaurants, hotels, and other local business.”[1] The impact of the 2014 NBA All-star game was estimated to be $106 million by University of New Orleans’ Hospitality Research Center (nba.com). The Major League Baseball (MLB) 2013 MLB All-Star game was expected to generate $191.5 million for New York City (Dicomo, 2012).

Although such predictions are widely accepted to be factual, there is, in fact, a striking lack of analysis regarding their validity. Some economic development professionals argue that such predictions are widely over stated. For example, David DuBois, president of the Fort Worth Convention & Visitors Bureau, the estimated impact of the 2010 NBA All-Star Game played at the Dallas Cowboys stadium was only in the tens of thousands of dollars falling well short of the multimillion dollar estimates.[2] Notably, cities and proponents of public investments rarely provide for ex post analysis of economic impacts of major attractions. (Andreff, 2012) Furthermore,

[1] http://www.baseball-almanac.com/asgbox/all_star_game_economic_impact.shtml
[2] http://www.bloombergview.com/articles/2015-02-18/was-nba-all-star-weekend-a-financial-winner

the empirical academic literature, which does investigate ex post impacts, often fails to substantiate the existence of net positive economic benefits of such investments.

The academic research has notable limitations, especially for understanding nuanced impacts of attractions which are inherently location based. Most research applies conventional regression models to economic outcome measures aggregated to the metropolitan statistical area level (Propheter, 2012); an approach which precludes analysis of spatially differentiated impacts. The construction of a sports stadium, for instance, will impact the geographic area closest to the venue the most and more distant areas the least. Additionally, using aggregate measures obscures industry-specific impacts. Normal economic fluctuations in a metro area can mask even the largest possible stimuli, such as an NFL Super Bowl mega-event (Baade et al. 2008). Typical aggregate measures such as total sales tax collections, or personal income, include variation in potentially hundreds of industries that are not connected with the attraction of interest. For example, a professional sports team is not likely to impact manufacturing, car sales, and many other industries in any meaningful way.

I address these limitations in two important ways; (1) by analyzing impacts in an explicit spatial context; and (2) by employing establishment level data to focus on industries most likely to be affected by the attraction. Notably, the National Establishment Time series (NETs) data includes the exact location of establishments, yearly sales, and industry identifiers. To demonstrate my approach, I capitalize on a unique case study: the relocation of the National Basketball Association's Seattle franchise to Oklahoma City (renamed the Thunder) in 2008. The Oklahoma City Thunder's arena is located in the central area of downtown Oklahoma City, near the entertainment district (known as Bricktown). Such a central, downtown location is shared by many major urban attractions such as convention centers.

My approach yields estimates of differential impacts across areas of the city rather than the net benefit of attracting the franchise. In particular I estimate impacts on sales for establishments that are located at various distances from the Thunder arena. As expected, the results reveal spatially differentiated impacts: with increased retail sales in the downtown area of Oklahoma City near the arena, but possibly decreased sales outside of downtown. Understanding and measuring spatially differentiated effects is important for assessing potential winners and losers associated with economics development investments.

Literature Review

Sports teams, sports stadiums, convention centers, and mega events, as well as many other large capital investments, are often associated with a large capital investment focused in a particular geographic location. Previous literature focuses on the aggregate effects and has only recently begun to emphasize the placed-based nature of such investments. Siegfried and Zimbalist (2000), Coates and Humphreys (2003), and Propheter (2012) provide good surveys of the literature on sports teams, stadiums, and mega events as growth engines for urban areas. Table 1 summarizes articles which are most relevant for understanding spatial aspects of place-based projects and highlights the extensions which I make to the literature. I use establishment level sales data to execute a spatial analysis and find differential impacts across industries and geographic locations.

Most papers find sports teams, stadiums and mega events to have negative impacts or fail to find significant effects on income, sales, or employment. Baade and Matheson (2001), Baade and Dye (1990), Baade et al (2008), and Coates and Humphreys (1999) all observe negative growth impacts. Some papers find mild positive or mixed impacts. Nelson (2001) reports positive impacts when stadiums are built in the central business district of a city.

Table 1: Summary of Selected Empirical Literature

Author and Year	Level of Aggregation	Negative or Zero Impacts	Mixed Impacts	Spatial Component	OLS	RE, FE, TS
Baade and Matheson (2001)	MSA	x			x	
Baade and Dye (1990)	MSA	x			x	
Coates and Humphreys (1999)	MSA	x				x
Coates and Humphreys (2002)	MSA	x			x	
Nelson (2001)	MSA		x	CBD Dummy	x	
Propheter (2012)	MSA		x			x
Baade et al (2008)	County	x			x	
Coates and Humphreys (2003)	County		x		x	
Harger, Humphreys, Ross (2015)	Census Tract		x	Limiting Distance	x	
Stitzel (2016)	Establishment		x	Distance Variable and Limiting Distance	x	

Coates and Humphreys (2002) find that playoff games are not associated with growth in income unless the city has a team that wins the Super Bowl. Coates and Humphreys (2003) find professional sports to have a positive effect on earnings per employee in the amusement and recreation industries but offsetting negative impact on earnings in other sectors. Harger et al. (2015) unearth mild positive impacts on employment for existing businesses near the team's stadium but finds no effect on the formation of new establishments near the stadium. Propheter (2012) finds that, whereas basketball stadiums do not cause growth on average, some cities have seen growth from new stadiums. Propheter (2012) is the first paper to include the Oklahoma City Thunder in an analysis and observes that the Thunder had a positive impact on the Oklahoma City MSA per capita income. My results support his conclusion that basketball-only cities see positive growth impacts from the presence of an NBA franchise. In particular, my analysis of OKC shows that any potential positive impacts are concentrated near the game venue location.

Most empirical research on sports team, stadium, and mega event impacts uses census data aggregated to the MSA level. Only one other paper brings micro data to bear on the question. Harger et al. (2015) uses the Dun and Bradstreet Marketplace data to investigate business formation in the presence of a newly established sports franchise at the Census track level.

Nearly all previous work in the literature uses ordinary least squares analysis with dummy variables to represent the outcomes before and after a change be it the construction of a stadium, occurrence of an event, or relocation or creation of a team. Notable exceptions include Propheter (2012), who uses both fixed effects and time series approaches, Coates and Humphreys (2003), who use a dynamic panel model, and Harger et al. (2015) who employ a difference in difference model.

Baade and Dye (1990) are the first to examine the relationship between sports (both stadiums and teams) and local income. They find that sports teams and stadiums are linked to lower per capita incomes and argue that this finding is consistent with the type of economic development typically associated with sporting events and stadiums. Stadiums are commonly surrounded by low skill, low paying jobs such as food service and retail work. Baade et al. (2008) use county level sales data in Florida to examine the power of strikes, lockouts, expansions, stadium construction and mega events on local economies. They acknowledge the value of confining analysis to the areas physically located near the stadium or event.

An important aspect of analyzing economic impacts is that spillover effects can vary with distance and type of economic activity from the epicenter of the project. There is a rising interest in addressing the spatial dimensions of major location based projects. Nelson (2001) and Harger et al. (2015) are pioneers in investigating spatial aspects of place-based projects. They make novel contributions and I build on their work with a more explicit spatial model. Nelson (2001) uses dummy variables with a large panel data set to determine the value of the location of the stadium. Nelson argues that the stadium's location relative to the city's central business district is important. Teams closer to the city's core generate more net benefit to the city and the clustering of sports teams in a central business district leads to increased growth. According to Nelson, "the metropolitan statistical area's share of regional wealth increases and that share rises as more major league teams play there." He measures growth via the metropolitan area's share of regional wealth. The Chesapeake arena, where the Thunder plays, resides within the downtown central business district of Oklahoma City. Nelson's results would imply that the Thunder occupies one of the best possible situations for stimulating economic growth since the stadium is close to the city's core and in the central business district.

A major limitation of the literature is potential aggregation bias associated with using data aggregated to the county or higher level. Harger et al. (2015) recognize that no other papers in the literature use micro data. They examine business activity in nearby census tracts, limiting their sample to census tracts within 1, 3, and 5 miles of the sports facility. I build on Harger et al. by using micro-level data at the establishment level. Using establishment level sales data allows for analysis of differential impacts across industries and geographic locations. Accordingly, my analysis provides insights regarding the spatial winners and losers associated with a new major attraction.

History of NBA Franchises in Oklahoma City

The relocation of an NBA franchise is an unusual event that offers a rare opportunity to advance empirical research. Since 2000 there have been five relocations and franchise startups. In 2001 the Vancouver Grizzlies moved to Memphis, Tennessee. In 2002 the Charlotte Hornets moved to New Orleans and was replaced by a new franchise, the Charlotte Bobcats, in 2004. The New Orleans Hornets, now the New Orleans Pelicans, were temporarily displaced by Hurricane Katrina and played two seasons in Oklahoma City.[3] Most recently, the Seattle SuperSonics moved to Oklahoma City and became the Thunder in 2008. (nba.com)

In other major American sports there have only been three major relocations and expansions since 2000. The Houston Texans of the National Football League began play as an expansion team in 2002. In Major League Baseball the Montreal Expos relocated to Washington DC to become the Nationals in 2006. In 2011 the Atlanta Thrashers of the National Hockey League moved to Winnipeg, Canada and became the Jets. The National Football League approved the most important relocation in modern sports history by allowing the Saint Louis Rams and San Diego Chargers to move to Los Angeles for the 2016 and 2017 seasons, respectively.

There are few opportunities to study relocations and even fewer in which a team moves to an area that does not already host another major sports franchise. Of the relocations and expansions since 2000, only the Thunder, Jets, and Grizzlies moved to cities that did not host other major professional teams. The other major relocations and expansions not only involved metropolitan areas with other major sports teams, they also involved stadiums located within a 10 minute drive of at least one other team's stadium. Accordingly, unique aspects of relocations in the regional context are important for internal and external validation. For example, a relocation that involves a new and solo major sports venue is likely to involve less cannibalization. On the other hand, there would be less opportunity to cluster facilities and share parking and transit networks.

[3] The implications of the presence of the Hornets in OKC is discussed below.

The Thunder moved to OKC in 2008, two years after the NBA approved the sale of the SuperSonics to Oklahoma City businessman Clay Bennett for $350 million. The transaction was highly controversial in Seattle; fans citywide protested the sale and relocation to Oklahoma City. There are still periodic news stories about the perceived injustice surrounding the event (Booth, 2012). Meanwhile the people of Oklahoma have embraced the team and have provided one of the most enthusiastic fan bases in the NBA[4]. Although the zero sum game aspect of such a location is provocative, my focus is on the impact of the Thunder relocation on OKC.[5]

The relocation of the NBA franchise could impact the OKC metropolitan area via direct spending impacts as well as indirect multiplier effects. The NBA franchise could directly increase local spending. Some argue that one avenue of economic growth impacts players spending their salaries in the city provide one avenue for economic growth (Rapport and Wilkerson 2001). As the only major professional sports team in Oklahoma City, the Thunder provides a novel source of entertainment to the area, one which the city has embraced whole heartedly. The Thunder averaged 18,003 in home attendance in 2010[6], in an arena with a capacity of 18,203, good for 98.9%[7]. Their total attendance for 2010 was 738,149. The Thunder has ranked in the top 12 of NBA home attendance percentage every year except 2008 when it came in 17th.[8] This demonstrates the strong demand for NBA entertainment in OKC.

[4] http://www.forbes.com/sites/christinasettimi/2015/01/21/the-nbas-best-fans/#1c825987298f710572f6298f
[5] A question for another paper would be comparing the magnitudes of the potential gain in OKC to the potential loss in Seattle.
[6] http://espn.go.com/nba/attendance/_/year/2010
[7] http://www.chesapeakearena.com/about-the-arena/fast-facts
[8] http://espn.go.com/nba/attendance

The net effect of Thunder-related spending depends on whether it was new spending or simply substituted for spending on other activities. Some businesses, such as; restaurants, bars, and retail establishments, are likely to directly benefit from the Thunder's presence. Other businesses, however, might be negatively impacted. Both the nature of the activity and the location are relevant factors. The Thunder might stimulate sales in the OKC downtown area at the expense of sales that would have happened anyway. These sales could be cannibalized from other OKC venues or from elsewhere in the city. For example, individuals who intended to visit and shop in downtown OKC might choose to shop elsewhere, or not at all, when a Thunder game is being played. The Thunder-related traffic could discourage would be visitors and shoppers who are not interested in the game. Alternatively, an individual visiting downtown OKC might forgo other forms of entertainment to attend a Thunder game. These examples illustrate how the Thunder could generate sales but not cause a net increase in sales in the region as a whole.

In order to assess the impact of the NBA franchise the counterfactual case must be considered. The literature focuses on estimating net growth impacts for the entire region. In contrast, I estimate impacts on sales activity as a function of distance from Chesapeake Energy Arena where the Thunder games are played. This spatial approach reveals the Thunder's impacts on different regions of Oklahoma City.

Empirical Specification

The goal is to develop an empirical approach to identify differential spatial impacts associated with the NBA franchise or other mega event that has an epi-center type impact. The economic outcome measure of interest is taxable sales at the establishment level. As Baade, Baumann and Matheson (2008) argue, taxable sales are ideal for measuring economic impacts. In addition, taxable sales are superior to various measures of income because fluctuations in income independent of the impact of interest, more readily obscure impacts of interest.

The estimation strategy involves a pooled ordinary least squares regression with a vector of distances and an interaction term between the distance vector and the treatment. Specifically, the basic econometric specification is as follows;

(1) $Y_{it}=\beta_0*D + \beta_1*D*Treatment + \beta_2*Near_i + \beta_3*X_C + \gamma + \lambda + \varepsilon.$

Y_{it} is individual establishment i's annual taxable sales in year t, where t includes observations from 1990 to 2010, a period which includes years before and after the presence of the Thunder in OKC. The establishment level data are from the NETs database which is derived from Dun and Bradstreet (D&B) establishment data. Covering all of the private businesses, non-profit, and government establishments required to have D&B ratings, it is a near 100% coverage of establishments. The detailed individual establishment records include exact longitude and latitude, industry classification, and annual taxable sales data.

The necessary identifying variable is distance, defined as the Euclidian distance from an establishment to the venue of interest, the Chesapeake arena. *D* is a vector of Euclidian distances from the arena to the establishment. It includes linear distance, distance squared and distance cubed. We know from previous literature that impacts of place-based projects are likely to be localized. We also know that impacts at greater distances are more likely to be diluted and impacted by other non-NBA impacts.

Euclidian distance does not account for features of roads such as, cul de sacs, one way roads, dead ends, exits and turn arounds. Notably, few road features result in more than a few hundred yards in difference of driving distance. Within a mile or two of the stadium, this difference could impact estimates but beyond that the difference between two miles and two miles plus two hundred yards would be unlikely to influence estimates.

Treatment is a dummy variable equal to one for years the NBA treatment is in effect. The benchmark treatment effect is the presence of a hometown NBA franchise. It equals one for the years the Thunder played basketball in Oklahoma City. The Thunder played their first game in the 2008-2009 season. Other treatments specifications are also estimated as discussed below.

Near, is a dummy variable equal to 1 when an establishment is within 500 meters of the arena. The purpose is two-fold. First, it prevents the estimation from forcing the sales to be zero when distance is zero. Second, it allows for a differential estimation of those businesses within walking distance of the stadium (Dronyk-Trosper 2015).

X_C is the vector of controls at the census tract level. The control variables, population density and income, come from the US Census Bureau. As discussed previously, other authors have argued that controls for income and employment are imperative. Baade and Dye (1990), and Propheter (2012), among others, use income and population at the MSA level. Of course, population density and employment are highly correlated at the census tract level. I present the estimates without employment as a control; the results are robust to the inclusion of the employment variable.

Population density is the population in a census tract divided by the area of the census tract. This is a better control than simple population since a larger census tract with the same population as a smaller census tract has different sales potential. Census population and income are only collected and reported every ten years. To gain more variation and to more closely reflect actual population and income from year to year, the variables are linearly interpolated between 1990 and 2000 and again between 2000 and 2010 using a simple average.

The remaining variables capture fixed and time effects. γ is a dummy variable for census tract in which the establishment is located. λ is a vector of year dummies. ε is the White's standard error term, implemented to correct for heteroskedasticity.

Table 2 includes summary statistics of several samples used in my analysis. The benchmark specification limits the sample to industries that are potentially related to the NBA product. Retail stores, restaurants, and bars are expected to be compliments with the Thunder's product, whereas businesses in the entertainment industry are almost certainly substitutes. The focus on related industries eliminates noise associated with non-treatment related variation in sales in unrelated activities. Approximately 20% of establishment in a given year are in related industries. When the model is estimated using the expanded sample, which includes all industries in the NETs database, the NBA relocation is not found to be significantly correlated with establishment sales at any distance from the Chesapeake Arena.

Tables 2 and 3 present summary statistics for the variables discussed above for the main sample which only includes to those industries likely to be impacted by the NBA Franchise. Building on Harger et al. (2015) and others, the benchmark specification is applied to three different geographic sub-samples, establishments within; one mile, five miles, and ten miles of the stadium. Results are robust to the distance restrictions chosen; other limiting distances do not significantly change the impacts.

Table 2: Summary Statistics by Distance

Summary Statistics for all businesses in all industries in the state of Oklahoma

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Sales	3,790,124	1,015,037	1.15E+07	0	3.28E+09
Distance	3,790,124	119,379	84,089	41.88	509,113

Summary Statistics for all businesses in related industries in the state of Oklahoma

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Sales	755,258	913,686	1.09E+07	2	2.39E+09
Distance	755,258	121,059	83,909	41.88	509,113

Summary Statistics for all businesses in related industries within ten miles of Chesapeake Energy Arena.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Sales	133,722	1,207,627	7.47E+06	2	3.86E+09
Distance	133,722	8,721	3,745	41.88	16,087

Summary Statistics for all businesses in related industries within five miles of Chesapeake Energy Arena.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Sales	58,712	1,139,820	5.65E+06	2	2.41E+08
Distance	58,712	5,289	2,176	41.88	8,050

Summary Statistics for all businesses in related industries within one mile of Chesapeake Energy Arena.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Sales	5,491	1,199,426	3.49E+06	2	7.72E+07
Distance	5,491	782	377	41.88	1,608

Table 3: Summary Statistics by Distance for Related Industries

Summary Statistics for all businesses in related industries.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Income	755012	34747.67	15772.92	-53625	166587
Density	755258	0.000648	0.000688	-0.001416	0.003724

Note: 1634 establishment-years are associated with a census tract that has negative income.[1] [2]

Note: 4013 establishment-years are associated with a census tract that has negative population density.

Summary Statistics for all businesses in related industries within ten miles of Chesapeake Energy Arena.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Income	133,735	34,548	15,582	(53,625)	127,404
Density	133,735	0.00117	0.00071	(0.00104)	0.00372

Summary Statistics for all businesses in related industries within five miles of Chesapeake Energy Arena.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Income	58,565	26,927	13,415	(53,625)	111,979
Density	58,565	0.00120	0.00079	(0.00045)	0.00372

Summary Statistics for all businesses in related industries within one mile of Chesapeake Energy Arena.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Income	5,491	11,458	21,224	(53,625)	58,295
Density	5,491	0.00078	0.00100	(0.00045)	0.00372

Estimation Results

The benchmark results are given in Tables 5 through 7. The estimates suggest the relocation of the Oklahoma City Thunder is correlated with a positive impact near the arena. All of the coefficients of interest, the interaction terms, are highly statistically and economically significant. In the Hometown franchise specification, all of the coefficients are significant at the 1% level. The coefficients of the treatment distance interaction at ten miles are not significant. Specifically, the coefficients on the distance-treatment interaction terms indicate the impacts on estimated sales in years after the relocation of the Thunder at various distances from the Chesapeake Arena.

The distance effect is best demonstrated with graphs since the direct interpretation of the estimated coefficients on distance is difficult to understand without a visual representation. Accordingly, Figures 1 through 3 plot the estimated sales for establishments located at various distances to the Chesapeake Arena prior to and after the relocation of the Thunder. The figures show that the Thunder potentially pull sales into the downtown area. Without the Thunder, sales fall quickly as firms are farther away from arena. With the Thunder the sales within a half mile increase dramatically and from a half mile to one mile the sales fall slowly.

The results suggest that the Thunder affects the economy significantly in the downtown area but has less affect farther away from the arena.

