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The Power of Information: Information, Leak Notices, and Water Conservation in Edina, MN

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Abstract

This paper provides evidence on the effects of information provision on households' water use. I use quarterly household consumption data from a utility in Minnesota to test the effect of a new residential water billing system on households' water consumption. The updated billing format was possible as the utility transitioned to an automated meter reading (AMR) system. I also study impacts of another source of improved information provision from AMR adoption, faster high-water consumption notices. I find mixed evidence of the impact of personalized information on households' water use. Households respond to high-consumption notices by significantly reducing consumption, even relative to baseline-levels. Reductions from these one-time notices wane over time as consumers return to baseline consumption levels after three quarters. Overall, my findings suggest limited consumer-side benefits of AMR adoption.

Keywords: Informational Nudges; Water Use; High Consumption Notices; Smart Water Meter Adoption.

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1. Introduction

The US uses 322 billion gallons of residential water per day from over 50,000 community water systems across the US (USGS, 2018). While water supply and distribution are hailed as one of the greatest engineering achievements of the 20th century, many water utilities rely on aging infrastructure. The US suffers about 240,000 water main breaks annually, losing an estimated 1 trillion gallons of clean drinking water per day, enough to supply water use in more than 11 million homes (EPA, 2009). On average, US utilities incur approximately 15 percent annual Non-Revenue Water (NRW) losses (Liemberger and Wyatt, 2019), meaning that 15% of clean treated water is lost due to leakage management issues. These problems have exacerbated in recent years, with water main break rates increasing 27% from 2012 to 2018 (Baird and Folkman, 2018). The Congressional Budget Office (CBO) concluded that current funding from all levels of government and current revenues generated from ratepayers will not be sufficient to meet the nation's future demand for water infrastructure. They estimate that an additional $10-20 billion dollars are required (CBO, 2003).

Innovation has provided new solutions to the challenges faced by water utilities, particularly with the development of data-driven technologies that allow for data collection automation and improvements in pipeline asset management. The 'Smart Water' movement, a new technological movement, offers improved management to confront challenges such as water scarcity, aging infrastructure, and uncertainty due to climate change. It is expected that water utilities in the US will spend $20 billion on software, data, and analytics solutions over the next decade with more than $15 billion of that spent on smart meters (Bluefield Research, 2017). These new smart meter water solutions include Automatic Meter Readers (AMR), which allow for precise, safe, and efficient data collection capabilities that create operational efficiencies. Other more sophisticated solutions such as Advanced Metering Infrastructure (AMI) provide better decision making through data analytics and real time insights. While smart water solutions such as AMR/AMI meters provide benefits such as advanced leak detection and water usage measurement and management, convincing water utilities to adopt these technologies remains a challenge (Freyberg, 2017). Unlike the electricity sector, where four in five electric utilities in the US have adopted new metering technologies, only one in five water utilities have adopted a smart meter infrastructure (Saiyid, 2017). While there is ample empirical research on the effects of smart metering technologies on household electricity use (Gans et.al., 2013; Gilbert and Zivin 2014; Jessoe and Rapson, 2014; Sexton 2015), there is more limited research about its effects in the water sector (Wichman, 2017; Jessoe, et.al, 2019).

This paper studies consumer-side impacts of smart meter adoption on water use in the city of Edina as the city transitioned from a manual meter reading system (MMR) to an automatic metering infrastructure (AMR). Specifically, I analyze the effects of personalized behavioral messaging and quicker-in home leak detection on water use to understand benefits of smart metering infrastructure. For my analysis, I combine household-level water consumption and water leakage data for 13,339 residents with detailed household-level characteristics and weather data.