Figure 1: One Mile

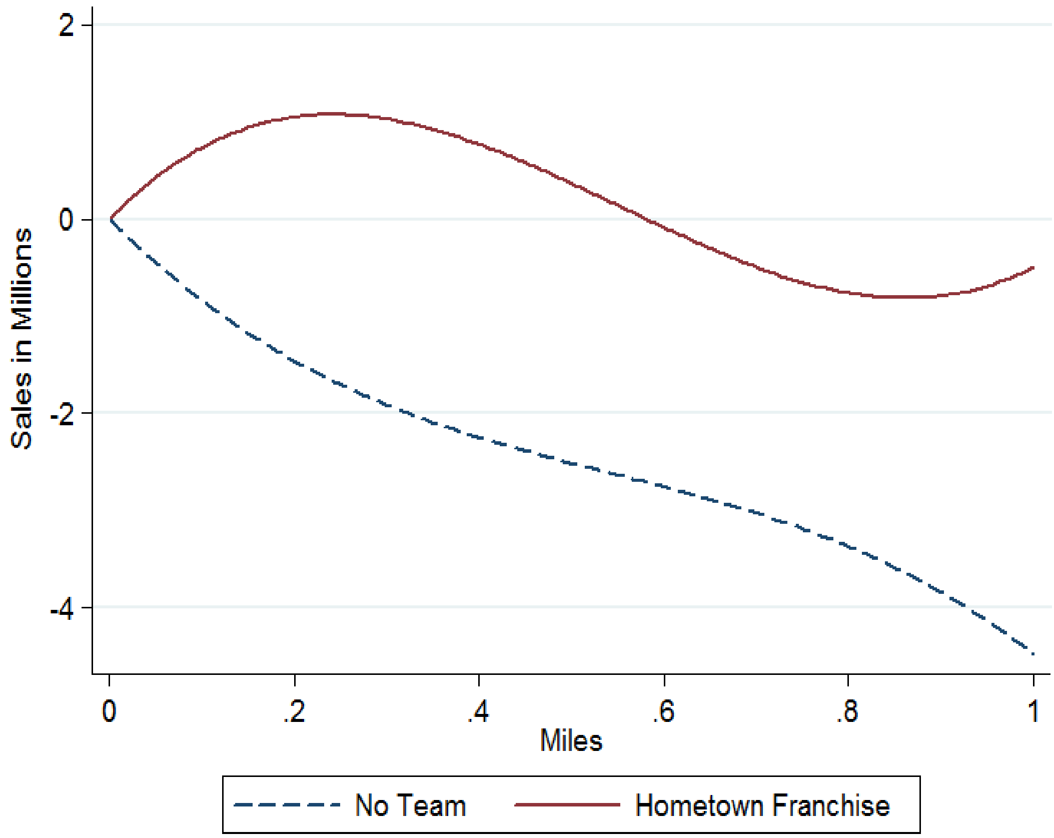


Figure 2: Five Miles

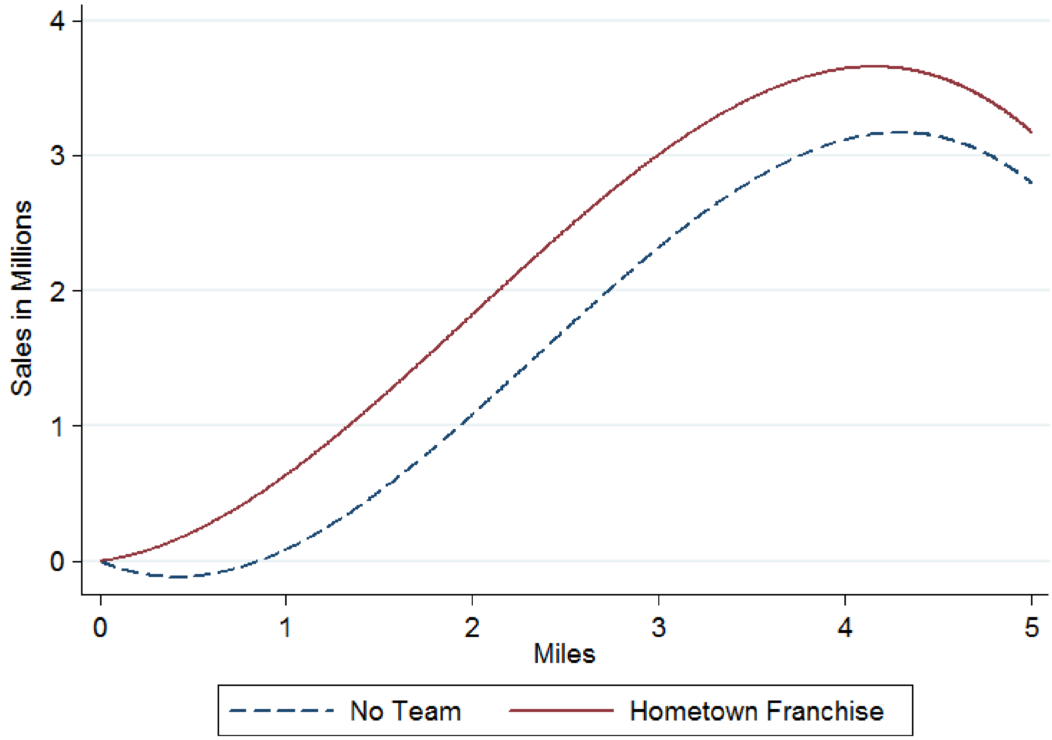
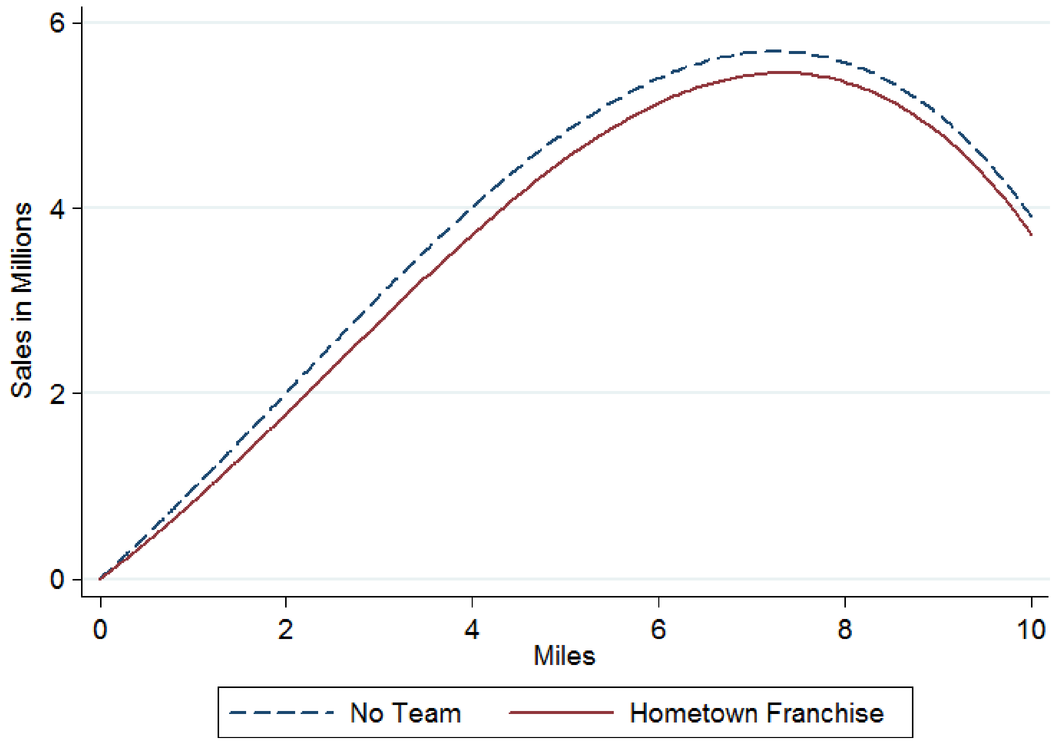


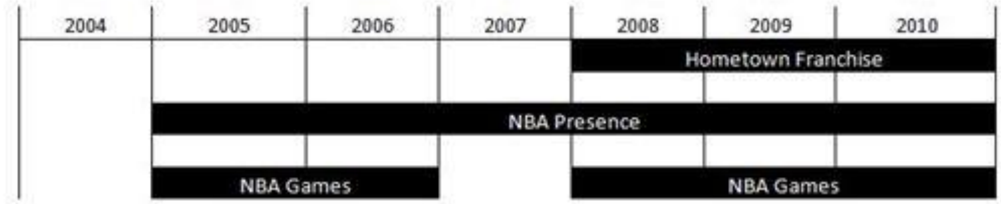
Figure 3: Ten Miles



Alternative Treatment: NBA Games and NBA Presence

A potential concern is that the brief presence of the New Orleans Hornets in Oklahoma City after Hurricane Katrina might confound the effect of the Thunder NBA franchise. To address this I explore two additional specifications of treatment years, "NBA Games" and "NBA Presence." See Table 4 for a visual representation.

Table 4: Alternate Definitions of the Treatment Variables



The NBA games specification defines the treatment as occurring in all the years from 2005 forward except 2007. This takes advantage of variation in the presence of an NBA franchise. The NBA games treatment is defined by actual playing of NBA basketball games in Oklahoma City. This begins with the Hornets' relocation in 2005, stops after the Hornets' leave and begins again when the Thunder arrives. The Hornets leave Oklahoma City in 2007 while the Thunder arrive in 2008, which means that although the City went most of a year without games being played, there is technically basketball being played in each year.

The NBA Presence treatment begins with the Hornets' temporary relocation to Oklahoma City in 2005 and continues through the end of the sample. Thus, the treatment dummy is equal to 1 for all years 2005 to 2010. This definition of the treatment represents the impact of drawing potential customers into the downtown area during game times. The Hometown treatment definition accounts for the "big league city" effect or the region's ownership of the team and might be reflected in increased sales more by the purchase of the hometown team's jerseys or of players spending their income locally. In contrast, the NBA games treatment focuses more on the attraction of potential customers into the physical area surrounding the arena, so far as annual data can represent such an idea.

The results are incredibly similar across the different specifications of the treatment years. As shown in Tables 5 through 7, all of the treatment coefficients in the NBA presence and NBA games specifications are significant at least the 10% level, with most being significant at the 1% level.

Table 5: One Mile

	Hometown		NBA Franchise		NBA Games Played	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Distance	-5,977.007*	3,218.49	-10,030.772**	4,013.20	-7,208.379**	3,531.04
Distance Squared	5.105	4.288	9.412*	5.106	6.179	4.585
Distance Cubed	-0.002	0.002	-0.003*	0.002	-0.002	0.002
Treatment Distance	12,086.167***	3,181.47	12,743.414***	4,323.74	9,607.540**	4,189.85
Treatment Distance Squared	-15.175***	4.113	-14.617***	5.67	-10.781*	5.717
Treatment Distance Cubed	0.006***	0.002	0.005**	0.002	0.004*	0.002
Income	2.367	3.662	3.661	4.121	3.887	3.933
Density	603,000,000**	253,400,000	668,500,000**	269,100,000	645,200,000**	266,800,000
Near	-433,000***	165,000	-467,000***	166,000	-443,000***	165,000
CT FE	x		x		x	
Year FE	x		x		x	

note: .01 - ***; .05 - **; .1 - *;

Table 6: Five Miles

	Hometown		NBA Franchise		NBA Games Played	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Distance	-368.126	487.415	-513.836	485.943	-454.53	487.183
Distance Squared	0.306***	0.108	0.333***	0.107	0.323***	0.108
Distance Cubed	-0.000***	0	-0.000***	0	-0.000***	0
Treatment Distance	482.938*	278.866	634.130***	243.772	569.844**	245.168
Treatment Distance Squared	-0.095	0.086	-0.115	0.072	-0.108	0.074
Treatment Distance Cubed	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Income	2.612	2.363	5.514**	2.428	3.755*	2.28
Density	-282,000,000	155,200,000	-227,200,000	163,300,000	-252,700,000	157,700,000
Near	-32,000	129,000	-23,000	129,000	-30,000	129,000
CT FE	x		x		x	
Year FE	x		x		x	

note: .01 - ***; .05 - **; .1 - *;

Table 7: Ten Miles

	Hometown		NBA Franchise		NBA Games Played	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Distance	562.878**	224.14	556.498**	225.46	563.075**	224.07
Distance Squared	0.029	0.029	0.029	0.029	0.029	0.029
Distance Cubed	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Treatment Distance	-102.875	94.208	-43.755	91.386	-71.340	92.362
Treatment Distance Squared	0.011	0.013	0.006	0.012	0.008	0.013
Treatment Distance Cubed	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Income	-1.503	2.414	-0.963	2.66	-1.388	2.514
Density	-86,400,000	67,700,000	-90,000,000	66,600,000	-90,200,000	67,200,000
Near	84,000.00	103,000.00	87,000.00	103,000.00	86,000.00	104,000.00
CT FE	x		x		x	
Year FE	x		x		x	

note: .01 - ***; .05 - **; .1 - *;

Alternative Treatment: One Mile Increments

Given the positive coefficients near the arena and the weakening of the impacts further away from the arena an interesting question arises; what distance separates establishments that benefit from the Thunder from those that do not? Since the Thunder's impact should be largest near the arena and smaller/negative further away from the arena, it is instructive to find the demarcation between potential winners and losers.

I approach this issue by specifying non-inclusive one mile increments from the Chesapeake Arena. For instance, the one mile increment from five miles to six miles away from the stadium includes only those establishments located at least five miles from the stadium but no more than six miles from the stadium. In this way, the distance vector can be simplified to a set of linear one-mile increment terms, which can capture non-uniform impacts across various distances. This is similar to a Kernel estimator. By breaking down the estimates into one mile increments, impacts can be evaluated in finer intervals, such as from 6 to 7 miles from the arena, rather than yielding impacts over 5 and 10 mile intervals.

The one mile increments will still include increasingly more establishments because the geographic area covered by an increment will increase as they move away from the arena.

Recall from above that in the three specifications featuring the five mile restriction the linear distance and treatment interaction coefficients are significant, but none of the squared or cubed distance coefficients are significant. As shown in Table 8, both the first and second mile increments have large positive coefficients, which fit with the results shown in the benchmark method. Beyond these, only the sixth (from five miles to six miles away from the stadium) and ninth mile increments have coefficients which are positive and significant at the five percent level. The geographical distribution of establishments in Oklahoma City is important and are apparent in the maps shown in Appendix A. The fifth to sixth mile increment includes three important areas; one on the Northwest expressway which includes the largest shopping mall in the metro area, another east of the arena which includes a casino, zoo and shopping area, and the third is a large group of retail establishments south of the arena on the major loop around the city. The eight to nine mile increment includes fewer major shopping areas but one of the most important shopping and entertainment areas outside the downtown area in the city of Moore. This area is one of the highest concentrations of shopping and restaurant establishments outside of Oklahoma City proper.

Taken together, an increase in sales for the one, two, six and nine mile increments demonstrates that the three areas with the highest concentration of retail shopping and restaurants all experienced growth coincidentally with the Thunder's relocation. (Figure 4)

An expectation based on previous literature would have been that establishments in industries the hometown franchise might impact which are located outside of the metro, like those in the sixth and ninth mile increments, would have suffered from the Thunder's presence by virtue of the substitution effect. Although the results reveal positive and significant impacts in the mile by mile model for some intervals beyond five miles, estimated coefficients are negative but insignificant in the ten mile benchmark models. It could be, as authors like Nelson (2001) suggest, the lack of other major professional sports in the area causes this to be a best case scenario for the growth engine theory. Perhaps a new franchise can provide a novel source of entertainment at minimal cost to other entertainment establishments without the presence of competing sports franchises. However, the evidence presented here is certainly not conclusive on the matter.

Another possibility is that city-wide growth trend drives the results estimated above. A growth trend felt equally, or randomly distributed, across establishments within the metro area could mask the estimated the treatment-distance interaction effect. Notably, the treatment interaction term is insignificant when the sample is broadened to include the full scope of industries. Thus, for a growth trend to impact my estimates it would need to affect only those establishments in the entertainment and retail industries, not be absorbed by year or census tract fixed effects, and do so in manner that originates at the Thunder's home stadium while having a differential impact over distance on establishment sales. This growth trend would also have to be positive to explain the estimates, which is unlikely given the timing of the recession.

Table 8: Mile by Mile

	One Mile		Two Mile	
	Coefficient/SE		Coefficient/SE	
Distance	-2,019.4***	276.5	-1,380.1***	349.6
Treatment Distance	937.5***	278.9	1,084.3**	426.7
Income	-4.24	7.71	-12.625	8.307
Density	-481,600,000	634,800,000	-285,200,000	595,400,000
Near	-1,410,000***	280,000		
CT FE	x		x	
Year FE	x		x	

note: .01 - ***; .05 - **; .1 - *;

	Three Mile		Four Mile	
	Coefficient/SE		Coefficient/SE	
Distance	-1,327.4***	292.3	2,687.0***	681.6
Treatment Distance	300.8	436.9	2,512.80	2,112.00
Income	-12.014	15.281	-24.95	16.912
Density	1,258,300,000***	424,500,000	-789,100,000	795,800,000
CT FE	x		x	
Year FE	x		x	

note: .01 - ***; .05 - **; .1 - *;

	Five Mile		Six Mile	
	Coefficient/SE		Coefficient/SE	
Distance	224.4	205.5	63.6	153.5
Treatment Distance	95	1,310.60	653.0**	310.9
Income	-4.294	6.708	-6.469	4.289
Density	1,637,800,000*	902,900,000	3,510,000,000***	921,000,000
CT FE	x		x	
Year FE	x		x	

note: .01 - ***; .05 - **; .1 - *;

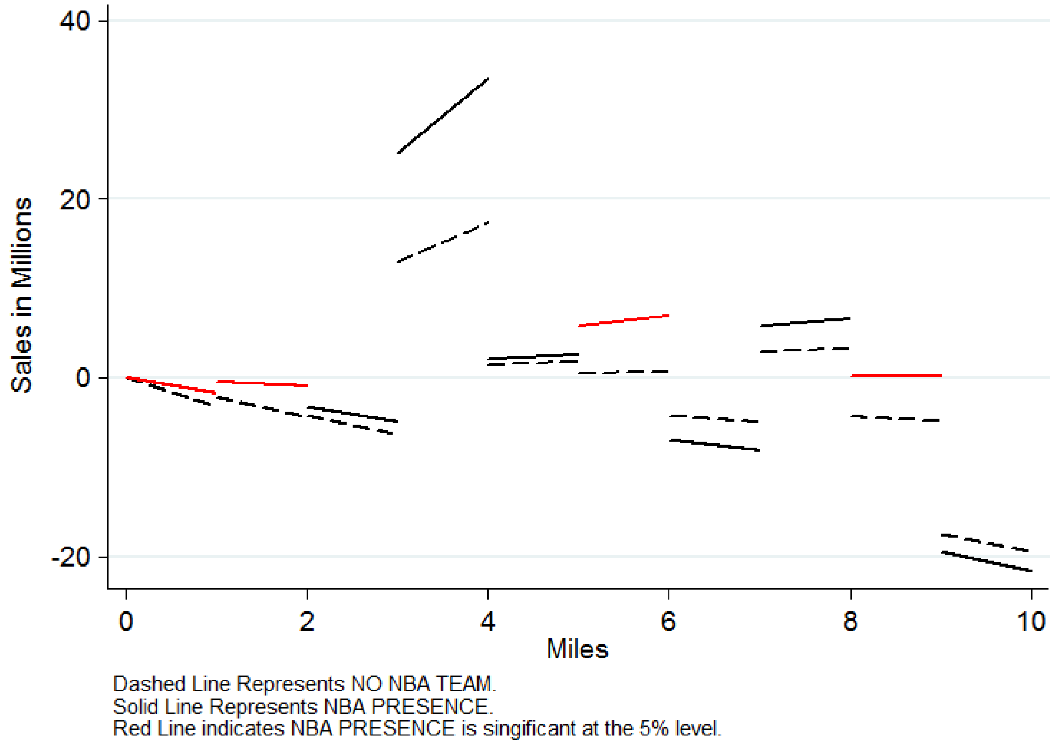
	Seven Mile		Eight Mile	
	Coefficient/SE		Coefficient/SE	
Distance	-443.3***	111.2	254.5***	74.1
Treatment Distance	-281.7	199.4	255.9	163.8
Income	2.649	3.487	27.374***	8.151
Density	-795,800,000**	336,000,000	-366,200,000	367,100,000
CT FE	x		x	
Year FE	x		x	

note: .01 - ***; .05 - **; .1 - *;

	Nine Mile		Ten Mile	
	Coefficient/SE		Coefficient/SE	
Distance	-338.1***	70.8	-1,212.7***	201.1
Treatment Distance	348.8**	153.3	-135.5	489.2
Income	-4.159	19.592	-30.241	39.525
Density	- 1,228,700,000***	338,400,000	-457,600,000	639,800,000
CT FE	x		x	
Year FE	x		x	

note: .01 - ***; .05 - **; .1 - *;

Figure 4: Mile by Mile



Conclusion

This paper finds that the presence of the Oklahoma City Thunder corresponded with an increase in sales within a one mile radius of Chesapeake Arena. The sum of the differences between the distance equation with and without the Hometown franchise treatment is around $4.5 billion depending on the specification. This suggests the Thunder's presence was associated with an increase of $4.5 billion in sales for the immediate downtown area (within one mile) over the three to five years of franchise presence. The predicted average growth in sales is $1.5 billion per year.

In the specification that includes up to a 5 mile radius from the Chesapeake Arena, the Thunder corresponds with $524 million in new sales in total for three years.

Estimated impacts using a 10 mile radius are not significant, which is unsurprising. As the concentric circles widen, there are more and more establishments included in the model which creates more noise. Any potential NBA franchise effect is expected to weaken farther away from the arena. If the sum of the differences is calculated for the ten mile radius sample in the same way as before, the estimated impact dwarfs the combination of the one mile and five mile estimated impacts. Under this calculation the Thunder cost the metro area $21 billion in sales over the full ten mile radius area. However, this effect is not statistically significant at any conventional level.

Establishments further from the arena may have suffered. The Thunder may have helped bring in millions of dollars in sales above and beyond the sale of their own tickets and products within the stadium. The critical evaluation is the specification including a five mile radius from the Chesapeake Arena. It suggests the Thunder corresponds with a net increase of over $500 million in sales for the core of the Oklahoma City metro. This would compare favorably with the $300 million spent by the city to renovate the Chesapeake Arena.

My results correspond with those of Propheter (2012) and Nelson (2001) and contrast those of Baade et al. (2008) and Coates and Humphrey (2002). Harger et al. (2015) find similarly mixed impacts but a far less positive impact of new franchises. Propheter (2012) considers basketball only cities and many of the newest sports facilities. My analysis focuses on a situation with a single major sports team in the city. Thus, it may not apply to cities that already have other major sports franchises.

The policy implications are interesting. In a city like Oklahoma City, where there is room for development in the downtown area surrounding the location of the arena, a major sports franchise could be a boon for the city. The Thunder potentially had such a positive effect because it provided a marginal improvement over having no major sports. The marginal impact of a second or third major sports franchise would almost certainly be less. Furthermore, consider two of Oklahoma City's closest major cities, Dallas, Texas and Kansas City, Missouri. Both feature multiple major sports franchises; Dallas has a National Basketball Association (NBA), a Major League Baseball (MLB), and National Football League (NFL) franchise, Kansas City has an MLB and an NFL franchise. In both cities, the MLB and NFL teams' stadiums are located adjacent to one another. If an NFL or MLB franchise were located near Chesapeake arena, it would be reasonable to suspect that the relocation effect might not be as strong since a similar product is already physically located nearby thereby cannibalizing its sales.

What do these results suggest about potential new NBA franchise locations? There exist a few obvious choices for NBA expansion based on television market size, population, and lack of other major sports. Raleigh, (North Carolina), Louisville (Kentucky), Virginia Beach/Norfolk (Virginia), Birmingham (Alabama), Providence (Rhode Island), Austin (Texas), Albuquerque (New Mexico), and Grand Rapids (Michigan) all lack major sports teams, and are comparable to Oklahoma City in both MSA population and television market size. Appendix B presents these selected cities with their television market size rank[9] and MSA population rank[10]. Austin and Grand Rapids have larger populations and television markets than Oklahoma City.

[9] As of January 2016. Nielsen's Local Television Market Universe Estimates
[10] AS of the 2010 census. Population Estimates. United States Census Bureau.

Although this paper's focus is an NBA franchise, it offers guidance for a wide range of extensions. Examining spatially differentiate impacts of other types of local public investment and other metropolitan settings would make valuable additions to the public investment literature. Attention to identifying the "winners" from the "losers" of a place-based investment is important for informing policies, particularly regarding how to finance public investments. If benefits are localized, then how should funding be structured so that those who stand to benefit the most pay their fair share of the costs of public investments?

Chapter Two: Social Messages and Water Conservation Strategy and Policy: A Field Experiment

The ubiquitous need for potable water is undeniable. Water is essential for the most basic aspects of human existence, including personal hygiene and sanitation. Access to clean, safe water is one of the most prevalent policy issues of this generation. Water scarcity is a growing concern at the global, national, regional and local levels. Globally, 1 in 10 people lack access to safe drinking water and face health risks due to lack of clean water.[11] The 2015 World Economic Forum, listed water crisis as the highest potential impact global risk and listed water crisis as the 7th most likely global risk.[12]

The United States is not immune to water scarcity issues. The US Government Accountability Office claims 40 of 50 state managers expect shortages somewhere in their state over the next ten years.[13] The United States Department of Agriculture (USDA) estimated that 50% of the State of Oklahoma faced extreme drought in 2014.[14] For the summer of 2014, the USDA estimated that 20% of the State of Texas faced extreme drought and 50% of the state faced moderate drought.[15] With aquifers depleted and constructed in a way that threatens their ability to replenish themselves, municipalities are becoming desperate for alternative water sources.

Communities across the US have resorted to increasingly desperate measures to provide drinkable water for their residents. In Texas, Big Spring and Wichita Falls are

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[11] http://water.org/water-crisis/water-sanitation-facts/
[12] http://reports.weforum.org/global-risks-2015/#frame/20ad6
[13] http://www.gao.gov/products/GAO-14-430
[14] http://droughtmonitor.unl.edu/Home/StateDroughtMonitor
[15] http://droughtmonitor.unl.edu/MapsAndData/DataTables.aspx?state,TX

just two communities among several that have resorted to exorbitantly expensive reverse osmosis systems to re-purify waste water for reuse and directly return it to surface water sources. Since 2013 both communities[16] have maintained Direct Potable Reuse Systems.[17] This method involves treating reclaimed waste water and mixing it with raw surface water before sending this new mix back to a traditional water treatment plant. Many other municipalities across the nation are exploring a range of supply-oriented options, such as purchasing water from larger cities, building reservoirs, and constructing reuse systems. These solutions are often costly and can take considerable time to implement.

Naturally, the water scarcity crisis is a two sided problem. In addition to supply-oriented policies, municipalities try to impact demand via conservation policies, such as watering restrictions, building regulations and requiring low flow faucets and efficient appliances, and conservation pricing. Conservation pricing involves setting higher fees for water use as well as charging higher fees during peak periods. The costs associated with installing time and flow sensitive meters needed for time-variant pricing can be substantial which may preclude implementation in all but the most dire circumstances. San Francisco, for example, installed smart meters in 180,000 homes and businesses in 2014 at the cost of $56 million.[18]

Social messages and awareness campaigns offer a non-pecuniary alternative to the conventional water management approaches. There is a growing interest in exploiting peer group influences to encourage conservation. Very little research,

[16] http://twri.tamu.edu/publications/txh2o/summer-2013/reclaiming-a-valuable-clean-resource/
[17] http://www.wichitafallstx.gov/Faq.aspx?QID=513
[18] http://www.sfgate.com/science/article/California-drought-S-F-gets-smart-water-meters-5496714.php

however, investigates the efficacy of these strategies for water conservation. What role, if any, can awareness campaigns and peer group comparisons play in water management? We address this question.

This paper investigates how residential water users respond to social awareness messages and peer group comparisons. We design and implement a field experiment to explore efficacy of conservation messages, tip sheets, and peer comparisons for water conservation. Through collaboration with the City of Norman and with financial support from the College of Arts and Sciences at the University of Oklahoma, we sent mailers to 2,163 randomly selected water utility customers of the City of Norman, Oklahoma. All selected customers received a general message about water conservation. Some also received a tip sheet about how to conserve water. Some also received comparisons about their usage relative to that of neighbors. Some received all three treatment instruments. This resulted in four distinct treatment groups.

Observations of treated and non-treated customers from before and after the treatment are used to analyze treatment impacts on residential water use. We construct a database that goes well beyond simple water consumption records. The customer-location level observations include detailed information about consumption, house features, and weather. Our data includes water consumption records, account records, weather records, and housing features. The level of detail in the database is unprecedented in existing literature allowing us to extended contemporary analysis in significant ways. The empirical specification includes several traditional approaches as well as a series of insightful robustness checks. Notably, we specify treatment variables using a sequential approach as well as exclusive categories.

Our main findings are similar but of larger magnitude than those found elsewhere in the literature. Both conservation letters and peer comparison messages have large and statistically significant impacts on water consumption. The tip sheet appears to have no impact on the whole sample but may reduce consumption for above average users. The highest tier users have the largest and most statistically significant response to the various instruments whereas the lowest users only respond to the conservation message if they respond at all.

The rest of the paper is organized as follows. Section two describes the literature. Section three outlines the experiment. Section four describes the estimation technique. Section five presents the results. Section six discusses and concludes.

Literature Review

Social messaging focuses on using non-price mechanisms to induce behavioral changes (Lowenstein et al 2007). This can be done by providing information to make features of behavior more salient in consumer decisions. The literature on social messaging investigates various issues, including charitable giving, food choice, organ donation, energy conservation, and water conservation (Downs et al, 2009, Johnson and Goldstein, 2003, Ayres et al, 2012, and Ferraro and Price, 2013). Some argue that social messages seem to be ineffective in changing behavior (Downs et al, 2009, Choi et al, 2005).

Recently, there has been an interest in peer-group comparisons as a means to anchor social norms (Ayres et al., 2012, Ferraro and Price, 2013, Brent et al, 2014). The impact of peer groups on behavior is widely studied, frequently in the context of how harmful behaviors are propagated (Trogdon et al 2008, Powell et al., 2005). The classic paper by Winickoff et al. (1984), poses this approach for dealing with surgeon performance. Falk and Ichino (2006) use peer comparisons to improve performance in a menial task. For a discussion of the use of social messages and peer comparisons in the context of charitable giving and of the literature on social-norm marketing refer to Ferraro and Price (2013).

This paper builds on a small but growing literature about norm-based messaging in the context of resource conservation. Figure 5 summarizes research which is most relevant for this study and highlights our contributions. Most of the studies mail messages which include a tip sheet on how to use fewer resources. Heterogeneous impacts are also commonly considered. Estimated conservation responses to receiving sending social messages fall roughly between 2 and 5%. In the seminal paper on peer comparisons and residential water use, Ferraro and Price (2013) take advantage of a large field experiment executed by the Cobb County Water Authority. They show that peer comparison messages have a stronger influence on users than conservation messages and technical advice. The treatment with a peer comparison combined with technical advice has the strongest impact: it induces an estimated 5% decrease in water consumption.

Figure 5: Summary of Selected Literature

Author and Year	Brent, Cook, and Olsen (2014)	Bernedo, Ferraro and Price (2014)	Ferraro and Price (2013)	Ayres, Raseman, and Shih (2012)	Allcott (2011)	Byrne, La Nauze, and Martin (2014)	Stitzel (2016)
Experiment Category	Water	Water	Water	Electricity	Electricity	Water	Water
Delivery Mechanism	Mailing and Email	Mailing	Mailing	Mailing	Mailing	Email	Mailing
Treatment Type: Comparison group	x	x	x	x	x	x	x
Conservation Message	x	x	x	-	-	-	x
Tip Sheet	x	x	x	x	x	-	x
Frequency of Message	Between 7 and 13 times in a month	Three waves over several weeks	Three waves over several weeks	"Periodically"	Monthly, Bimonthly, or Quarterly	Biweekly and portal access	One Time
Housing Controls	x	-	-	x	-	x	x
Weather Controls	x	-	-	x	-	-	x
Heterogeneity	x	x	x	-	x	x	x
Results: Treatment impact	2-6%	2% one year later	4.8%	1.2-2.1%	2%	6% increase	5-8%
Boomerang Effect	-		-	x	x	x	x
Comparison Group	Households in city with same observables (Occupants and Lawn size)	County	County	Comparable Homes	Nearby houses with same observables (Square ft of house and heating type)	Not Described	Meter Route

We make three key improvements on Ferraro and Price (2013) some of which are also implemented in other places in the literature. First, we use a more appropriate comparison group. We compare customers to their neighbors within the same meter route. Meter routes divide the city into manageable regions for utility employees because water meters must be read manually. Thus, houses in the same meter route are physically proximate to each other. In contrast, Ferraro and Price compare users to that of the median Cobb County resident. Cobb County is one of the one hundred largest counties in the United States with almost 700,000 residents.[19] Given the diversity across neighborhoods, the median resident may not provide a meaningful anchor for a peer comparison. As a social norm, the proximate neighborhood is more salient to customer decision making. Additionally, we compare the customers to a "water conscious neighbor", one which uses less than 80% of others in the same meter route. In the water research, using only lower tiered user as an anchor is unique. Brent et al. (2014) use both a low tier comparison, an "efficient neighbor" with similar housing and occupant characteristics in the bottom 20% of use of all users, as well as the median user to anchor the treated customer.

Our second improvement is that all of our treatment letters were mailed at the same time. In contrast the Cobb County experiment involved mailing various implements in waves that were weeks apart, making it hard to control for relevant control variables such as weather. A single wave provides multiple advantages, the foremost being the consistency across customers when the message is received. This

[19] http://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=bkmk

provides assurance that customers receive the message at the same time in month so that both the amount of days left in the month and the external conditions such as rain, temperature, and exposure to information, is the same for each household in the same meter route.

The third improvement is a refinement of estimation of heterogeneity in treatment effects (Allcott, 2011 and Ferraro and Price, 2013). Ferraro and Price correctly point out that customers using more than median user should respond differently to the treatments than users below the median use. We extend this analysis by dividing the sample according to standard deviations away from the median: one standard deviation below the median, less than one standard deviation below the median, less than one standard deviation above the median, and more than one standard deviation above the median. As expected, we find that the further above (below) the median the greater (less) the response to the treatment is. We find no evidence of the boomerang effect, where customers below the median use more after receiving the comparison message.

A closely related literature focuses on conservation impacts in residential energy markets (Allcott, 2011 and Ayres et al., 2012). These find that communicating social norm messages, known as the pro-social norm, and providing peer comparisons can lead to decreases of residential energy use of around 2% per month.

This paper is also indirectly related to literature on conservation pricing of water. The literature expresses the concern that high income individuals, who are also likely to be higher volume users, may not be very responsive to price increases aimed at conservation. Furthermore average cost pricing could be regressive if lower income individuals pay a greater share of their income for water. Non-pecuniary strategies, like those studied here, provide additional tools for municipalities looking to reduce residential water demand. Social messages and peer-group comparisons may be powerful complements to conservation pricing strategies because they can target those customers least sensitive to price. Such a concern is common in the literature (Ferraro and Price, 2011), but, as I show in *Estimating Water Demand under a Block Rate Structure* all customers are price insensitive, have inelastic demand, and those customers that consume more are more price sensitive than those who use less.

Experimental Design and Environment

Background

The City of Norman lies in Cleveland County just ten miles south of Oklahoma City, Oklahoma. Norman is the third largest city in the state with a 2010 population of approximately 110,925 people.[20] The City of Norman Water Utility Division services approximately 35,000 single family homes. Not all Norman residents are connected to the city's water system. Norman's water sources include both surface water and groundwater. The City shares its surface water source, Lake Thunderbird, with Del City and Midwest City,[21] under the authority of the Central Oklahoma Master Conservancy District.[22] The city has 36 active water wells in addition to several wells taken off line due to water quality deficiencies. Three of the 36 active wells have some issues with arsenic. Two of the three are able to reach the arsenic standard by being mixed with

[20] http://www.normanok.gov/content/demographics
[21] http://www.normanok.gov/sites/default/files/Utilities/images/2060%20SWSP%20-%20August%202014%20Final%20-%20Report%20Only.pdf
[22] http://www.comcd.net/history/

water from other wells to meet EPA standards. The third well is being used to pilot an arsenic removal system using chloramination.[23]

Norman changed its water rate fee structure in March of 2015 preceding our experiment by five months.[24] To our knowledge the City of Norman was not engaged in any new conservation efforts during the experiment window. Norman periodically sends tip sheets along with a customer's water bill, but these are sent to all customers at a given time. Norman implemented permanent watering restrictions for all of Norman in 2014.[25] Norman had considerably more rainfall in the summer of 2015 than in the summer of 2014 but about the same as in the summer in 2013. The average monthly rainfall for the months April through September was 17.23 cm in 2015, 5.37 cm in 2014, and 13.65 cm in 2013. See Figure 6 for these figures as well as the analogous ones for July through September. City of Norman water utility staff emphasized the importance in rainfall for predicting water consumption. To that end, we account for the variance in rainfall in multiple ways. The most critical is the randomization of the treatments such that the deviation in rainfall does not systematically bias our estimates of treatment responses. Additionally, we investigate models which include rainfall variables to explicitly control for precipitation. Finally, we estimate multiple regression specifications, such as including observations from 2012 and 2013 which are more representative of the rainfall of summer 2015.

[23] http://www.cdc.gov/healthywater/drinking/public/chloramine-disinfection.html
[24] http://www.normanok.gov/content/new-water-rates-effective-march-2-2015
[25] http://www.normanok.gov/content/psst-renewal

Figure 6: Rainfall

Year	Rainfall Apr-Sept (tenths of mm)	Rainfall July-Sept (tenths of mm)
2013	1,365	1,182
2014	537	476
2015	1,723	828

Experimental Design

The City of Norman graciously collaborated with us to execute a mail-based randomized field experiment. The City of Norman GIS department provided information on house and lot features for each water utility customer so as to facilitate a sophisticated analysis without disclosing private customer information or addresses.

Our experiment targeted single family homes. Some customers are eliminated from the sampling pool due to the nature of our experimental design. To facilitate comparisons before and after treatment, locations for which there was a customer change in either 2014 or 2015 were excluded. We limit the sample, both control and treated, to single family homes with consumption between one hundred and one million gallons in a single month. These combine to eliminate homes that are empty, experience major leaks, or are severely over charged. Leaks and billing errors are not tracked. The results, however, are not sensitive to the choice of restriction so we impose the least restrictive standard. There is no reason to believe that the restrictions lead to systematic bias in our estimates. Of the 34,737 homes served by the City of Norman in July of 2015, 26,524 households were retained in the sampling pool.

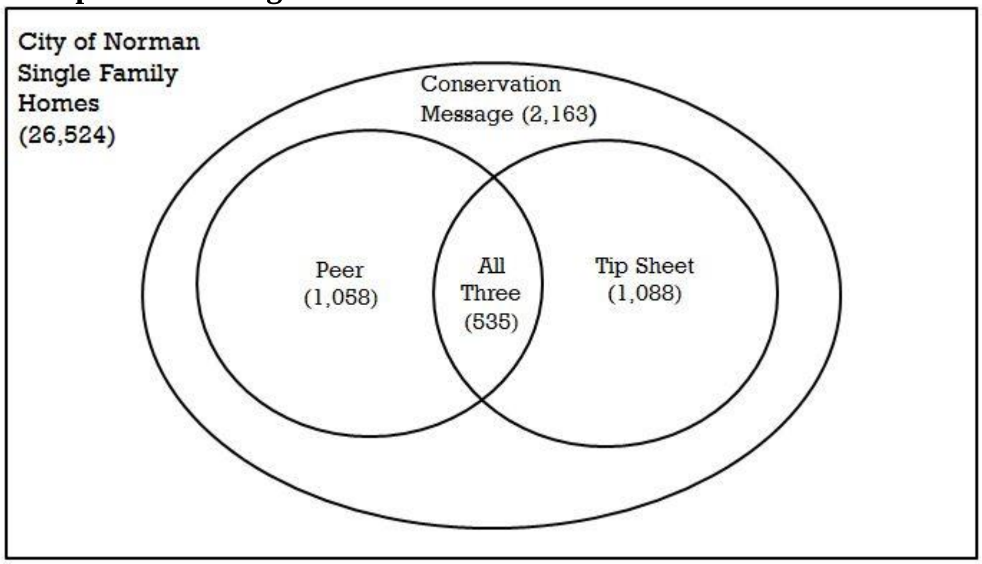
The City of Norman has 75 routes with an average of 400 homes per route. We randomly selected customers within 38 odd numbered meter routes to receive treatments. By limiting to only half of the routes, we were able to treat approximately 57 customers per meter route for a total of 2,163 treated homes (8% of the sample pool). The remaining 24,361 non-treated homes served as the control group. Letters were mailed in July of 2015 using City of Norman official envelopes to increase the likelihood of customer exposure to the treatment messages.