I first study the impacts of information provision enabled by the switch to an AMR billing system. Between 2012 and 2013, most residents saw a change in the format of their water bills, including more comprehensive information about their historical consumption patterns. Different empirical designs provide contrasting evidence on the effect of this new information, where either the switch to AMR billing increased consumption by 2% to 6% or did not affect consumption. Consistent with prior work, I find evidence heterogeneity in households' response to the new information, with low-baseline water consumers potentially increasing consumption 2% to 4% more than high-baseline water consumers. Second, I explore the benefits of quicker leak detection from AMR systems by studying the effects of high consumption notices on consumer behavior. After a leak or high-consumption notice, consumers decrease consumption by 19% to 26%. The decrease is sustained for more than two quarters, after which consumers return to baseline water use levels.

My work provides important evidence of potential consumer-side benefits of smart meter adoption. A key challenge for smart water metering adoption is the high fixed costs of installation. There is a large disparity between smart meter adoption between energy and water utilities. Much of this disparity can be explained by variations in population served, which constrains the amount of capital a utility can raise. Water utilities are best classified as natural monopolies (Ferro et al., 2011).[1] Smaller utilities, of which there are many in the US, have both higher average costs and lower capital thresholds, which may deter investment in AMR and AMI infrastructure.

[1] Ferro et al., 2011 show variations in efficiency of water provision for populations in the range of 100,000 to 1 million people served, where there are decreases in average costs. They found remarkable economies of scale for the smaller utilities, and moderate economies of scale for average sized utilities.

Benefits of AMR/AMI infrastructure include labor cost savings, quicker leak detection, and increased ability to message consumers. Utility cost savings from smart meter adoption are relatively easy to determine. Traditional manual meter reading takes 50 days on average, limiting utility's ability to bill customers once every two to three months (Atkinson, 2016). Additionally, misreads using manual meter reading systems (MMR) are common, as the process was a manual visual process. AMR meters, the least expensive smart metering infrastructure, reduces these labor costs and improves accuracy of reads. AMR meters uses a drive-by system, or "truck rolls," that allows utilities to multi-task, collecting meter reading as they are out for maintenance work or other services. More sophisticated, yet more expensive, metering systems such as AMI meters can provide additional detailed real time hourly-consumption data not just monthly-consumption data. Additionally, AMI meters allow for the identification of system leaks, not just individual customer location leaks. [2] Less is known about consumer-side AMI/AMR impacts. Understanding consumer benefits, should they exist, may therefore be important in determining whether AMR/AMI infrastructure is a worthwhile investment for water utilities.

This paper first discusses the current literature of the effects of social norms on consumption and the importance of billing frequency in Section 2. I then provide background and discuss the setting of this study, presenting the data and describing their limitations in Section 3. In Section 4, the paper will present the identification strategy for the average treatment effect of both changes in water bills and the average treatment effects of high consumption/leak notices. Section 5 presents results and Section 6 concludes.

2. Literature Review

AMR meters allows utilities to better automate collection of data, which can later be used in a variety of ways to engage residential water consumers, particularly in utility water conservation efforts. Water agencies have implemented a range of conservation measures for managing residential water demand including mandatory water restrictions (Kenney et al.,2004; Grafton et al., 2008), market-based policies such as water pricing (Arbues et al., 2003; Dalhuisen et al. 2003), subsidies for water saving devices (Campbell et al., 2004), and the promotion of water conservation attitudes through information policies (Wichman, 2015; Olmstead and Stavins,

[2] For example, AMI system installation cost $14 million for 64,000 metering systems for the city of Madison, Wisconsin in 2012. Smaller utilities such as the city of Rowlett, Texas oversaw a $2.7 million project as they upgraded 18,000 meters from AMR to AMI in 2017.

2009; Ferraro and Price, 2013 ; Jessoe et.al., 2017). Although economic theory suggests that water price-based approaches are economically efficient (Griffin, 2001), prices in the water sector are politically difficult to change (Wichman, 2015). For most utilities it is infeasible to increase prices to marginal cost, spurring increased attention of non-pecuniary measures such as informational nudges.