Similar to Ferraro and Price (2013), we use three distinct treatment instruments: a conservation message (weak social norm), a peer comparison (strong social norm), and a tip sheet listing ways to reduce water use (technical advice). These are described in detail below. Customers received a partial treatment or full treatment. All homes which were selected for treatment received the same conservation message. The partially treated groups received either a unique peer comparison or a common tip sheet in addition to the conservation message. The full treatment group received all three instruments. This resulted in four roughly equal sized treatment groups as shown in Figure 7. Figure 8 provides a visual representation of how the treatment groups overlap.

Figure 7: Randomized Experiment Design

	Partial Treatment			*Full Treatment*	*No Treatment*
Item included in message	*Conservation Message only*	*Message and Tip Sheet*	*Message and Peer Comparison*	*Message, Tip Sheet, and Peer Comparison*	
Number of Observations	552	553	535	523	24,361

Figure 8: Experiment Design



The conservation message has three distinct parts. First, it describes the supply, infrastructure, and drought conditions facing the city. It discusses the surface water limitations and the shared surface water arrangement discussed in the introduction. Second, the message explains peak load demand issues. On high use days, Norman purchases water from Oklahoma City at a premium price. Water use restrictions have also been implemented in the past. This section also discussed the need for increased water infrastructure and the cost associated with the various plans the city was considering. The third component was a pro-social conservation message urging the customer to take personal responsibility for helping with water scarcity especially during summer months. It also appealed to potential cost savings of reducing water use. See Appendix A, for a copy of the message letter.

A second partial treatment included a common tip sheet with the conservation message. The tip sheet was adapted from the one provided by the City of Norman.[26] It

[26] http://www.normanok.gov/utilities/wt/water-treatment-water-quantity

was slightly altered to fit on a single page. The tip sheet presented ways to reduce both outdoor and indoor water usage. For example, the tip sheet encourages users to water their lawn and garden in the early morning or at night when the sun does not cause as much evaporation. See Appendix A, for a sample of the tip sheet.

The third partial treatment group received a unique peer comparison in conjunction with the conservation message. The comparison consisted of five lines of text added to the conservation message letter so that all of the information could be displayed on a single page. The comparison communicated the customer's total consumption for the months of June through September of 2014 and the same total for a "water conscious neighbor". The water conscious neighbor is defined as the customer that used less than 80% of other users in the same water meter route. Anchoring the comparison to a lower level of use instead of the median helps to avoid potential boomerang impacts since fewer uses would fall below the anchor (Fischer, 2008). Other experiments use similar low use comparison group techniques (Ayres, 2012, Brent et al. 2014).

The percentage difference between the consumer's use and the water conscious neighbor's use was included in a third line of text. This "water conscious neighbor" is defined as the neighbor who used less than 80% of others in the meter route. It clarified that the comparison home was a water conscious user and the criteria were explicitly communicated. Congratulations were included for those customers who consumed less than the water conscious neighbor, but no admonition was included for other customers. This was done to avoid potentially upsetting consumers in response to negative feedback as discussed in Ayres et al. (2012). See Appendix A, for a sample of the message letter with the peer comparison.

Due to a miscommunication with the city, the total summer consumption amounts were systematically over reported.[27] However the error did not substantially influence the reported peer comparisons reported to customers because the amount of the water conscious user was also overestimated. No customers received a message that they used less water than their "water conscious neighbor" when they had actually used more. Furthermore, the reported percentage difference between the customer's use and the water conscious neighbor's use were only slightly lower than the actual amount on average (three tenths of a percent). See Appendix B for scatter plots and empirical tests regarding the nature of the misreporting as well as empirical estimations including the level of error. As detailed in Appendix B, the magnitude of the misreporting does not impact the estimates of consumption and treatment impacts. We find weak evidence that the misreported peer percentage suppressed impact of the peer comparison treatment. The city received some calls and complaints about the message but did not track the customers. Thus, we could not econometrically account for the customers who noticed a discrepancy between their actual use and the reported use. It seems likely that most customers did not check the reported numbers against their water bills from over a year ago. Our mailings were not sent along with water bills and instead were sent in a

[27] The mistake stemmed from using the transaction amount times 1,000 as opposed to using the consumption amount times 100, because the consumption numbers are stored in hundreds of gallons used. This resulted in over reporting of about a factor of four and a half at the median user. For example, a user who consumes 7,000 gallons (approximately the median during the summer), their transaction amount would be $30.95 and we reported their consumption as 30,950 gallons.

separate mailing, further decreasing the odds that customers checked these numbers against a bill.

The experimental design allows for a variety of comparisons. We can compare all treated customers to untreated customers; the homes that received the peer comparison to those that did not; customers that received the tip sheet and those that did not; and customers that received all three treatments with to those that did not. Figures 9-12 demonstrates the various comparisons we make. The shaded groups are the treated group whereas the white area is the control. Furthermore, we can compare different treatment groups with each other.

Figure 9: Comparison Groups; Treated vs. Non-Treated

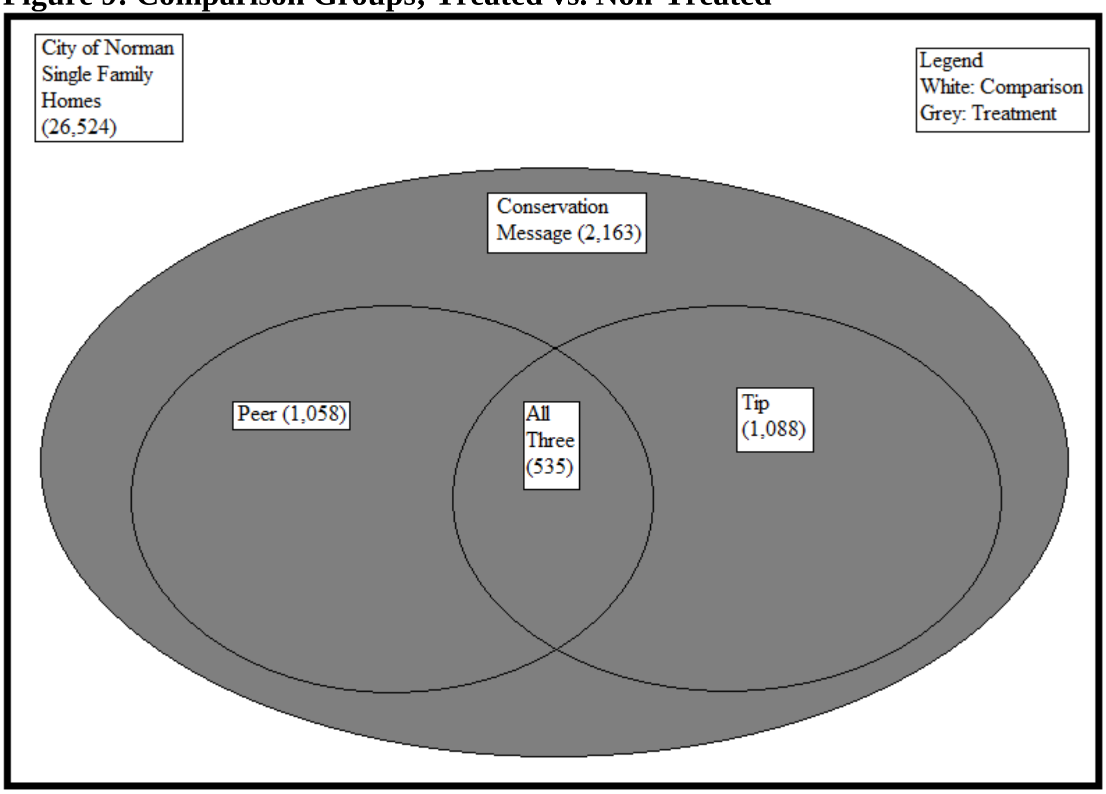


Figure 10: Comparison Groups; Peer vs. Non-Peer

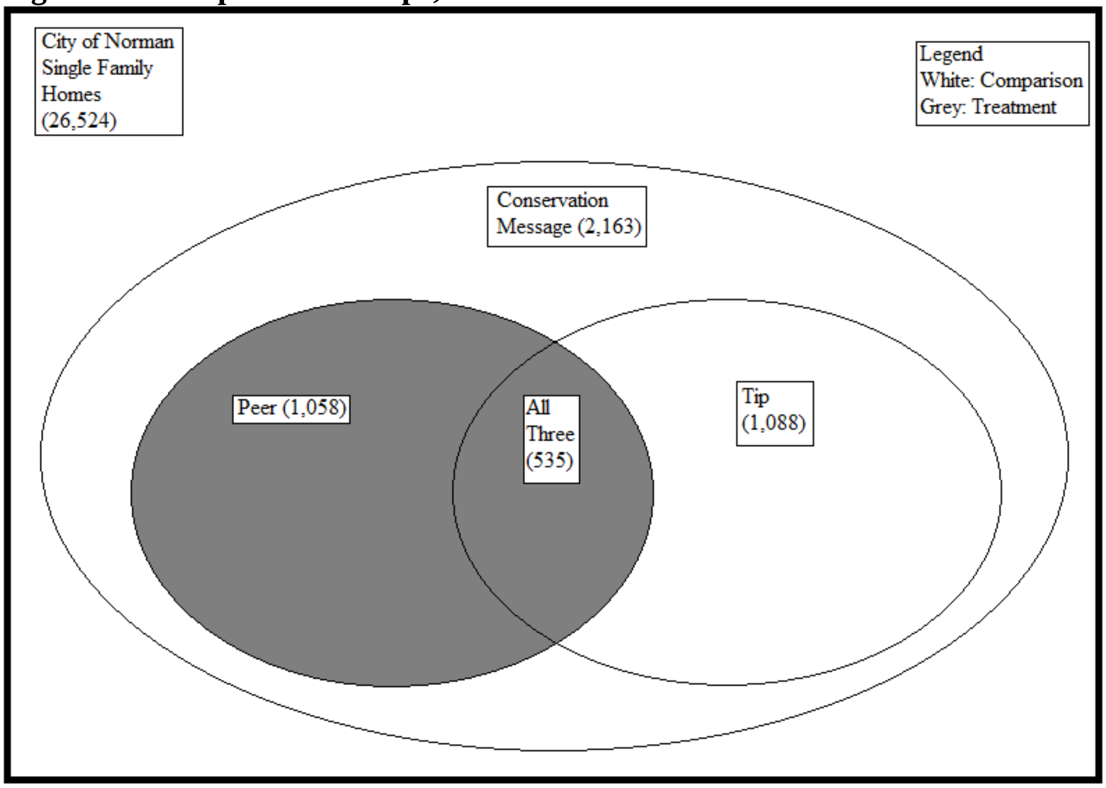


Figure 11: Comparison Groups; Tip vs. Non-Tip

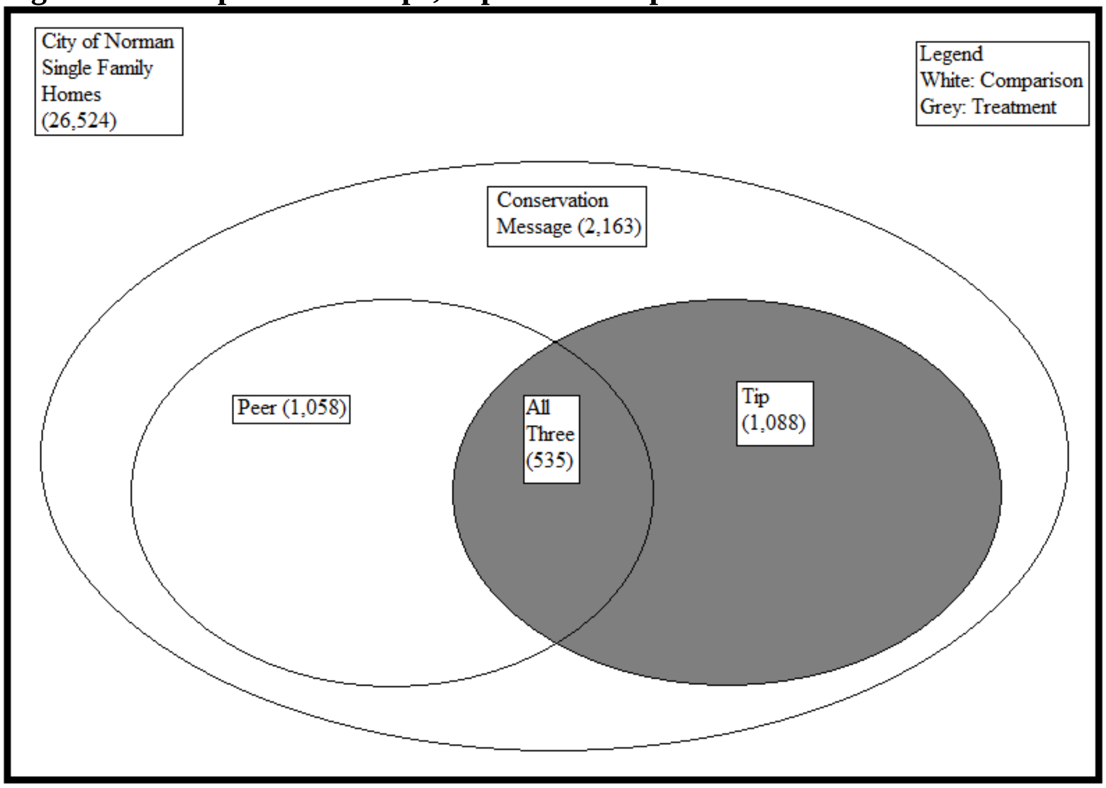
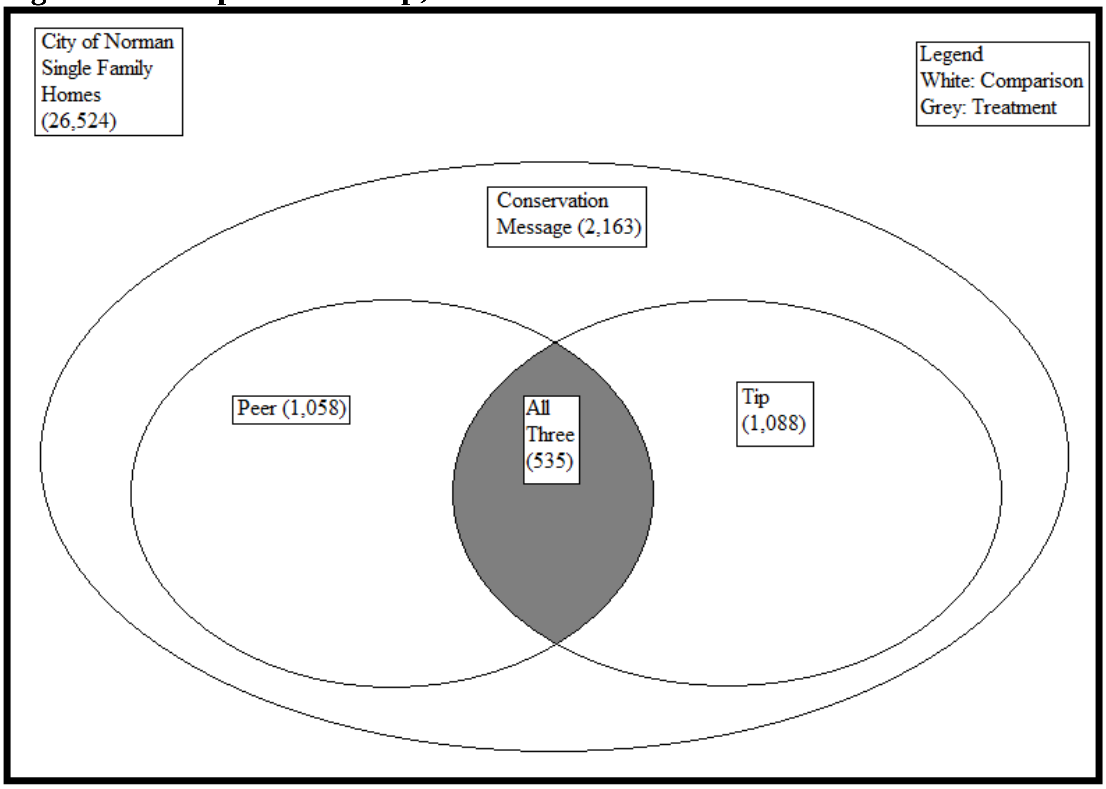


Figure 12: Comparison Group; Full Treatment vs. Non-Full Treatment



The comparisons facilitate a simple cost benefit analysis concerning the efficacy of such conservation programs for the City of Norman as well as other water utilities in the US. Using water usage records and fixed effects we can control for similarities/differences between the treated and untreated groups ex ante.

Empirical Specification

Data and Variables

The dataset merges information from three unique and detailed sources: The City of Norman Water Utility Division, Cleveland County Assessor, and the National Weather Service. Each is summarized below. Summary statistics are presented in Table 9.

Table 9: Summary Statistics for Single Family Homes

Water Data[28] [29]

	Observations	Mean	Std. Dev.	Min	Max
Charged Consumption	272,910	69.53	113.62	1	13,559

	Observations	Mean	Std. Dev.	Min	Max
Water Conscious User	2,999	38.82	13.75	23.20	87.29

Housing[30]

	Observations	Mean	Std. Dev.	Min	Max
Market Value	21,316	157,753.00	282,671.40	0	3.88E+07
Total Area	21,316	1,813.90	784.31	0	14344
Year Built	21,211	1,979.19	28.68	0	2014
Baths	21,316	2.20	0.82	0	30
Pool Area	21,316	52.80	173.98	0	3088.781

Weather[31]

	Observations	Mean	Std. Dev.	Min	Max
Rainfall	59,224	475.93	323.16	0	1,660

Norman's residential water data records include customer and location identifiers, rate class, cycle and route identifiers, charged consumption, transaction amount, and date of meter reading for the years 2002-2015. The customer identifier tracks a particular account held by a water utility customer. Thus, it changes when a new customer establishes a new account with the city. The location identifier is unique for each parcel and does not change with account changes. The rate class identifies the customer type: single family, multifamily, commercial, or other. For this paper we focus solely on single family homes. The charged consumption is gallons of water consumed

[28] Year 2014, consumption greater than zero, and customers unchanged.
[29] WC_User is the water conscious neighbor defined in the peer comparison letter. The 20% user in 2015
[30] 2014 cross section of housing data.
[31] Summer months July-Sept of 2014.

(in hundreds) at a location. The transaction amount is the amount the customer paid in dollars. We also know the exact date of the meter reading. Meters are read manually by city employees. Customers within the same meter route have their meters read on the same day. Meter reading routes are scheduled throughout the month so that not all meter routes are read on the same week of the month. Figure 13 shows the City of Norman's meter route map. Meter routes control for many relevant neighborhood factors for which we do not have data.

The second source of data is from County Assessor Office which the City of Norman's GIS staff graciously merged with the water utility records. This provides a cross section of housing features that includes market value, assessed value, total area, year built, rooms, bedrooms, baths, lot size, road area, pavement area, parking area, pool area, and building footprint for the year 2014.

Finally, the National Weather Service tracks precipitation using a series of sensors located throughout the City. A map of the sensors locations is displayed in Figure 14. Rainfall, measured in tenths of millimeters, is mapped from sensor to household by census tract. The daily precipitation data is summed to yield a monthly observation.

Figure 13: Map of Meter Routes

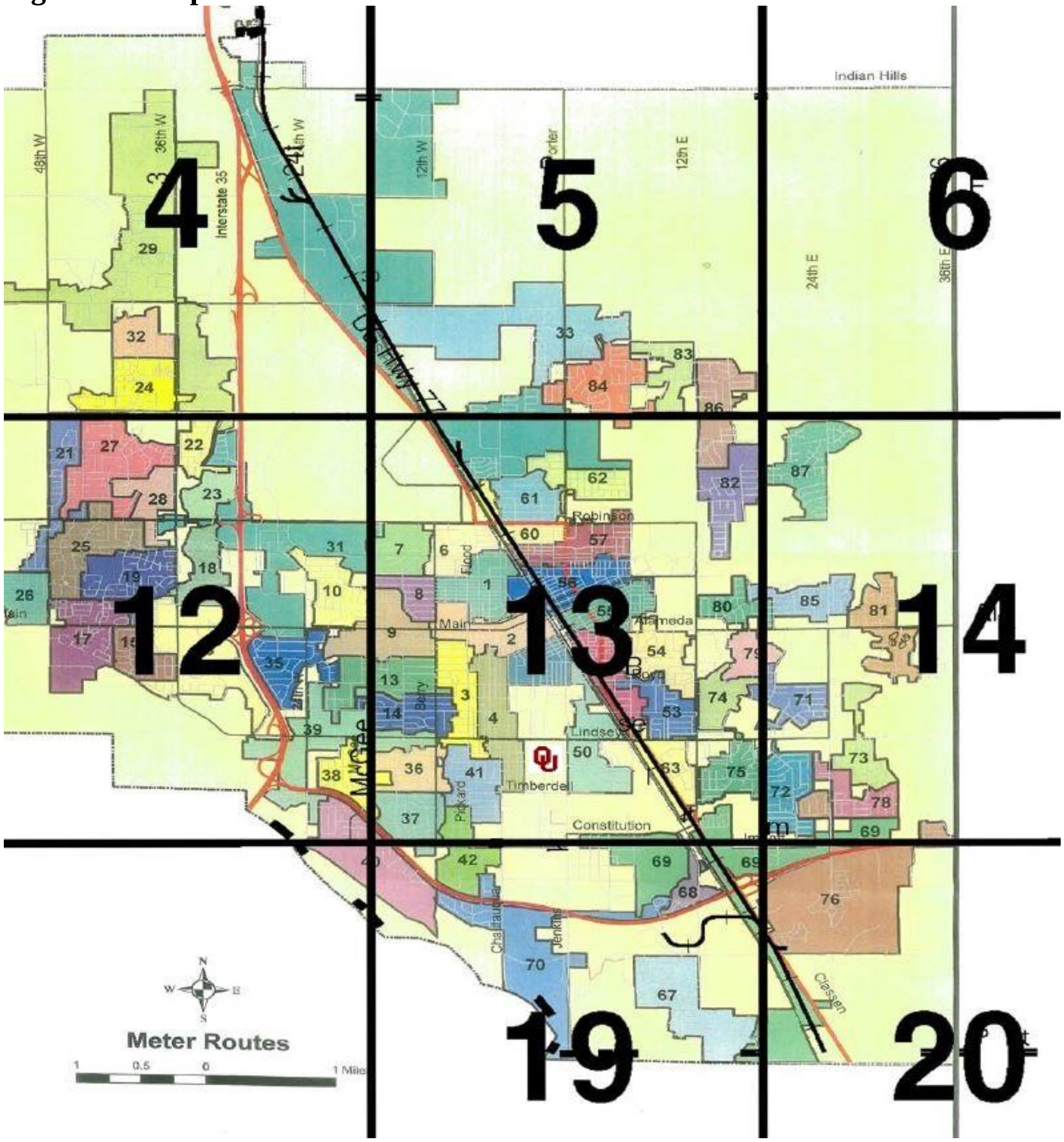
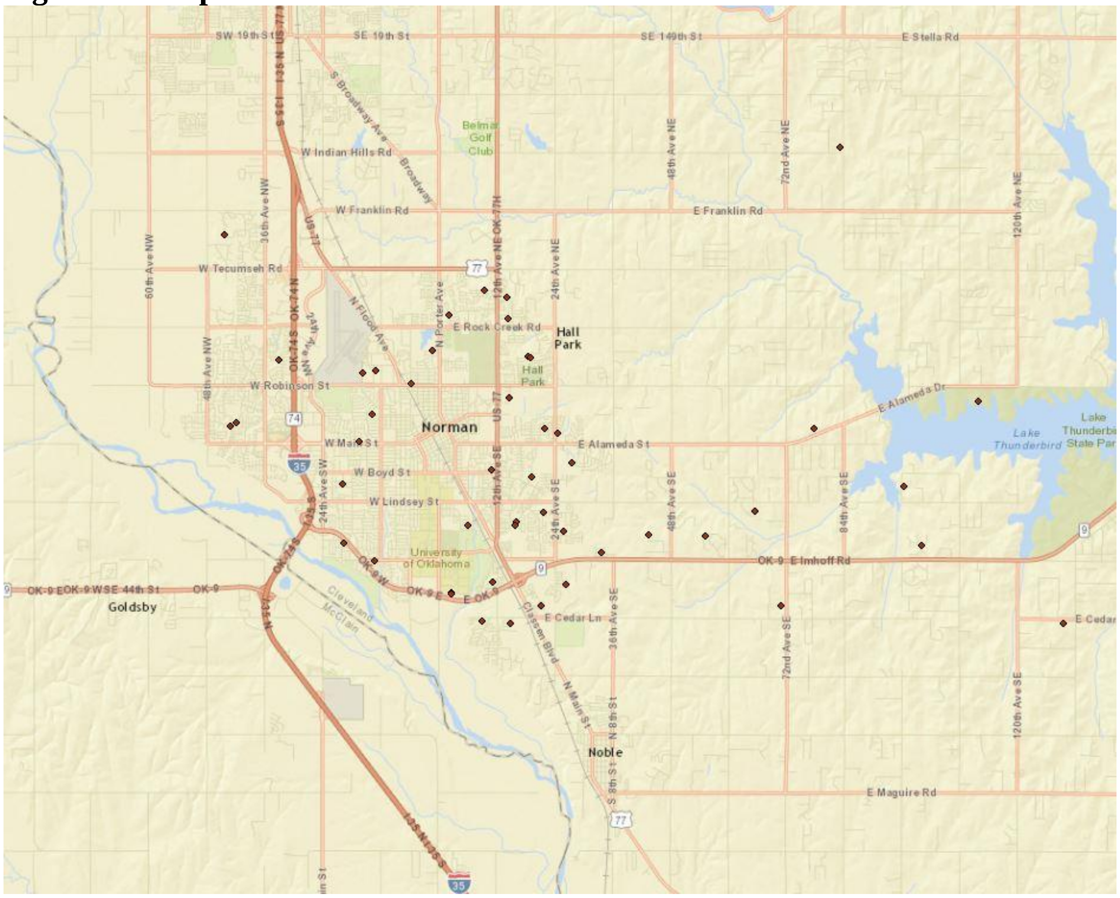


Figure 14: Map of Rain Fall Sensors



Test for Randomization

We confirm that treatments were randomly assigned to customers by evaluating differences of mean water consumption by group. Table 10 shows the means for the treated and non-treated customers for different treatment combinations using all months in 2014. We apply a t-test of means for two samples which compares the means from the two variables: the null hypothesis is that the difference between the means is zero. This encompasses all groups that receive the various implements. Notice that by testing the CM group (conservation message), we test the entire treatment group against the untreated group. We fail to reject the null of no difference in means between the treated and non-treated groups for all tests. This gives us confidence that the randomization was effective in creating treatment groups that are the same as the untreated group with respect to our outcome of interest.

Table 10: Evidence that Treatment Groups are Random

	Observations	rMean	Std. Err.[32]	Std. Dev.[33]
CM	27,261	67.73	0.66	108.69
Control	253,148	67.27	0.23	113.45
CM_PEER	13,333	67.51	1.00	115.89
Control	267,076	67.30	0.22	112.85
CM_TIP	13,631	65.92	0.66	77.06
Control	266,778	67.39	0.22	114.53

[32] The standard error of the mean
[33] The standard deviation of variable

Panel Data Specifications

We are interested in examining the efficacy of using non-pecuniary strategies to encourage water conservation. The basic empirical approach estimates water consumption as a function of policy treatments in a panel data setting which allows for household specific and month fixed effects. The general specification is as follows:

(2) $C_{it}=\alpha + \beta Treatment_{it} + \delta * X_{it} + \gamma H_i + \lambda M_t + \varepsilon_{it}$,

where C_{it}, is charged water consumption in 100s of gallons for customer i at month t, α is the constant term, the vector X of time varying control variables such as rainfall, H accounts for individual customer fixed effects, M is a set of monthly dummy variables, and ε is the error term. Our baseline specification uses monthly consumption data for the months from April to September for 2014 and 2015. Thus we have three months of observations in 2015 before and after the mailings occurred. We also include the same months in 2014 as a baseline for the customers. In addition, spring and summer months are associated with more outdoor watering needs which are more likely to be influenced than winter months where basic water needs (showers, flushing toilets, laundry) drive water consumption. Finally, these are months when peak period demands are likely to exceed supply. For robustness we consider adding more years of historical consumption (e.g., 2012-2015, and 2013-2015) as well as limiting the sample to just the summer months (months after the treatment messages were mailed).

Treatment is a vector of variables indicating months for which a customer has been exposed to a given type or combination of treatment messages (intent to treat). As discussed below, the manner in which treatment variables are specified is flexible. The β coefficients provided estimates of different treatment impacts on water consumption.

Estimation Results

Estimates with Incremental Treatment Variables

The most common approach for specifying treatment impacts is to define variables in an incremental fashion (Ferraro and Price, 2013, Brent et al, 2014). Following this approach, a variable is created for each of the three individual treatment instruments: conservation message (CM), tip sheet (TIP), and peer group comparison (PEER). If the customer receives a particular type of treatment message, then the corresponding variable is set to 1 for all months after June of 2015 (post treatment period), and is set to zero otherwise. For example, if a customer receives the conservation message, then CM is set to equal one in all months after June 2015, and is zero otherwise. If the customer also receives the peer comparison, then both the CM and PEER dummy variables will be set to one after June 2015. If a customer receives the conservation message and the tip sheet, then both CM and TIP variables will be set to 1 in the post treatment period. Finally, if a customer receives the full treatment, then all three treatment dummy variables will be set to one in the post treatment period.

The corresponding empirical specification is as follows:

$$(3)\quad C_{it}=\alpha + \beta_1 CM + \beta_2 TIP + \beta_3 PEER + \delta X_{it} + \gamma H_i + \lambda M_t + \varepsilon_{it},$$

In this specification, β_1 represents the impact of sending customers only the conservation message compared with sending no message. β_2 captures the incremental change in water consumption associated with sending the TIP message beyond the impact of sending only the conservation message. Similarly, β_3 represents the incremental effect of sending the peer comparison along with the conservation message compared with sending only the conservation message. The estimated impact on water conservation for an individual receiving the full treatment would be the sum of the β coefficients.

The estimates corresponding to Equation 3 are shown in Table 11. The first column includes water utility usage from 2014 to 2015 and serves as our benchmark estimates. The estimated coefficients for the conservation message and peer comparison are negative and statistically significant at the 1% and 5% levels, respectively. The conservation message has an economically important impact. Sending only this weak social norm message leads to an estimated 723 gallon (9.9% of the median) reduction in monthly water use. When combined with the conservation message, the peer comparison reduces predicted water consumption by an addition 365 gallons per month (5% of the median). This effect is stronger than that found in the previous literature which may be due in part a priming effect. As discussed above, the citizens of Norman faced a water rate change in the months leading up our experiment, and while this price impact is universal to all customers in Norman, it may have made citizens more aware of the nature of water issues, making those recipients of our social messages more receptive.

Table 11: Estimation Results with Incremental Treatment Variables.

	2014		Summer		2013		Rain	
	Coefficient/SE		Coefficient/SE		Coefficient/SE		Coefficient/SE	
Peer Comparison	-7.226***	1.841	-8.238***	2.161	-9.334***	1.672	-0.401	1.77
Conservation Message	-3.648**	1.876	-3.696*	2.12	-5.046***	1.705	-3.829**	1.802
Tip Sheet	2.53	2.129	3.538	2.458	2.864	1.939	1.028	2.037
Rain							-0.001***	0
Lagged Rain							-0.003***	0
Constant	80.408***	0.356	88.675***	0.376	81.965***	0.277	88.499***	0.367
Household FE	x		x		x		x	
Month FE	x		x		x		x	
Year FE							x	
Months Covered	Apr-Sept		July-Sept		Apr-Sept		Apr-Sept	
Years Covered	`14-15		`14-15		`13-15		`13-15	

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

In contrast to the conservation message and peer comparisons, the tip sheet appears to be ineffective in inducing additional water conservation. The estimated coefficient associated with TIP is positive and statistically insignificant. Receiving the tip sheet in addition to the conservation message would result in an estimated 470 gallon reduction[34] in water consumption (6.4% of median). Ferraro and Price (2013) also find that the tip sheet is not particularly effective. Their results suggest no greater than a 1% decrease in water consumption in response to receiving technical advice. Because Norman was facing the water rate change, it is possible that consumers were more exposed to technical advice than usual, as a description of ways to help them save money after the rate change, that our technical advice may have had less of an impact.

The second column of Table 11 presents estimates when only observations for summer months July through September are included. Given randomization, we don't need the pre-treatment observations from spring to identify the treatment impacts on summer consumption. In fact, focusing on the summer period may create less noise in our estimates. The estimated coefficients vary slightly from those presented in column 1. The signs and significance are unchanged. The relative differential in size of coefficients associated with treatment variables are of the same order magnitude.

Column 3 of Table 11 presents results when we include observations from 2013. This provides additional historical observations of customer's water consumption which are captured in the household fixed effects. One reason to expand the years of coverage is because 2014 was an unusually dry summer when compared with 2015. A second reason is the price change in 2015. The weather in summer of 2013 was more similar to

[34] From Table 11 column 1: -723+253=470 gallons

that of 2015.[35] The signs and levels of significance are the same on all estimated coefficients and the estimated treatment impacts are larger (more negative). We find very similar results to those the 2013-2015 estimates when taking the data back to 2012, 2011 and 2010. [36]

The fourth column of Table 6 shows results of estimating equation 2 when weather variables are included. RAIN is the sum of rainfall for the month in tenths of millimeters (micrometers). Lagged RAIN is the previous month's sum. As expected, rainfall is a powerful predictor of water consumption. For example an extra centimeter (10 millimeters) of rainfall in a month reduces consumption by about 50 gallons a month. The previous month's rainfall has a similarly sized or larger effect. Our estimates suggest that, at a constant marginal impact, rainfall in a given month and the previous month account for about 1,000 gallons of a consumer's use on average for the months of April through September. Regarding treatment impacts, the sign and significance is similar for the conservation message coefficient. The size and level of significance for the peer comparison treatment impact falls. We look further into the robustness implications using the alternative specifications below.

Typical approaches include treatment interaction variables as well as pre and post treatment variables in a difference in difference type specification (Brent et al, 2016, Ferraro and Price, 2013). We avoid this due to the sheer volume of potential interactions as well as the difficulty of interpreting interaction terms when treatments

[35] The customer change definitions remain unchanged from the baseline specification.
[36] For brevity we do not report these results. Note that the condition of no change in customer identification is not applied for years prior to 2014. Thus, if there were changes, then the prior residents would be assumed to be the same customer. This is done to preserve the size of the treated group. Given randomization, it should not systematically influence our results.

are defined using incremental approach. Furthermore, since we have customer and house level data we can utilize customer specific effects.

Exclusive Sub-treatment Categories

As an alternative to the incremental approach, treatment effects can be investigated by defining mutually exclusive treatment categories. For example, CMO is defined as a dummy variable representing months after June 2015 for customers which received only the conservation message. CM_TIP is set to one for months after June 2015 for customers who receive both the tip sheet and the conservation message, but not the peer comparison. Similarly CM_PEER is an indicator variable for customers which receive the conservation message and peer comparison, but not the tip sheet. Finally, CM_TIP_PEER is set to one in months after June 2015 for customers who receive the full treatment.

The corresponding regression specification is:

$$(4)\quad C_{it} = a + \beta_1 CMO_{it} + \beta_2 CM\_TIP_{it} + \beta_3 CM\_PEER_{it} + \beta_4 CM\_TIP\_PEER_{it} + \delta X_{it} + \gamma H_i + \lambda M_t + \varepsilon_{it},$$

Creating a variable for each possible treatment combination avoids the need for interaction variables and makes interpretation of treatment impacts straight forward. The drawback is the loss of some power in the estimation process. Reducing the number of observation in each treatment group increases the risk incurring type two errors.

The estimates corresponding to Equation 4 are given in Table 12. The first column uses consumption data for April through September of 2014 and 2015. All of the estimated treatment group coefficients are negative, and all except CM_TIP, are significant at conventional levels (5% for CM and 1% for CM_PEER and CM_TIP_PEER). The estimated impacts range from a high of -0.267 for the CM_TIP group to a low of -6.320 for the CM_PEER group. Sending a combined conservation message and peer group comparison message leads to an estimated 632 gallon reduction in monthly water consumption, which is an additional 182 gallons per month in conservation compared with sending only the conservation message. In contrast to the estimates from above, the estimates generated using the exclusive treatment categories fit closely with the theoretical predictions: the strong social norm (peer comparison) is expected to generate a larger behavioral responses than a weak social norm (conservation message).

The tip sheet and conservation letter combination has an economically and statistically insignificant impact in the baseline estimation of Equation 4. Adding the tip sheet with the CM message reduces conservation: if just the conservation message is sent, 450 gallons would be conserved, but if both the tip sheet and the conservation message are sent, only an estimated 26 gallons would be conserved. Similarly, comparing the estimated coefficients for CM_PEER -6.32) and CM_TIP_PEER (-5.582) also suggests that sending the TIP sheet in combination with other messages is counterproductive. In this case, the strong social norm appears to counter the negative reaction to the tip sheet to a greater extent.

Table 12: Estimation Results with Exclusive Treatment Variables.

	2014		Summer		2013		Rain	
	Coefficient/SE		Coefficient/SE		Coefficient/SE		Coefficient/SE	
CMO	-4.503**	2.115	-5.270**	2.116	-6.276***	1.922	-7.000***	2.255
CM_Tip	-0.267	2.11	-1.286	2.114	-0.956	1.918	-4.696**	2.241
CM_Peer	-6.320***	2.176	-9.782***	2.179	-8.031***	1.979	-8.841***	2.316
CM_Tip_Peer	-5.582***	2.152	-7.636***	2.154	-7.745***	1.956	-9.815***	2.31
Rain							0.000***	0
Lagged Rain							-0.006***	0
Constant	80.408***	0.356	82.031***	0.29	81.965***	0.277	59.900***	0.513
Household FE	x		x		x		x	
Month FE	x		x		x		x	
Year FE							x	
Months Covered	Apr-Sept		July-Sept		Apr-Sept		Apr-Sept	
Years Covered	`14-15		`14-15		`13-15		`13-15	

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

As before, we investigate alternative specifications. Column three shows that extending the data to include 2013 increases the size of the estimated treatment impacts. Estimates using just the summer months are very similar to those using April to September months. The specification adding the rain variables is notable. The size of all the treatment coefficients increase slightly and the estimated coefficient for CM_TIP, which are insignificant in other regressions, becomes more negative and significant. Given the importance of rain in driving water consumption, a clearer understanding of this result is warranted. We leave refinements and extensions to future work.

Heterogeneity

Heterogeneity of impacts across classes of users is a major topic in the literature. To address this, we split the sample into four tiers according to whether customers use more or less than the median and whether they are more than a standard deviation away. The lowest (highest) tier includes customers who use more than one standard deviation above (below) the median level. The low (high) tier includes customers who fall within one standard deviation below (above) the median. These groups are all defined using the customer's 2014 summer use relative to the distribution in 2014. The median consumption for the full sample is 6,900 gallons for the entire sample pool, 17,700 gallons for the highest tier, 7,400 gallons for the high tier, 4,000 gallons for the low tier, and 3,800 gallons for lowest. The estimates for both the incremental and the exclusive treatment group specifications are presented in Tables 13 and 14.

Table 13: Heterogeneity Estimation Results with Incremental Treatment Variables.

	Highest		Higher		Lower		Lowest	
	Coefficient/SE		Coefficient/SE		Coefficient/SE		Coefficient/SE	
Conservation Message	-13.232*	6.843	-4.948**	2.418	-3.922**	1.902	-0.572	5.151
Peer Comparison	-7.383	7.713	-5.835**	2.872	-0.211	2.155	2.609	5.931
Tip Sheet	1.926	7.720	-0.394	2.855	2.762	2.151	-1.910	5.930
Rain	0.003***	0.000	0.001***	0.000	-0.000	0.000	-0.001**	0.000
Lagged Rain	-0.015***	0.000	-0.005***	0.000	-0.002***	0.000	-0.001***	0.000
Constant	208.955***	1.384	87.536***	0.480	36.732***	0.479	40.299***	0.969
Household FE	x		x		x		x	
Month FE	x		x		x		x	
Year FE	x		x		x		x	
Months Covered	`4-9		`4-9		`4-9		`4-9	
Years Covered	2012-2015		2012-2015		2012-2015		2012-2015	

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

Table 14: Heterogeneity Estimation Results with Exclusive Treatment Variables.