Smart water meters also allow utilities to increase customer of their water use and water prices. Water demand management is necessary because consumers engage in water market with limited information. Most households do not understand that they are part of a transaction every time they open their faucet. Consumers tend to only realize the implications of their water use when they receive their bills, which in many cases occurs infrequently.[3] A key requirement for markets to behave efficiently is that agents behave with perfect information. In water and electricity markets, consumers imperfectly perceive prices and quantities (Ito, 2014). As such, providing consumers with more information can affect their behavior through improved price and quantity perception. More generally, increased information provision often reduces consumption as consumers generally underestimate quantity and prices (Gans et al., 2013; Gilbert and Zivin, 2014; Sexton, 2014). Here, I describe key research studying the impacts of information provision and nudges on water use and other similar settings.

2.1 Information Provision, Nudges, and Water Use

Information provision is a cost-effective way to abridge consumer's knowledge gap, without relying on coercion or significant changes in economic incentives. However, there are many kinds of information and, depending on the type of information, the literature has seen contrasting effects on consumer behavior. Variability in results occur as the effects of an increase in information depend on how the consumer perceives prices and quantity prior to receiving more information. If consumers under perceived prices or quantity, then an increase in information may decrease quantity consumed and vice versa. It is also possible to encounter opposing forces from prices and quantity such as an under perception[4] of quantity and an over perception[5] of price. In

[3] For example, Edina provides water bills every quarter.
[4] An under perception of quantity is when a user believes that they are consuming less water than their actual consumption quantity.
[5] An over perception of price is when a user believes that the cost for the use of water is greater than its actual cost. For example, they believe that the cost of taking an additional one minute for each shower costs is greater than the actual cost.

these cases, the effect of increases in information frequency will depend on which effect is greater, price or quantity (Chetty et al., 2009; Wichman, 2015). The following sections explores how each type of information provision helps correct customer's misperceptions and its potential effects on consumption reduction.

Own-consumption feedback is one way to provide information. Results differ in the literature as to the effects of this type of information provision. Geller et al (1983) explore the effect of weekly mail-based consumption information about past consumer patterns. The authors find no impact of their intervention on consumption patterns. In contrast, Kenney, et al (2008) provided consumers with in-home displays (IHD) that included real-time information about water consumption and found a 16% increase in consumption.[6] Finally, Sonderlund et al. (2016) shows that installing shower alarms to alert high consumption levels lead to a 26% decrease in shower related consumption.

Another type of information provision, social norms messaging provides consumers information about how their consumption compares to that of their neighbors. Social norms seek to change consumption patterns by correcting the customer's misperceptions or by presenting a standard against which consumers can compare their behavior. Yet, the utilization of social norms can have differential effects to different types of consumers as can act as a magnet for behavior for individuals both above and below average consumption levels (Allcott, 2011). Because of this magnet effect, households already consuming at a low rate may have a boomerang effect after receiving social comparisons messages, which may increase their consumption. Fortunately, the inclusion of positive reinforcement to initially low-rate consumers has shown to mitigate the boomerang effect (Schultz, 2007; Ferraro and Price, 2013; Bernedo, 2013). Recent empirical studies on social norms messaging have shown the extent of the effectiveness of these "nudges" as a cost-effective water and energy conservation policy (Allcott and Mullainathan, 2010; Ferraro and Price, 2013; Brent et al., 2015; Jessoe, et.al, 2017).

Empirical evidence in a large-scale water conservation program for 100,000 households in Atlanta, Georgia indicates that norm-based messages have led to a 2 percent decline in average water use, where additional social comparison messages led to a further 4.8 percent decline in

[6] The study however does suggest that the increase can be attributed to the variable rates pricing structure, where consumers moved to a cheaper low-rate hour as a financial incentive.

average water use.[7] The study shows that the social comparison messages had a greater influence on behavior among high consuming households, who tend to be the least price sensitive (Ferraro and Price, 2013). This means that the appeal to social norms is most effective amongst high-use households, suggesting that there might be heterogeneity in treatment effects depending on the user type. For most studies in the literature, social norms messaging has shown a decrease in average household water use and a comparatively greater influence on high consuming households (Ferraro and Price, 2013; Bernedo, et.al, 2013; Bolsen and Ferraro, 2014; Brent, et.al, 2015). However, other studies show limited effect of social norms messaging on water consumption, especially for low baseline consumers (Ferraro and Miranda, 2013; Jessoe, et.al, 2017; Kažukauskas, et.al, 2017). In contrast to my setting, most utilities in these studies provided social norms messaging every month, and often in separate mailers. As I describe below, frequency of information is important.

Although information can reduce consumption immediately, evidence suggests that the effects can wane over time (Gilbert and Zivin, 2014). This is consistent with the “Focus Theory of Normative Conduct” in psychology, which argues that social norms affect behavior only when at top of mind (Kallgren, et al., 2000). For example, empirical evidence on the effect of information on electricity bills shows that consumers decrease consumption after the receipt of a utility bill, but they revert to their baseline level at the end of the month (Gilbert and Zivin, 2014). Yet it is possible that the normative appeals encourage the adoption of water-efficient technologies, which would lead to long-term decreases in consumption. However, given the large up-front costs associated with new technologies such as low flow shower heads or high efficiency toilets, it is likely that it will affect fewer households (Ferraro and Price, 2013).

AMI meters and to a limited extent AMR meters provide utilities the opportunity to communicate their data to their customers and much more quickly through notifications that directly reach households with consumptive use information and notifications of customer-side leaks. Some notification systems help households identify the type of leak based on volume and other factors. One example of real time consumer communication is Roseville, California, which experienced a 4.6% reduction in water use. Its reduction was largely attributed to its communication interphase, which provided households quick communication through prompts and reminders, high-use alerts, and leak alerts. Educational programs and real-time consumer

[7] Norm-based messages inform users about the need to reduce water consumption. Appealing to the protection of resources.

communication have gotten households more interested in their water use habits, a step towards promoting conservation behavior (West Governor's Drought Forum, 2015). Closer to my setting, a 2010 Duluth study on the electricity sector showed that continuous engagement with a feedback interface was critical because households genuinely interested in reducing their consumption need reminders and prompts to correct their consumption and engage with the communication interface (Bensch et al. 2014).

Frequency of engagement and the frequency at which households receive reminders about their consumption is another way policymakers can increase conservation effort. Information policy literature highlights the importance of the frequency of information for consumer's attention. Increases in frequency of information has also shown evidence of increased conservation efforts and habit formation (Jessoe and Rapson, 2014). Given that these transactions are not instantaneous in the eyes of the consumers, increasing the frequency of utility bills or reminders through a communication interface offers consumers an opportunity to update their consumption in response to external feedback. However, some empirical studies show that customers increase consumption as billing information increases in response to more frequent information. (Wichman, 2015). Explanations to this consumption increase range from low prices set below the long run marginal cost (Mansur and Olmstead, 2012), or information presented was not-user friendly making initially interested households on data feedback lose their willingness to engage with the data due to its complexity (Bensch et al., 2014).