	Highest		Higher		Lower		Lowest	
	Coefficient/SE		Coefficient/SE		Coefficient/SE		Coefficient/SE	
CM	-19.732**	7.933	-4.961*	2.737	-1.677	2.203	0.348	5.915
CM_Tip	-5.290	7.634	-5.328**	2.706	-3.522	2.259	-3.393	5.883
CM_Peer	-15.132**	7.295	-10.765***	3.172	-6.218***	2.124	1.112	5.927
CM_Tip_Peer	-25.702***	8.235	-11.192***	2.943	0.647	2.090	1.128	6.162
Rain	0.003***	0.000	0.001***	0.000	-0.000	0.000	-0.001**	0.000
Lagged Rain	-0.015***	0.000	-0.005***	0.000	-0.002***	0.000	-0.001***	0.000
Constant	208.961***	1.384	87.536***	0.480	36.731***	0.479	40.299***	0.969
Household FE	x		x		x		x	
Month FE	x		x		x		x	
Year FE	x		x		x		x	
Months Covered	`4-9		`4-9		`4-9		`4-9	
Years Covered	`12-15		`12-15		`12-15		`12-15	

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

Three important results emerge. First, the farther above the median the customer is, the more she responds to treatment messages. The estimated reduction of consumption associated with sending the conservation message only (CMO) ranges from 167 gallons for the low tier customers (4.2% of median for the lowest tier group) to 1,973 gallons for the highest tier users (10.7% reduction). The estimated coefficients are significant only for the high and highest tier groups. The full treatment impact ranges from a reduction of 1,129 gallons (14.5% of the median) to 2,570 gallons (13.9% of the median) for the high and highest tiers, respectively. As pointed out by Ferraro and Price (2013) this is key because it gives municipalities a way to influence the consumption of those users who are least likely to be sensitive to price.

Second, while low tier uses do respond to combined conservation and peer message, the lowest tier users do not. The differential response suggests the power of social messaging given that median use between the two groups is only 200 gallons per month (about 5 loads of laundry). The lack of response to social messages for the lowest tier customers is not unexpected. These customers may feel less need to reduce their usage as they are already efficient, or perhaps they simply have less ability to adjust their consumption. Unlike high tier customers with big lawns and swimming pools, the lowest tier customers probably use water almost exclusively for things such as showering, cooking, and personal hygiene, which are not easily adjusted or have very small impacts on their consumption. There is likely to be a very small financial impact for conservation as well.

Third, we find no evidence of a boomerang effect. Other papers, especially those studying electricity, have found that presenting customers with information about their relatively low use sometimes leads to an increase in consumption (Ayres et al., 2012). It is likely that we find no such evidence because we compare the customers in our study with their water conscious neighbor (in the 20th percentile of the neighborhood consumption distribution) instead of with the mean or median for aggregate area.

Discussion and Conclusion

We investigate whether social messages influences water consumption by implementing a carefully designed random experiment. The experimental design allows for alternative specifications of treatment variables, both the traditional sequential approach as well as exclusive treatment group approach. Not all results are robust to the empirical specification of treatment groups. However, some general conclusions emerge.

Taken as a whole, our estimates suggest that there is strong behavioral response to several of our treatment instruments. We see decreases between 300 and 900 gallons per month for the various implements and combinations. This translates to roughly an 8% decrease, which is much larger than results found in the literature (in the range of 4% per month). The setting for our experiment is different than other studies in key ways including; the rainfall differences between 2014 and 2015, and the 2015 water rate change.

Whereas the literature has generally found the peer comparison message to be more effective than a simple conservation message (weak norm), we find mixed evidence on the matter. This is likely a result of the difficulty of implementing the sequential treatment groups. The peer comparison message leads consumers to decrease their consumption by 8.7%, while the conservation message leads to a 6.2% decrease according to the incremental specification. Consistent with previous literature, we find the tip sheet to be ineffective. The estimated coefficients on the tip sheet treatments are insignificant is most specifications. This is unsurprising, as technical information has been generally found to have little to impact on consumers' behavior in regards to water consumption.

Perhaps most useful for policy makers is the evidence of heterogeneity in behavior responses to treatments. Specifically, higher than median users display greater responses to social messages. The estimates suggest that sending a conservation message to the highest tier customers leads to an estimated two thousand gallons, or 10.7%, reduction in water consumption for customers in this tier. Consumers who use within one standard deviation above the median level of consumption respond to a conservation message with about 500 gallons a month (6.4%) reduction in consumption. Even the low tier users (within one standard deviation below the median) respond to conservation messages by reducing consumption by 400 gallons a month (4.2%). The response is even greater when the full treatment (conservation message, peer comparison and tip sheet) is sent to customers.

Our results provide practical guidance for water utility managers. Notably, the common practice of sending tip sheets is probably not effective in encouraging conservation. Instead, conservation messages and peer comparisons appear to be more cost effective. An upper bound estimate of the cost to send social messages to water utility customers is about $.50 each (sending to all 35,000 customers would cost roughly $18,000), less if included with water bill.[37] A small amount of staff time would be needed to develop the conservation and peer comparison messages following the procedure used in our experiment.

The City of Norman produced 217 million gallons of water in July of 2014 for single family homes, and about 500 million gallons for all users. An 8% reduction in consumption for all Norman single family homes would save the city 17.4 million gallons a month, or roughly an entire peak summer use day of savings per month.[38] Treatment plant cost per gallon is about $3.25 per 1,000 gallons. So 17.4 million gallons saved leads to $55,600 savings in production costs.[39] Thus, a very conservative estimate on the return on mailing to ALL single family homes Norman water utility customers would be around $55,600 in production costs ($3 per $1 spent in mailings) for a single summer month.[40]

This however, does not consider water utility fee revenue implications. Notably, Norman has an inverted rate structure where rates for all gallons consumed increase with consumption tiers.[41] For instance, customers who use over 20,000 gallons per month pay $6.80 per thousand gallons[42] compared with customers using less than 5,000 gallons who pay $3.35 per thousand gallons of consumption. Thus conservation from the higher tier users could impact water utility revenues in a negative fashion.[43]

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[37] This is the price we were charged. The actual cost is certain to be less.
[38] Based on saving 8% of July single family home use for 2014
[39] http://www.normanok.gov/utilities/wt/water-treatment-plant
[40] Mailings cost about 50 cents each
[41] http://www.normanok.gov/content/new-water-rates-effective-march-2-2015
[42] For those gallons above 20,000; they still pay $3.35 for their 1,000-5,000 gallons.
[43] The City of Norman recently agreed to a contract worth over $700,000 per year with Oklahoma City to provide water. https://stateimpact.npr.org/oklahoma/2015/10/15/norman-wants-water-independence-but-still-needs-oklahoma-city-for-now/

There are important limitations for making out of sample predictions either for the City of Norman or for other cities based on our results. Notably the City of Norman implemented a water rate increase in March of 2015. This may have influenced the generalizability of our estimates in several ways. First, the rate increase required obtaining a majority vote in a local election. Thus, there was considerable discussion about water issues just prior to our treatment implementation. Second, customers probably adjusted to the new rate increase over the months following the rate increase. This omitted factor may bias our estimates. Finally, the high and highest tier users may have been primed to respond to the conservation and social messages due to observing the water rate increases on their water bills. This could be driving heterogeneity in responses. Another potential mitigating factor is the drastic weather differences between 2014 and 2015. We attempt to account for these factors by using month and year fixed effects in various specification. However, caution is warranted in making causal inferences from our results.

There are many potential extensions to this research. For example, in a separate chapter, we estimate price elasticity of water demand using the March 2015 water rate changes in Norman, Oklahoma. It would be interesting to investigate alternative measures of weather impacts in model of water consumption. We also hope to conduct a similar experiment in other cities or even repeat it in Norman so as to provide further robustness test of our main results. Such extensions will be useful for further informing water utility managers about non-pecuniary strategies for managing water demand.

Chapter Three: Estimating Water Demand under a Block Rate Structure: Unraveling Demand and Supply

There is a great interest in understanding water demand. Conservation pricing and impacts on utility revenues are important in the growing era of water scarcity. Economists are hardly strangers in this discussion. There are a great many papers estimating water demand.

Water utilities often impose block rate structures rather than a flat fee or a uniform rate. Block rate structures group users by consumption and charge different rates for consumption within each block. Block structures can be increasing or decreasing. Increasing rate structures are consistent with conservation pricing and marginal costs pricing. For instance, communities with multiple water sources tend to rely on the cheapest source first (usually well water) and add other sources as demand dictates. Large volume users and increasing demand push a city utility toward the higher cost options.[44]

Estimating demand is more complex in the presence of an inverted rate block structure, in which the rate per unit of consumption increases across blocks. Under these structures customers choose their utility rate and consumption simultaneously. To estimate demand, a researcher must know in which block a customer falls. With a rate increase, some customers may reduce consumption, thus reducing both the marginal cost of their consumption as well as their average rate for all quantities consumed. Without accounting for the block rate structure, researchers end up estimating supply curves- how much customers in each rate group consume. Furthermore, without

[44] http://water.usgs.gov/wrri/AnnualReports/2010/FY2010_OK_Annual_Report.pdf

observing rate structure changes, it is also difficult to tease out demand and supply factors. Accordingly, it is crucial to account for the block rate structure when estimating demand and demand elasticities. We estimate separate demand curves for individual block rate groups.

Our major contribution is explicitly accounting for the block rate structure by estimating water demand for individual rate block groups. To our knowledge this approach has not been used for estimating water demand. Additionally, we leverage a more powerful data set, possessing a longer time horizon, greater numbers of customers, and more robust available controls. Our data on water billing records are more comprehensive than the previous literature in that we observe water billing records on a more disaggregated level in a panel setting.

Our data allows us to investigate water demand responses surrounding two rate changes that occur in the City of Norman, Oklahoma. Both the estimation approach and the superior data allow us to address shortcomings in previous empirical research.

We use a dataset spanning from 2002 to 2015 to evaluate rate structure changes in 2006 and in 2015. We employ monthly customer level panel data of consumption and weather variables as well as detailed house and lot features for 2014. We find that consumers respond to price increases by reducing consumption. Our analysis reconciles previous estimates of upward sloping demand curves with the Law of Demand. Our results are consistent with the economic theory concerning demand and support conservation pricing to meet water demand.

The rest of the paper is organized as follows. Section two describes the literature. Section three describes the estimation technique. Section four presents the results. Section five discusses price elasticities and concludes.

Literature Review

The literature on water demand is long and detailed. Economists have been estimating water demand since the late 1960s. Intuitively estimating demand is straight forward: estimate quantity demanded at different prices. However, this is not so straightforward when different customers face different prices: the aggregate demand reflects different prices for different customers. While price discrimination is certainly not a new topic it appears to have been largely neglected in the water demand literature. It is even more difficult if price changes are not observed. A review of the literature suggests that both of these issues arise when estimating water demand.

The literature essentially breaks down into two broad categories, those whose datasets that do not include observations of price changes (Foster and Beattie, 1979; Nauges and Thomas, 2003; Bell and Griffin, 2011; Olmstead et al, 2007) and those whose datasets do (Billings and Agthe, 1980; Agthe and Billings, 1980; Nieswiadomy and Molina, 1989; Hansen and Narayanan, 1981; Hewitt and Hanemann, 1995; Pint, 1999; Carver and Boland, 1980; Dandy et al, 1997; Danielson, 1979).

Papers that do not include price changes observe multiple jurisdictions in order to get price variation. This is done by using regional aggregates (Foster and Beattie, 1979), city aggregates (Nauges and Thomas, 2003; Bell and Griffin, 2011) or households across different cities (Olmstead et al, 2007). These studies estimate demand curves for water aggregated to an entire region. This presents an obvious interpretation issue because these cities and regions face innumerable differences from their water rate structures to their economies. Furthermore, water rates are endogenous: cities with lower rates may have lower consumption but water conservation norms may also lead to the lower rates. Thus, estimating demand by relying on price variations across city or region instead of within jurisdiction, introduces potential endogeneity between rates and water consumption. Some of these papers address the issues that coincide with increasing block rate price structures by using advanced econometric techniques such as, dynamic models (Nagues and Thomas, 2003; Bell and Griffin, 2011) and discrete choice models (Hewitt and Hanneman, 1995; Olmstead et al, 2007).

Studies that include price changes use pooled cross section datasets (Billings and Agthe, 1980; Agthe and Billings, 1980; Nieswiadomy and Molina, 1989; Hansen and Narayanan, 1981; Hewitt and Hanemann, 1995; Carver and Boland, 1980) or have small panels (Pint, 1999; Dany et al, 1997; Danielson, 1979). These studies universally face small sample sizes. The largest panel dataset includes only 600 households (Pint, 1999). The pooled cross sections are also small. For example, Nieswiadomy and Molina (1989) include only 100 sampled homes per year and Hewitt and Hanneman (1995) use this same dataset. The results from these studies uncover a correlation between higher prices and higher water use. Pint (1999) appropriately points out that Ordinary Least Squares and fixed effect models fail to produce estimates of downward sloping demand curves when increasing block rates are not considered. Thus, the unexpected results stem from modeling assumptions and not a violation of the Law of Demand.

Naturally, all of these papers share the common assumption that there exists a single demand for all users, whether users are within a single municipality or not. That some studies using a single city with an increasing block rate structure find an upward sloping demand curve is understandable: variation in price comes from the increasing block rate structure and not from actual price (rate structure) changes. Such studies actually estimate supply curves: the amount of demand fulfilled for different block groups. In contrast other studies obtain variation in price by including multiple municipalities in the sample. This introduces potential for policy endogeneity: previous consumption is likely to impact price structures across municipalities. To the extent that increased consumption may exceed supply capacity, consumption trends may drive price increases due to the need to expand capacity (Olmstead et al, 2007).

We improve upon previous literature by using detailed panel data to estimate separate demand curves for individual block rate groups before and after price changes. To our knowledge no other papers in the water research uses this approach. This simultaneously avoids assuming a common demand curve along the block groups and common consumption behavior across municipalities.

Empirical Specification

Background on Norman's Water Utility Rates

Our empirical strategy involves investigating two water utility rate changes in the City of Norman, Oklahoma, which is in the southern portion of Oklahoma City's metropolitan area. With a 2010 population of approximately 110,925 people, Norman is the third largest city in the State of Oklahoma. Norman's water sources include Lake

Thunderbird, well water, and purchases from Oklahoma City. Like many cities across the country, population growth and increasing regulatory standards have stressed its water utility division. The need to expand and upgrade water treatment infrastructure has driven water rate increases.

The City of Norman is unique in that utility rate increases require voter approval in local elections.[45] This makes rate increases less frequent and of larger magnitude than if the City Council or the Utility Department had the authority to adjust rates at their own discretion. This offers an interesting and unique opportunity to explore customer responses to changes in water rates. Notably, however, Norman's policy environment is not representative of most municipalities. We investigate consumption patterns surrounding Norman's 2006 and 2015 water rate increases. The 2006 increase was the first successful change since water utility rates were first implemented in 1999. Table 15 summarizes the rate structures in place prior to the 2006 rate increase, between 2006 and the 2015 rate increase, and after the 2015 rate change. Notice the "inverted" rate structure in which the block rates charged per 1000 gallons used increase with consumption. This structure corresponds to conservation pricing as well as increased marginal costs associated with peak demand costs.

45 http://www.normanok.gov/sites/default/files/Features/City%20of%20Norman%20Water%20Rate%20Increase%20Special%20Election%20January%2013%2C%202015.pdf

Table 15: Water Rates and Rate Structure.

	1999	2006	2015
Base Fee	$0.00	$4.00	$6.00
Cost per each 1,000 gallon in each consumption range			
<=1,000	$2.01	$2.00	$3.35
1,000 < C <= 2,000	$1.73		
2,000 < C <= 5,000	$1.14		
5,000 < C <= 15,000*		$2.10	$4.10
15,000 < C <= 20,000	$2.00	$2.75	$5.20
c > 20,000	$4.00	$4.95	$6.80

We investigate the 2006 and 2015 rate changes in separate analyses. We do this to find the elasticity at each point in time rather than to capture the average elasticity over a 13 year period. Separate evaluation acknowledges the potential that other factors could have influenced elasticities. Furthermore, we are able to frame the 2006 change with more years of data. For 2006, we include data from 2002 to 2010. For the 2015 change we include 2010 to 2015 data. The data and empirical specifications are described below.

Data and Variables

We take advantage of three unique and detailed data sets: the City of Norman Water Utility administrative billing records, the Cleveland County Assessor records, and the National Weather Service data for the city of Norman. We summarize these by block rate group in Tables 16 and 17.

Table 16: Summary Statistics by Group 2002-2010

Group One

Variable	N	Mean	Std. Dev.	Min	Max
Consumption	79,775	43.19	313.90	1	87,600
Log Consumption	79,775	3.41	0.87	0	11.38
Rainfall	13,429	8.99	6.51	0	31.71
Market Value	1,209	144.35	83.88	0	1,391.79
Year Built	1,178	1999	4.11	1992	2014
Baths	1,209	2.11	0.66	0	8.00
Pervious Surface	1,209	6.43	26.78	0.21	663.35
Pool Area	1,209	1.04	7.41	0	78.64

Group Two

Variable	N	Mean	Std. Dev.	Min	Max
Consumption	156,506	88.94	63.97	1	6,391
Log Consumption	156,506	4.28	0.69	0	8.76
Rainfall	34,783	9.31	6.57	0	31.71
Market Value	3,369	172.67	85.41	0	1,477.35
Year Built	3,327	1998	4.08	1992	2014
Baths	3,369	2.27	0.69	0	8.00
Pervious Surface	3,369	7.03	30.27	4.2E-07	1,216.55
Pool Area	3,369	2.78	12.62	0	308.88

Group Three

Variable	N	Mean	Std. Dev.	Min	Max
Consumption	30,379	151.59	89.73	1	2,095
Log Consumption	30,379	4.83	0.68	0	7.65
Rainfall	5,781	9.87	7.03	0	31.71
Market Value	675	220.45	85.00	0	616.58
Year Built	669	1999	4.03	1992	2014
Baths	675	2.68	0.80	0	5.00
Pervious Surface	675	9.01	28.55	0.22	461.47
Pool Area	675	8.01	19.74	0	145.70

Group Four

Variable	N	Mean	Std. Dev.	Min	Max
Consumption	35,154	254.00	466.55	1	75,501
Log Consumption	35,154	5.25	0.80	0	11.23
Rainfall	5,404	9.99	7.29	0	31.71
Market Value	758	306.92	175.09	0	2,082.46
Year Built	755	1998	4.17	1992	2007
Baths	758	3.18	1.00	0	8.00
Pervious Surface	758	10.92	25.33	1.04	411.10
Pool Area	758	19.53	30.63	0	185.27

Table 17: Summary Statistics by Group 2010-2015

Group One

Variable	N	Mean	Std. Dev.	Min	Max
Consumption	188,680	40.66	282.16	1	90,143
Log Consumption	188,680	3.36	0.85	0	11.41
Rainfall	96,920	9.32	9.59	0	61.03
Market Value	3,147	156.65	69.83	0	1,218.19
Year Built	3,078	2002	6.08	1992	2014
Baths	3,147	2.12	0.63	0	8.00
Pervious Surface	3,147	6.77	27.78	2.41E-06	1,070.58
Pool Area	3,147	0.83	8.10	0	308.88

Group Two

Variable	N	Mean	Std. Dev.	Min	Max
Consumption	183,209	92.96	221.53	1	88,239
Log Consumption	183,209	4.28	0.74	0	11.39
Rainfall	113,885	9.35	9.65	0	64.39
Market Value	3,919	208.66	118.94	0	1,907.63
Year Built	3,875	2002	6.05	1992	2014
Baths	3,919	2.49	0.93	0	30.00
Pervious Surface	3,919	7.59	25.98	4.15E-07	1,216.55
Pool Area	3,919	4.30	15.63	0	185.27

Group Three

Variable	N	Mean	Std. Dev.	Min	Max
Consumption	24,719	166.22	123.00	1	3,558
Log Consumption	24,719	4.83	0.84	0	8.18
Rainfall	14,221	9.45	9.70	0	61.03
Market Value	539	280.42	123.53	0	944.43
Year Built	535	2002	6.44	1992	2014
Baths	539	3.05	0.96	0	7.00
Pervious Surface	539	8.08	9.59	0.49	90.25
Pool Area	539	11.10	23.77	0	169.19

Group Four

Variable	N	Mean	Std. Dev.	Min	Max
Consumption	19,738	297.75	556.25	1	16,952
Log Consumption	19,738	5.22	1.00	0	9.74
Rainfall	8,526	9.23	9.36	0	61.03
Market Value	364	390.69	234.03	78.955	2,468.12
Year Built	364	2002	6.73	1992	2014
Baths	364	3.56	0.98	2	7.00
Pervious Surface	364	11.55	14.37	1.46	83.05
Pool Area	364	21.15	30.93	0	194.27

Norman's residential water data records include customer and location identifiers, rate class, cycle and route identifiers, charged consumption, transaction amount, and date of meter reading for the years 2002-2015. We focus on single family residences which account for approximately 86% of the water utility customers (27,044 in 2005 and 31,317 in July of 2015).[46] The charged consumption is the amount of gallons, in hundreds, consumed at the location. Date of meter reading is a key variable. Meters are read manually by city employees. Meter reading routes are scheduled throughout the month so that each route is read within the same week of the month. Customers within the same meter route have their meters read on the same week. Meter routes control for many relevant neighborhood-specific factors for which data are not available. Figure 13 shows the City of Norman's meter route map.