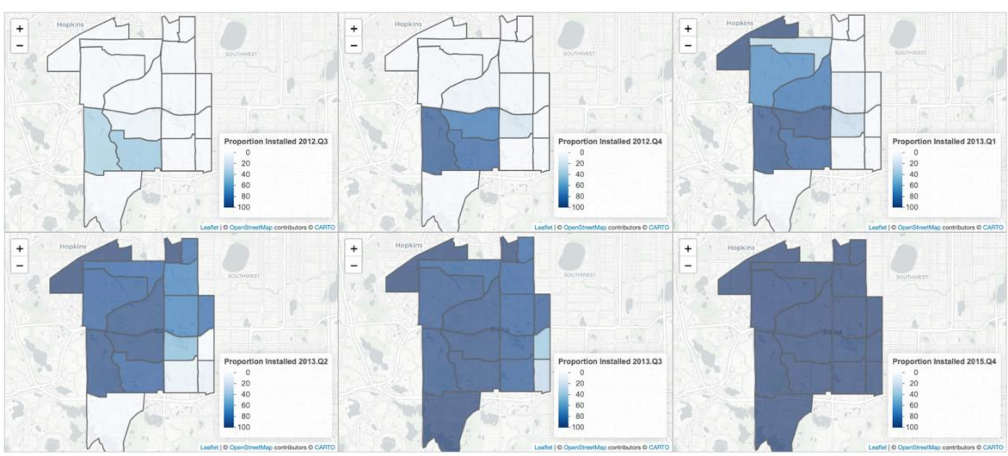
3. Setting

The City of Edina went through a substantial $3.6 million dollar restructuring of their water metering infrastructure from 2012-2013 The utility replaced their manual metering system (MMR) to an automatic meter reading system (AMR). The smart water project that was announced in 2010 and provided free installation of AMR meters to all their customers. The AMR metering system is considerably more expensive ($270 per device) compared to MMR devices ($25 per device). According to the utility, the main motivation for such an investment was to reduce labor costs associated with the billing process and improvements in asset/pipeline management. AMR meters provide enhanced tracking of usage and more efficient billing by collecting usage and consumption data through radio networks. AMR metering systems allow for easier data collection which can be used to better evaluate location of leaks and predict potential pipeline failures. This new system has saved the City of Edina the expense of periodic trips to each physical location to read a meter, reducing billing labor costs related to billing. Also, by replacing older infrastructure, AMR meters can provide more accurate billing with a more standardized meter inventory.

Once installation of the new metering system was completed, households in Edina transitioned to a new water bill. The major difference between the new and old bill was the inclusion of a graph of historical, own consumption patterns for every household. Importantly, the graphic does not compare households' usage to other households or provide an injunctive norm. It may, therefore, be hard for consumers to update their beliefs as to whether their own consumption is high or low relative to an average or standard. However, the new format does provide households with more information about their historical consumption patterns for which consumers can evaluate against and see if they are reducing or increasing consumption compared to previous periods. The water bill frequency was unchanged from its original quarterly billing system.

The installation of the new AMR system was completed in phases by neighborhoods. As seen in Figure 1, the first neighborhoods to see the new metering systems were in the south-west of Edina in between Braemar and Creek Valley Park during the second quarter of 2012. Next, households in the north part of Edina had meters installed in the first quarter of 2013. Finally, neighborhoods in the south east part of the city had their metering systems change at the end of the third quarter of 2013. By the end of 2013, nearly all households had the new AMR meter installed in their homes.

Figure 1: AMR Installation Over Time



The city of Edina provides an interesting case study as the city is relatively affluent compared to the rest of the US. The average median household income in Edina was $99,295 and the median property value was $459,200. This is considerably higher than the US average median household income of $64,300 and the median property value of $217,500 (US Census Bureau, 2015). Given that water bills are a small proportion of income, it is possible that conventional market-based policies do not have a great effect on reducing consumption in an affluent neighborhood like Edina. Therefore, it is important to analyze how own-past consumption information could be used as a conservation measure.