The City of Norman's GIS staff graciously merged records from the County Assessor's Office with the water utility records. This data covers 28,509 homes of single family residential water utility customers in Norman. This cross section of housing features includes market value, assessed value, total area, year built, baths, lot size, and pool area, for the year 2014. We assume that the housing characteristics from 2014 are valid for the homes in the sample for all observed years. To ensure this assumption is reasonable, we drop homes built before 1992 from the sample. Homes built after the relevant price changes and not included in the corresponding price change analyses. For example, a home built in 2006 is not included in the estimation of the 2006 price change because the home did not exist in 2005. Since there are no observations of consumption prior to the price change, it is not possible to assign this customer to a block rate group.

[46] There were 30,771 (31,188) single family resident customers out of 36,317 (36,810) customers in July of 2014 (2015).

Market value is measured in thousands of dollars. Year built indicates when the house was completed. Baths measures the number of bathrooms, a full bath (1) has a toilet and a shower or bath tub and a half bath (0.5) indicates a toilet without a tub or shower. We calculate pervious surface area by subtracting all impervious surfaces—including the house's footprint, the pavement, and road area—from the lot size. Measured in thousands of square feet, pervious surface represents the outside areas of a parcel that would potentially require watering. The data includes the surface area of a pool in tens of square feet as measured through satellite imagery by Norman's GIS staff.

Finally, the National Weather Service tracks precipitation using a series of sensors located throughout the City. A map of the rainfall sensor locations is displayed in Figure 14. Rainfall, measured in tenths of millimeters and normalized to centimeters, is mapped from sensor to household by census tract. Because rainfall values are assigned to those homes in the same census tract, some homes do not have rainfall observations. Rainfall values are available for approximately 19,000 homes.[47] The daily precipitation records are used to calculate the monthly sum as well as the monthly standard deviation.

Estimation

Customers are grouped based on their consumption and the City of Norman's water rate block group ranges effective from 2006 onward. The first group includes customers consuming up to and including 5,000 gallons. The second group includes

[47] 18,866 in July of 2014. As an extension we could map rainfall data from the nearest census tract.

customers consuming between 5,001 and 15,000 gallons. The third group includes customers consuming between 15,001 gallons and 20,000 gallons. The fourth includes customers consuming more than 20,000 gallons. Table 15 presents the rate brackets and associated rates in effect from 1999 onward. Both the 2006 and 2015 rate changes are included.

There are several options for assigning customers to groups, especially since use varies by month and season. We calculate the customer's average use in the summer months of the year preceding the price change. This smooths consumption to allow for different timing of intense water use such as filling a swimming pool. For the price change implemented in May of 2006, customers are assigned based on their average monthly consumption from May through September of 2005. For the price change effective in March of 2015, customers are assigned based on their average consumption from March through September of 2014. Notably, the group assignment is static even if a consumer reduces consumption enough to bump to a lower group following the price change.

By estimating each group's consumption, we can identify responses to the price change controlling for initial consumption patterns. We do not explicitly model prices since each group faces a unique block group price schedule pre and post rate changes. The corresponding empirical specification is as follows:

$$(5)\ C_{it} = \alpha + \beta_1 \mathit{Price}_t + \beta_2 \mathit{Weather}_{it} + \beta_3 \mathit{House}_i + \gamma \mathit{Month}_t + \lambda \mathit{Route}_i + \varepsilon_{it},$$

where C_{it} is the natural log of water consumption for household i in month t. $Price_t$ is post price change variable, that is a dummy variable marking the month in which the price change occurred and is equal to one for all months after the price change. $Weather_{it}$ is a vector of weather variables, including sum of monthly rainfall, lagged monthly rainfall, standard deviation of rainfall, lagged standard deviation of rainfall. *House* is a vector of household characteristics. These include market value, total area of the house, lot area, pool area, number of bathrooms and year built. $Month_t$ is a set of month dummy variables used to account for seasonal variation. $Route_i$ is a set of dummies to capture meter route fixed effect.

Estimation of Equation 5 generates a demand curve for each block rate group. The implicit assumption is that customer's average summer consumption in the year prior to the price change represents their inherent consumption pattern. We then follow these customers after the price change.

We make several important data restrictions. First, observations are limited to the months corresponding to the price change (May for the 2006 price change and March for the 2015 price change) through September. This limits the sample to summer months, which are the most important months for supplying water, while containing the months immediately following the price change. It also includes observations of consumption behavior in the months immediately following the price change. Second, we omit observations with consumption amounts less than 100 gallons. This eliminates negative consumption amounts, which stem from misreading meters or billing errors as well as houses that are vacant for large parts of the month. Third, we drop houses that were built before 1992. This ensures that the oldest houses in our sample are no more than 10 years old in 2002 and no more than 23 years old by the end of our sample. This helps to mitigate concerns about unobserved changes in household features (remodeling, renovation) during our sampling period since the housing features variables are only available for 2014. Thus, the analysis is limited to newer houses which are less likely to be significantly modified. The final samples include 6,011 customers for the 2006 change and 7,969 customers for the 2015 change.

Estimation Results

The main results are presented in Tables 18 and 19 corresponding to the 2006 and 2015 price changes, respectively. Each set of columns corresponds to a different customer group based on the average summer consumption in the summer prior to the price change as explained above. The coefficients on the price change variables represent the responses to the water rate increase in the post rate change period holding other factors constant.

For the 2006 price change, the estimated coefficients for price change variables are negative for the second, third and fourth rate groups and positive for the first group. The impacts are statistically significant for the first, second, and third groups. The second group is predicted to reduce consumption by 10.3% after the price increase. The third group reduced its consumption by an estimated 13% in response to the price increase. The fourth Group, those users who consume more than 20,000 gallons in a month, decreased their consumption by an estimated 6.7% in response to the rate increase. The failure to find an impact statistically different from zero for the last group, suggests that the high volume users were not very responsive to the 2006 price change.

Table 18: Estimates for 2006 Rate Change

	Group One		Group Two		Group Three		Group Four	
	Coefficient/SE		Coefficient/SE		Coefficient/SE		Coefficient/SE	
Price Change	0.152***	0.030	-0.103***	0.014	-0.130***	0.037	-0.067	0.043
Rainfall	-0.000	0.001	-0.000	0.001	-0.004***	0.002	-0.005***	0.002
Lagged Rainfall	-0.011***	0.001	-0.017***	0.001	-0.024***	0.002	-0.027***	0.002
Std of Rainfall	0.000*	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Lagged Std of Rainfall	0.000***	0.000	0.000***	0.000	0.001***	0.000	0.001***	0.000
Market Value	0.001***	0.000	0.002***	0.000	0.000	0.000	0.000**	0.000
Year Built	0.019***	0.002	-0.006***	0.001	-0.003	0.003	-0.023***	0.004
Baths	0.074***	0.021	-0.002	0.009	0.064***	0.020	0.088***	0.016
Pool Area	0.007***	0.001	0.002***	0.000	0.001***	0.000	0.002***	0.000
Pervious Surface Area	0.001***	0.000	-0.000***	0.000	0.001**	0.000	-0.003***	0.001
Constant	-33.553***	4.090	15.543***	2.469	12.043*	6.480	51.216***	7.839
Month FE	x		x		x		x	
Route FE	x		x		x		x	
Months	May-Sept		May-Sept		May-Sept		May-Sept	
Years	2002-2010		2002-2010		2002-2010		2002-2010	

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

Table 19: Estimates for 2015 Rate Change

	Group One		Group Two		Group Three		Group Four	
	Coefficient/SE		Coefficient/SE		Coefficient/SE		Coefficient/SE	
Price Change	-0.065***	0.007	-0.094***	0.005	-0.113***	0.014	-0.166***	0.021
Rainfall	-0.003***	0.000	-0.003***	0.000	-0.003***	0.001	-0.003*	0.001
Lagged Rainfall	-0.007***	0.000	-0.011***	0.000	-0.018***	0.001	-0.016***	0.001
Std of Rainfall	0.000***	0.000	0.000	0.000	-0.000**	0.000	-0.000**	0.000
Lagged Std of Rainfall	0.000***	0.000	0.000**	0.000	0.000***	0.000	-0.000	0.000
Market Value	0.001***	0.000	0.000***	0.000	0.000***	0.000	0.001***	0.000
Year Built	-0.004***	0.001	-0.006***	0.000	-0.004***	0.001	-0.013***	0.002
Baths	0.053***	0.006	0.060***	0.003	0.022**	0.009	0.042***	0.012
Pool Area	0.001***	0.000	0.002***	0.000	0.001***	0.000	0.001***	0.000
Pervious Surface Area	-0.000	0.000	0.000**	0.000	0.004***	0.001	0.001**	0.001
Constant	10.742***	1.232	15.677***	1.025	10.824***	2.965	30.077***	3.791
Month FE	x		x		x		x	
Route FE	x		x		x		x	
Months	March-Sept		March-Sept		March-Sept		March-Sept	
Years	2010-2015		2010-2015		2010-2015		2010-2015	

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

The first group, the smallest volume users, had the largest predicted response to the price change among the groups. The results suggest that customers in this group increased their consumption by 15.2% in response to the rate increase. This is counter to demand theory for normal goods.[48] It is, however, consistent with the boomerang effect found in some research on conservation (Delmas and Lessem, 2014). As discussed above, rate increases in the City of Norman require a local election. Such elections involve a tremendous amount of public education about the nature of the change as well as impacts on customers across the distribution. Accordingly, it is possible that the low consumption group became aware of their relatively small use relative to the average or median customers. This could have encouraged more consumption rather than less. As discussed below, the estimated response was in the opposite direction for this group after the 2015 price change.

As shown in Table 19, every group was predicted to decrease consumption in response to the 2015 rate increases. All the estimated price change coefficients are significant at the 1% level. The first block rate group responded to the 2006 rate increase by increasing consumption, but responded to the 2015 change by reducing consumption. The estimated negative predicted responses correspond to negatively sloped demand curves. The estimated responses were increasing from group one, which had an estimated 6.5 % reduction in water consumption, to group four, which had an estimated 16.6 % reduction.

[48] A price increase could lead to more consumption in the case of a Giffen good. Water, however, is unlikely to fall into this category by its nature and by the small share of income that it absorbs.

Notably, the literature has little to say about price responsiveness of high tier users compared with lower tier users. The literature universally estimates a single demand curve for entire city or region which prevents such a comparison. Our results suggest that highest tier users were more responsive to the 2015 rate changes compared with lower tier users. For the 2006 rate changes, however, the highest tier reduced consumption less than lower tiers and the estimated impact was not found to be statistically significant. We explore this further by calculating elasticities below.

Other Explanatory Variables

The control variables reveal interesting trends by group. Rainfall and lagged rainfall take on the expected sign (negative) and all lagged rainfall coefficients are significant whereas the concurrent rainfall coefficients are only significant for the larger groups. The coefficients imply that another centimeter of rainfall in the previous month leads to a 1.1% decrease in consumption for the smallest group and a 2.7% decrease for the largest group. In general for both the 2006 and the 2015 specifications the higher the consumption group the larger the response to lagged rainfall. This is also true for concurrent rainfall in 2006 as the two lower block rate groups are unresponsive to current rainfall but the two larger groups respond with a roughly 0.5% decrease. Interestingly, the response to current rainfall in 2015 is a uniform 0.3% decrease. Estimated coefficients for Standard deviation of rainfall and lagged standard deviation are mostly statistically significant but economically insignificant. The variability of rainfall has a limited impact on consumption.

The estimated coefficients for housing characteristics also reveal that the groups behave differently. The market value of the house increases consumption in the all groups in both specifications. For each 1,000 dollar increase in a home's value we see a 1/10 of percent increase in consumption. The implication being a $50,000 increase in a home's value would correspond to a 5% increase in consumption. The estimated coefficients on a home's age were also as expected with exception of the low tier users in 2006: the newer the house, the less the predicted consumption, holding other factors constant. For the higher tier groups, age has the biggest predicted impact on consumption. The number of bathrooms increases predicted consumption by about 5% per bathroom. The number of baths has a significant impact except for group two in the 2006 estimates.

Lot features are also salient. The estimated pool area coefficients are positive and significant in all cases. Except for the smallest group in the 2006 results, the estimated coefficients imply a 1 or 2 tenths of percent increase in consumption for every 10 square feet of surface area of pool. The estimated coefficients on pervious surface are positive and significant in all cases except group two and group four in the 2006 specifications. In general, the amount of pervious surface area in a lot appears to increase water consumption by a few tenths of a percent per thousands of square foot.

Price Elasticity of Water Demand Estimates

Water utility managers are greatly interested in revenue implications of water rate changes which depend on consumption responses across rate block groups. If the highest demand customers pay a premium above the production costs, then big reactions to rate increases could reduce utility revenues at the same time it encourages consumption. The elasticity of water demand across income groups is ambiguous in theory. Since higher tier groups face higher prices, it is possible that customers in this group are more responsive to price changes compared with users in lower tiers. On the other hand, since higher tier customers are likely to be wealthier, water costs may be only a small share of income leading to little responsiveness to water rates. This is the conventional view (Mansur and Olmstead, 2007).

To evaluate the price responses from a revenue perspective, we estimate basic price elasticities which include the price changes for each block group. Table 20 presents basic elasticity calculations for each group for the two rate changes. We calculate the elasticity using the midpoint formula by using the estimated change in consumption (estimated B_1 coefficients) and the amount of the price change.

Our findings suggest that higher demand users are relatively more responsive to rate increases than lower demand users. In 2006 we see a price elasticity of 0.46 for the lowest users, the only positive elasticity among the groups in either price change. The second group has a price elasticity of -0.17. The third group has a price elasticity of -0.41, which is the largest negative elasticity of the 2006 groups. The fourth group has a price elasticity of -0.32.

Table 20: Price Elasticity of Water Demand Estimation

2006 Rate Change

Change in Q Estimated B_1	Change in Price*	Percentage Change in Price +	Elasticity
0.152	$0.57	0.33	0.46
-0.103	$0.96	0.59	-0.17
-0.13	$0.75	0.32	-0.41
-0.067	$0.95	0.21	-0.32

2015 Rate Change

Change in Q Estimated B_1	Change in Price	Percentage Change in Price +	Elasticity
-0.065	$1.35	0.50	-0.13
-0.094	$2.00	0.65	-0.15
-0.113	$2.45	0.62	-0.18
-0.166	$1.85	0.31	-0.53

*The 1999 prices were not uniform below 5,000 gallons. The first 1,000 gallons were $2.01, the next 1,000 gallons were $1.75, and the 3,000-5,000 gallons were $1.14 per 1,000 gallons. We use a weighted average price for the pre change price. ($2.01+$1.73+3*$1.14)/5=$1.43

+ Calculated as (new price - old price) / ((new price + old price)/2)

In 2015 we find negative elasticities for all groups, with increasing price sensitivity as consumption increases. The smallest tier users respond the least to the price change with a -0.13 elasticity which switched direction as discussed above. The second group had a price elastic a little higher (-0.15) and similar to that from the 2006 rate change (-0.17). The third group had a much smaller elasticity in the 2015 estimates than it did in the 2006 estimates, dropping from -0.41 to -0.18. The largest group had two of the biggest price elasticities, including the largest of all groups across both specifications (-0.53 in 2015).

Whereas we do find results suggesting that higher demand users respond more strongly to rate changes, all but one of the estimated price elasticities were negative and less than one (inelastic). The revenue implication is that rate block price increases swamped consumption decreases, thus potentially enhancing utility revenues.

As a robustness check we relax the year built restriction and find similar results. We still estimate a positive coefficient associated with the price change variable for the first group in 2006. The coefficient is still significant at the1% level although its magnitude is somewhat smaller compared with estimates using the year built restriction. The coefficients on the price change for the fourth group in the 2006 regression is still negative but is now significant. (Table 21). The coefficients on the controls are largely the same. All four of the price change coefficients in the 2015 price change regressions are negative and significant as before. (Table 22).

A second robustness check adds a dummy variable that accounts for times when the city of Norman implemented mandatory watering restrictions. We set the dummy variable equal to one for months when the mandatory watering restrictions are in place. The regressions are presented in Table 23, which presents the baseline 2015 specification with the dummy variable, and Table 24, which presents the 2015 specification with the year built restriction removed and the dummy variable added. We find that the main variables of interest are unchanged. The mandatory watering coefficient for the lowest group in the 2006 estimates remains positive and significant. The rest of the mandatory watering restrictions are negative and significant at the one percent level.

Table 21: Water Consumption Estimates for 2006 Rate Change Relaxing Year Built Restriction

	Group One		Group Two		Group Three		Group Four	
	Coefficient/SE		Coefficient/SE		Coefficient/SE		Coefficient/SE	
Price Change	0.095***	0.029	-0.128***	0.014	-0.134***	0.036	-0.145***	0.041
Rainfall	0.000	0.000	0.000***	0.000	-0.000***	0.000	-0.000**	0.000
Lagged Rainfall	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Std of Rainfall	-0.000	0.000	-0.000***	0.000	-0.000	0.000	-0.000	0.000
Lagged Std of Rainfall	0.000	0.000	0.000***	0.000	0.000***	0.000	0.001***	0.000
Market Value	0.001***	0.000	0.001***	0.000	0.000***	0.000	0.001***	0.000
Year Built	0.004***	0.000	0.000	0.000	-0.001**	0.001	-0.005***	0.001
Baths	0.042***	0.011	0.016***	0.006	0.067***	0.011	0.029***	0.009
Pool Area	0.005***	0.001	0.003***	0.000	0.002***	0.000	0.002***	0.000
Pervious Surface Area	0.000	0.000	-0.000***	0.000	0.000	0.000	-0.002***	0.000
Constant	-4.654***	0.898	3.785	3,065.187	7.708***	1.314	13.879***	1.470
Month FE	x		x		x		x	
Route FE	x		x		x		x	
Months	May-Sept		May-Sept		May-Sept		May-Sept	
Years	2002-2010		2002-2010		2002-2010		2002-2010	

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

Table 22: Water Consumption Estimates for 2015 Rate Change Relaxing Year Built Restriction

	Group One		Group Two		Group Three		Group Four	
	Coefficient/SE		Coefficient/SE		Coefficient/SE		Coefficient/SE	
Price Change	-0.080***	0.004	-0.103***	0.004	-0.134***	0.011	-0.163***	0.014
Rainfall	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Lagged Rainfall	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Std of Rainfall	0.000***	0.000	0.000***	0.000	0.000	0.000	-0.000	0.000
Lagged Std of Rainfall	0.000***	0.000	0.000**	0.000	0.000***	0.000	0.000***	0.000
Market Value	0.001***	0.000	0.000*	0.000	0.000***	0.000	0.001***	0.000
Year Built	0.000	0.000	-0.000	0.000	0.001**	0.001	-0.007***	0.001
Baths	0.025***	0.003	0.063***	0.002	0.013**	0.007	-0.009	0.008
Pool Area	0.002***	0.000	0.002***	0.000	0.001***	0.000	0.002***	0.000
Pervious Surface Area	-0.000*	0.000	0.000***	0.000	0.000	0.001	0.003***	0.000
Constant	3.264	5,543.745	3.981***	0.188	2.488**	1.183	17.878	15,378.104
Month FE	x		x		x		x	
Route FE	x		x		x		x	
Months	March-Sept		March-Sept		March-Sept		March-Sept	
Years	2010-2015		2010-2015		2010-2015		2010-2015	

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

Table 23: Water Consumption Estimates for 2015 Rate Change Accounting for Mandatory Watering

	Group One		Group Two		Group Three		Group Four	
	Coefficient/SE		Coefficient/SE		Coefficient/SE		Coefficient/SE	
Price Change	-0.080***	0.007	-0.075***	0.006	-0.053***	0.016	-0.099***	0.023
Rainfall	-0.000***	0.000	-0.000***	0.000	-0.000	0.000	-0.000	0.000
Lagged Rainfall	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Std of Rainfall	0.000***	0.000	0.000	0.000	-0.000***	0.000	-0.000***	0.000
Lagged Std of Rainfall	0.000***	0.000	0.000*	0.000	0.000**	0.000	-0.000	0.000
Market Value	0.001***	0.000	0.000***	0.000	0.000***	0.000	0.001***	0.000
Year Built	-0.004***	0.001	-0.006***	0.000	-0.004***	0.001	-0.013***	0.002
Baths	0.053***	0.006	0.060***	0.003	0.022**	0.009	0.042***	0.012
Pool Area	0.001***	0.000	0.002***	0.000	0.001***	0.000	0.001***	0.000
Pervious Surface Area	-0.000	0.000	0.000**	0.000	0.004***	0.001	0.001**	0.001
Mandatory Watering	0.024***	0.006	-0.033***	0.005	-0.105***	0.013	-0.121***	0.018
Constant	10.771***	1.232	15.633***	1.025	10.699***	2.958	29.736***	3.782
Month FE	x		x		x		x	
Route FE	x		x		x		x	
Months	March-Sept		March-Sept		March-Sept		March-Sept	
Years	2010-2015		2010-2015		2010-2015		2010-2015	

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

Table 24: Water Consumption Estimates for 2015 Rate Change: Mandatory Water and Relaxing Year Built Restriction

	Group One		Group Two		Group Three		Group Four	
	Coefficient/SE		Coefficient/SE		Coefficient/SE		Coefficient/SE	
Price Change	-0.095***	0.005	-0.097***	0.004	-0.094***	0.012	-0.114***	0.015
Rainfall	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Lagged Rainfall	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Std of Rainfall	0.000***	0.000	0.000***	0.000	-0.000	0.000	-0.000	0.000
Lagged Std of Rainfall	0.000***	0.000	0.000*	0.000	0.000***	0.000	0.000**	0.000
Market Value	0.001***	0.000	0.000*	0.000	0.000***	0.000	0.001***	0.000
Year Built	0.000	0.000	-0.000	0.000	0.001**	0.001	-0.007***	0.001
Baths	0.025***	0.003	0.063***	0.002	0.013**	0.007	-0.009	0.008
Pool Area	0.002***	0.000	0.002***	0.000	0.001***	0.000	0.002***	0.000
Pervious Surface Area	-0.000*	0.000	0.000***	0.000	0.000	0.001	0.003***	0.000
Mandatory Watering	0.023***	0.004	-0.009***	0.003	-0.069***	0.009	-0.084***	0.011
Constant	3.251	5,542.284	3.982***	0.188	2.582**	1.182	17.851	15,364.564
Month FE	x		x		x		x	
Route FE	x		x		x		x	
Months	March-Sept		March-Sept		March-Sept		March-Sept	
Years	2010-2015		2010-2015		2010-2015		2010-2015	

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

Conclusion

In a world of increasing water scarcity, there is a pressing need to better understand water demand behavior and the role of pricing strategies for water utility management. Due to data limitations and inappropriate empirical strategies, the literature provides little guidance, and in some cases misleading conclusions, about water demand behavior. Using comprehensive data with a large number of water utility customers and fourteen years of water consumption data encompassing two rate increases, we address the major the shortcomings in the literature.

A major issue is how to estimate demand behavior when prices are determined using a block rate structure. Simply regressing consumption and charges (as some do) results in what appears to be an upward sloping demand curve (but what is actually a supply curve). Including multiple municipalities with different rate structures introduces other issues (and still has the block rate problem). Instead of estimate a single demand curve for a municipality, we estimate responses to rate increases for different groups of users based on where they are located in the block rate structure. We apply our approach for the 2006 and 2015 rate changes in the City of Norman, Oklahoma. We uncover negatively sloped demand curves and substantial heterogeneity in responsiveness to rate changes.

To our knowledge, we are the first to explore the heterogeneity of water demand response to rate changes by estimating demand curves for individual block groups. Dissecting the demand curve in this manner is useful for understanding revenue and supply implications for water utility managers. In our analysis of the City of Norman, we find conservation responses, but not enough to reduce expected revenues (demand is inelastic). Our results, however, may not generalize for other cities given Norman's unique election requirements for water utility rate changes. Furthermore, we estimate demand for only single family residents in Norman.

There are many potential extensions to our research. For instance, it would be interesting to expand our sample to include older homes. Do customers in older homes respond differently than those in newer ones? Instead of limiting our sample to homes in census tracts with weather sensors, we could map a home to its nearest sensor. This would give us more complete coverage of the city and increase our sample size and allow us to investigate robustness of our results to the precision of weather data. How much precision is needed for water demand studies?

The timing of response to water rate changes is another potential extension. Do customers respond to rate changes immediately or does it take several months to modify behavior? Is there a persistent price change effect? A related investigation would narrowly focus on customers near rate block discontinuities. How different is price responsiveness for these marginal customers? Finally, we could investigate aspects of long run and short run demand. This could be done by reducing the years included in the sample to find a short run impact.

No matter the particular research question, researchers need to seek out more comprehensive data on customer usage. Fortunately, customer billing data combined with GIS capabilities make this increasingly feasible. We encourage other scholars to replicate our analysis using data from other cities. This will add to our global understanding of water demand.

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Appendix A: Experiment Documents

Sample Flyer

Month Day, 2015

Dear Norman Resident,

As you are aware, the City of Norman as well as the rest of the State of Oklahoma has suffered drought conditions over the past few years. The City's main source of drinking water is Lake Thunderbird which is shared with Del City and Midwest City and is managed by the Central Oklahoma Master Conservancy District (COMCD). Norman has exceeded its allotment of water from Lake Thunderbird, 15 times since 1988 due to population growth and insufficient rainfall.

Even with adequate rainfall, the City faces limits on its infrastructure capacity, and high demand on summer days causes the City to have to purchase water from Oklahoma City. The City has adopted mandatory conservation policies such as even-odd watering days throughout the year, and a drought contingency plan to encourage conservation when needed.

The City of Norman, in conjunction with the COMCD, is working on several plans to address Norman's current and future water scarcity issues and all of them are expensive. Building new wells, expanding water treatment plant capacity, and purchasing water from Oklahoma City on an emergency basis place significant fiscal burdens on the City budget. To address infrastructure needs, voters in the City of Norman approved increased water rates this year.

Addressing water scarcity is everyone's responsibility. Summer is the most critical time for conservation.

Reducing your consumption will save you money and help the City to manage scarce water resources. Included in this envelope is a list of ways you can reduce your water use. Use these tips to reduce your household's use and preserve the city's priceless water resources.

Sample Tip Sheet

How you can help conserve
Norman's water

Outdoor

- Water the lawn and garden in the early morning or at night when the sun won't cause as much evaporation. Avoid sprinklers with fine mists, they increase evaporation.
- Keep grass two to three inches long to enhance root development with minimal watering.
- Use drought-tolerant plants. Ask your local nursery about plants and trees appropriate for Oklahoma.
- Wash your car with a bucket and sponge rather than with a running hose. This cuts usage by as much as 90 gallons.
- Pay careful attention to sprinklers to prevent watering driveways, streets and sidewalks.
- Water your lawn with only one inch of water every seven to ten days. (Less often if there has been recent rain.) Overwatered lawns and plants grow shallower roots and are more likely to die during droughts.
- Use mulch in gardens to minimize weed growth, slow erosion, and diminish evaporation.
- Check for leaks in pipes, hoses, faucets, couplings, and lawn sprinkler systems. Repair any problems immediately! One broken sprinkler can use an additional 100 gallons in a typical 10 minute watering cycle.
- Use a low flow nozzle on your hose. Using a standard nozzle on your hose to wash your car or water your plants can require hundreds of gallons more than a low flow nozzle.
- Avoid using a hose to clean your driveway or sidewalk. Use a broom to save hundreds of gallons of water.

Indoor

- Install low flow showerheads. They are easy to install and save both water and energy.
- Install low flow toilets or install a toilet tank displacement insert or dam to reduce the volume of water used per flush. Placing a plastic jug filled with water in the tank is an effective displacement device.
- Check for leaks inside toilets. Leaks can waste up to 200 gallons of water a day. Toilet leaks can be detected by adding a few drops of food coloring to water in the toilet tank. If the colored water appears in the bowl, the toilet is leaking.
- Never use the toilet as a wastebasket.
- Operate the dishwasher and washing machines only when completely full.
- Don't let the faucet run continuously when brushing your teeth or shaving.

Sample Peer Comparison

Month Day, 2015

Dear Norman Resident,

As you are aware, the City of Norman as well as the rest of the State of Oklahoma has suffered drought conditions over the past few years. The City's main source of drinking water is Lake Thunderbird which is shared by Del City, Midwest City and is managed by the Central Oklahoma Master Conservancy District (COMCD). Norman has exceeded its allotment of water from Lake Thunderbird, 15 times since 1988 due to population growth and insufficient rainfall.

Even with adequate rainfall, the City's ability to provide clean drinking water is limited by infrastructure capacity. On high demand summer days when water capacity is insufficient, the City imposes mandatory conservation policies such as even-odd watering days, and days when no outside watering is allowed.

The City of Norman, in conjunction with the COMCD, is working on several plans to address Norman's current and future water scarcity issues and all of them are expensive. Building new wells, expanding water treatment plant capacity, and purchasing water from Oklahoma city on an emergency basis place significant fiscal burdens on the City budget. To address funding needs, the City of Norman increased water rates this year.

Addressing water scarcity is everyone's responsibility. Summer is the most critical time for conservation.

[INSERT FOR FULL TREATMENT GROUP]
For the months June through September of last year,

Your total consumption was:	**X gallons**
Your water-conscious neighbor's total consumption was:	**X gallons**

<u>You used X% more than your most water-conscious neighbors.</u>*

*water-conscious neighbors use less than 80% of neighbors in same water meter route.

[END INSERT]

Reducing your consumption could save you money and help the City to avoid water scarcity. Included in this envelope is a list of ways you can reduce your water use. Use these tips to reduce your household's use and preserve the city's priceless water resources.

Appendix B: Details and Tests Regarding Misreporting

Misreporting impacted only the peer treatment groups. Two components of the peer comparison letter were influenced: the amount of water used by the customer in the previous year, and the difference between the customer's use and the water conscious neighbor which is expressed in percentage terms. The concern is that the errors in the reported messages are systematically related to the estimated treatment impacts. This appendix presents evidence to mitigate these concerns.

The usage reported to the customers was incorrectly calculated based on the billing amount rather than the usage amount in the utility billing records. Because of the graduated rate structure, the billing amounts are related to the usage, but not in a strictly linear fashion. The error would greatly depend on the usage and the discontinuities in the rate structure (the breaks). Given the randomization of the treated groups, we don't expect the inflation of reported usage to be important. Results in Table 25 confirm this. Table 25 provides estimates of water consumption for a variety of specifications. The estimated coefficients on the percent reported usage error are very small and statistically insignificant in all the specifications.

Next we consider the impact of the misreporting on the peer messages. As discussed in the text, both the calculation of the individual customer usage and that of the water conscious neighbor (the comparison anchor) were affected. However, the relative usage ranks were not impacted. Recall that the peer messages reported relative differences as a percent: "you used X% above/below the water conscious neighbor." The reported peer comparisons could have been larger or smaller than the actual differences. Given that peer comparisons were rounded to the nearest whole number, many of the calculation errors did not result in reporting errors on the peer messages. Figures 16 and 17 show scatter plots of the misreported peer comparisons (difference between the percent reported and the actual percent) plotted against customer's consumption for the observations which receive the peer message. For most of the sub-sample the difference is small and the average size of the misreported peer comparison is only three tenths of a percentage. Notably, the highest misreport of percentage use was for a customer who consumed over 300,000 gallons in July of 2014. The next highest misreport was less than 10% different from the correct percent. There does appear to be a systematic increase in misreporting at larger levels of consumption. The estimates in Table 26 confirm that the peer comparisons were systematically over reported for customers who used more water. The estimates indicate that on average each 1% of misreported peer comparison is associated with from 310 to 390 extra gallons consumed per month. This raises concerns that that the estimated peer treatment impacts are biased.

To investigate whether the misreporting impacted estimates of treatment impacts, we add variables which measure the misreporting to the benchmark model corresponding to Equation 5 which uses incremental treatment variables. The results shown in Table 27 suggest that the misreporting likely had little impact on the peer treatment. The estimated coefficient for misreported consumption variable is small and statistically insignificant. The coefficient on misreported peer comparison variable is also insignificant, but not of negligible size. Notably, the estimated peer comparison treatment impact is robust across the specifications. The impact of the tip sheet message remains insignificant. The estimates impacts of the conservation message only treatment, however, become smaller and fail to achieve significance. This is unexpected.

Table 28 presents a similar set of estimates using the exclusive treatment variables. We find that the estimated coefficients associated with the misreported variables are again insignificant. Once again the estimated coefficient on the conservation message only variable falls in size and become insignificant when the misreported peer comparison variable is included. The effect of the tip sheet remains insignificant. Notably, the estimated coefficients for the peer comparison treatment variables (CM_PEER and CM_PEER_TIP) are robust and increase in size.

Taken as a whole these estimates ease concerns that the reporting errors influence our estimates of the peer comparison treatments.

Table 25: Test for impact of Misreporting

	2013 Summer		2012 Summer		2013		2012		2013 Rain		2012 Rain	
	Coefficient/SE		Coefficient/SE		Coefficient/SE		Coefficient/SE		Coefficient/SE		Coefficient/SE	
PEER	-3.417	2.37	-7.938***	2.423	-2.257	2.065	-9.596***	2.163	-1.199	2.36	-9.055***	2.604
Misreported Usage %)	-0.083	0.328	0.044	0.312	-0.198	0.26	-0.121	0.267	-0.29	0.469	-0.278	0.524
Rain									-0.001***	0	-0.001***	0
Lagged Rain									-0.003***	0	-0.006***	0
Constant	77.348***	0.368	122.769***	0.367	45.042***	0.319	36.374***	0.313	81.865***	0.395	106.426***	0.392
Household FE	x		x		x		x		x		x	
Month FE	x		x		x		x		x		x	
Year FE	x		x		x		x		x		x	
Months Covered	Apr-Sept		July-sept		Apr-sept		Apr-Sept		Apr-Sept		Apr-Sept	
Years Covered	2013-2015		2012-2015		2013-2015		2012-2015		2013-2015		2012-2015	

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

Table 26: Test for Impact of Misreporting of Peer Comparison Percentages

	Fourteen		Summer		Thirteen		Twelve		Rain	
	Coefficients/ SE		Coefficients/ SE		Coefficients/ SE		Coefficients/ SE		Coefficients/ SE	
Peer	-2.855**	1.215	-1.047	1.881	-4.779***	1.198	-4.403***	1.205	2.923	2.750
Misreported Peer Comparison	3.598**	1.725	0.084	3.089	3.404*	1.762	3.003*	1.748	3.868	5.616
Rain									-0.002***	0.000
Lagged Rain									-0.000	0.000
Constant	87.028***	0.256	85.525***	0.260	87.017***	0.214	82.931***	0.235	84.614***	0.567
Household FE	x		x		x		x		x	
Month FE	x		x		x		x		x	
Year FE			x				x		x	
Months Covered	Apr-Sept		July-sept		Apr-Sept		Apr-Sept		Apr-Sept	
Years Covered	2014-2015		2012-2015		2013-2015		2012-2015		2013-2015	

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

Table 27: Test for Impact of Misreporting Using Incremental Treatment Variables

	Benchmark		Adding Misreported Consumption		Adding Misreported Peer Comparison	
	Coefficient/SE		Coefficient/SE		Coefficient/SE	
Peer Comparison	-4.418***	1.257	-4.313***	1.364	-4.491***	1.320
Conservation Message	-2.393*	1.235	-2.389*	1.236	-1.520	1.299
Tip Sheet	0.765	1.427	0.758	1.428	-0.120	1.499
Misreported Consumption			-0.044	0.223		
Misreported Peer Comparison					-1.129	4.630
Constant	87.106***	0.239	87.106***	0.239	79.116***	0.251
Household FE	x		x		x	
Month FE	x		x		x	
Year FE						
Months Covered	Apr-Sept		Apr-Sept		Apr-Sept	
Years Covered	2014-2015		2014-2015		2014-2015	

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

Table 28: Test for Impact of Misreporting Using Exclusive Treatment Variables

	Benchmark		Adding Misreported Consumption		Adding Misreported Peer Comparison	
	Coefficient/SE		Coefficient/SE		Coefficient/SE	
CMO	-3.105**	1.420	-3.105**	1.420	-1.847	1.494
CM_TIP	-0.923	1.413	-0.923	1.413	-1.317	1.484
CM_PEER	-3.667**	1.458	-3.543**	1.558	-4.146***	1.531
CM_TIP_PEER	-4.389***	1.443	-4.281***	1.519	-4.947***	1.515
Misreported Consumption			-0.050	0.223		
Misreported Peer Comparison					-1.156	4.630
Constant	87.106***	0.239	87.106***	0.239	79.116***	0.251
Household FE	x		x		x	
Month FE	x		x		x	
Year FE						
Months Covered	Apr-Sept		Apr-Sept		Apr-Sept	
Years Covered	2014-2015		2014-2015		2014-2015	

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

Figure 15: Scatter Plot of Misreported Peer Comparison (Reported percent minus actual percent)

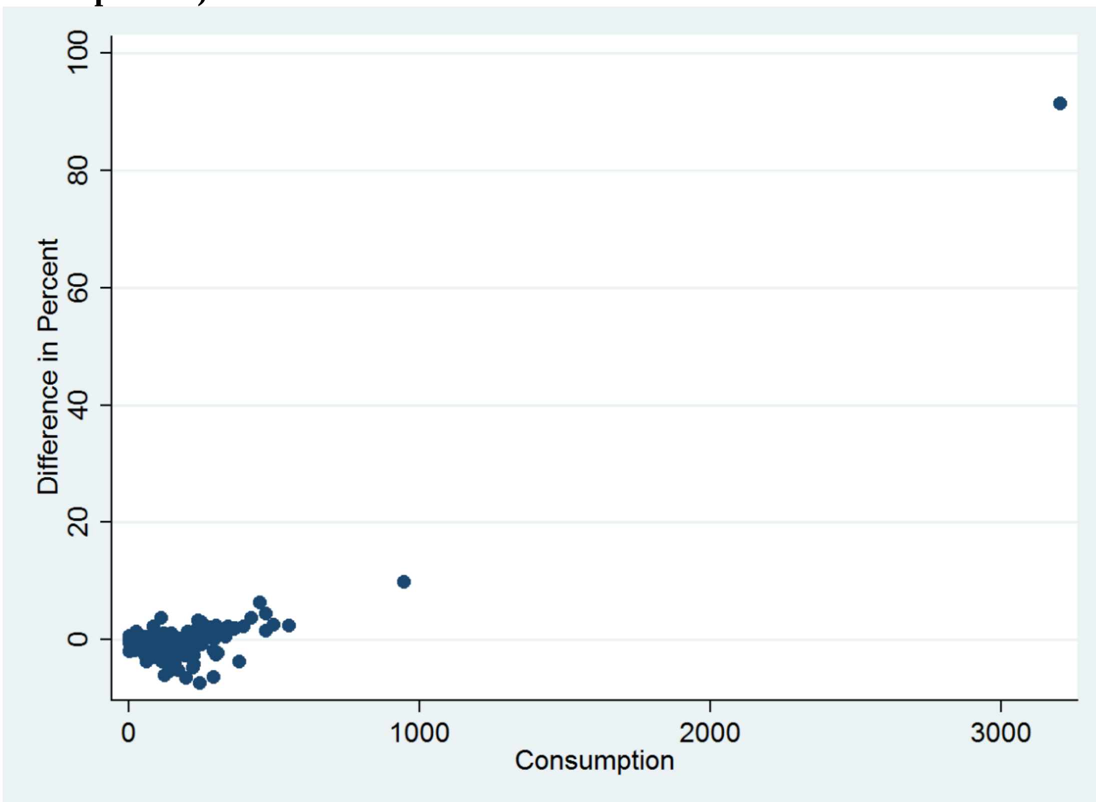

Figure 16: Scatter Plot of Misreported Peer Comparison (Reported percent minus actual percent)