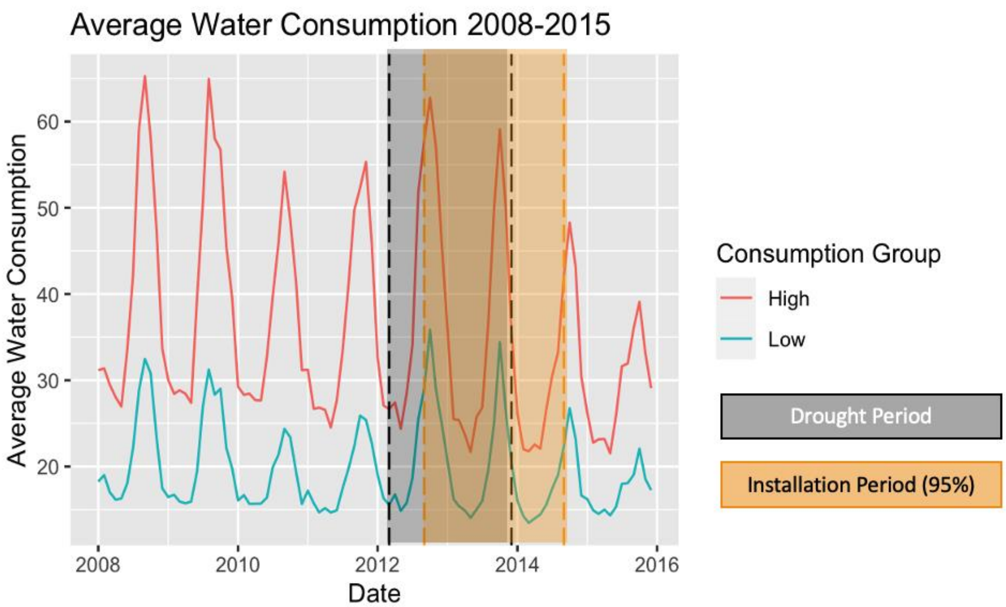


Figure 2: Average Quarterly Water Consumption (2008-2015)[8]

3.1 Data

I use water billing data and leak notices data provided by the City of Edina, Minnesota. Included in the data are quarterly water and wastewater use, the location of the household, the date of their latest water meter change, and their current water meter. I matched consumption data with geocoded county parcel data from 2020 obtained from Hennepin County. The county parcel data includes assessed property market values and parcel lot area estimates. To account for weather influences on water consumption I collected quarterly precipitation, snow, and

[8] Black dotted lines represent the drought period, and the orange lines represent the installation rollout period for most households. High and Low consumers were divided based on their consumption prior to installation, and they were divided by the mean of the sample.

temperature data from the National Oceanic and Atmospheric Administration (NOAA).[9] The total and mean values for each weather variable is matched to each households' billing cycle.

Important to my study, the city of Edina experienced a drought in 2013, which coincides with the installation of these devices for many households in the region. Figure 2 shows a spike in consumption during 2013, at the same time when there was one of the worst widespread droughts in in its history. The State of Minnesota during 2013, experienced what's called a "concrete frost" – an impenetrable layer of frozen soil. In response to the concrete frost and degrading soil conditions, many households increased their outdoor water consumption to maintain their lawns. Figure 2 shows how consumption spikes during the drought period. Although there have been other droughts in our timeframe that we can use to control for this effect, the effects of droughts vary depending on their length and intensity. While it is possible to control for drought intensity, the unique nature and length of the 2013 drought makes controlling for its effect empirically challenging. Nonetheless, I control for such droughts use drought indicators from the US drought monitor classification[10]. Droughts are defined in different levels. In our study we will only evaluate two different levels. Drought Level 1 which is when water shortages are common, and some utilities impose water restrictions. Drought Level 2 indicates widespread water shortages and there are extreme drought experiences across the county. One potential limitation of using this strategy is that droughts severity is not only expressed by intensity but also by length. Unfortunately, these drought level indicators do not capture potential differences in intensity, and in addition longer droughts tend to also have long-term consequences. This can mean that consumption might increase even after the end of a drought.

I restrict my analysis to a balanced panel of single-family residential homes,[11] ensuring I observe each household for the full timeframe of the study, 2008 to 2015.[12] This study drops multi-family homes, non-residential properties, seasonal recreational residential houses, apartments/condos, and properties with multiple accounts. I remove the latter to reduce the impact of renters who might have water bills as part of their rent. The final sample of our study

[9] I calculate the total and average values for each weather estimate to match each household each to their billing cycles which have different quantity consumption months, even if they have similar billing quarters.
[10] National Drought Mitigation Center (NDMC), 2021. United States Drought Monitor
[11] I restrict the dataset from the original 13,339 households in the billing dataset provided by Edina
[12] Edina updated their prices every year from 2008-2015, and they charge water using an increasing block pricing structure with a fixed yearly charge for their services.

consists of 6,332 single-family residential households with water use from the first quarter of 2008 to the fourth quarter of 2015.

Summary statistics are shown in Table 1. The columns break up household and water use characteristics by the quarters in which households transitioned from MMR to AMR billing. The last column provides summary statistics for the entire sample. Every characteristic looks similar across installation waves. The only large differences are seen across installation waves with very few households. For example, the installation of AMR meters for 2013 quarters 3 and 4 look to have big differences in housing prices but this is mainly because only a few houses are present in the sample, therefore they are more sensitive to high priced outliers. Outside of those estimates, it looks like each installation wave does not have significant differences in household statistics as they do not drift away too far from the full sample estimates. For households who installed their water meters during 2013Q3 or after, it seems that they have a higher house market value (a proxy for their wealth) and larger parcel areas. The higher the parcel area, we would expect households to consume more water due to greater outdoor irrigation consumption, which is why households in these periods seem to have a slightly greater average water consumption level. For the average household in the sample, the mean house market value is around $625,000, telling us about the affluent nature of our sample and of the city of Edina. The average parcel area is 14,500 square feet, around a third of an acre, and on average houses are 50 years old as of 2012.

Table 1: Summary Statistics for households that received first AMR bill for each installation wave (2008-2011 averages)[13]

	Installation Wave					
Average	2012.Q3 or less	2012.Q4	2013.Q1	2013.Q2	2013.Q3 or more	Full Sample
Quarterly Water Use	26.52	24.98	25.02	26.45	23.60	25.49
	(16.7)	(15.9)	(15.9)	(17.4)	(16.9)	(16.3)
Age of home (as of 2008)	46.27	55.16	56.69	52.45	46.09	52.44
	(12.9)	(20.1)	(19.0)	(16.0)	(26.2)	(18.6)
House Value ($1000)	494	536	526	516	625	524
	(172.9)	(253.6)	(235.7)	(233.9)	(421.3)	(239.8)
Parcel Area (1000 sq feet)	14.1	13.1	10.3	12.0	14.3	12.7
	(8.6)	(8.7)	(4)	(6.4)	(39.2)	(11.1)
Count	1,747	2,164	1,570	573	278	6,332

Overall, Table 1 shows that installation were not targeted to particularly high consuming households first, and overall household characteristics look to be very similar across installation waves. This is evidence that the assignment of automatic meter reading and the subsequent change to a new billing system is plausibly exogenous to the households. Although there are variations in household characteristics these variations are likely due to different neighborhood characteristics, rather than explicit selection for the purposes of reducing demand by the utility. Installation of AMR devices occurs in quick succession and by the end of 2013 more than 95% of the households end up treated. Concerns about exogeneity come as the utility decides which neighborhoods receive their AMR. There may be concerns if the utility strategically decided which neighborhoods received AMR's first. There are also concerns of unintended selection bias but the time at which you are selected for installation should not necessarily affect your water consumption patterns.

[13] Standard Errors in parentheses

Figure 1 highlights that water consumption exhibits a cyclical pattern, where consumption tends to spike during the summer where there are more opportunities for irrigation or other water-intensive activities. We also see an overall consumption decline since 2008, signaling potential technological changes during the time period and a justification to use year fixed effects to prevent omitted variable bias.

I also use a high consumption notices dataset, provided by the City of Edina, where consumption values that were two standard deviations above the expected consumption values were flagged for review for potential leaks. Although it is not a perfect label for a leak, I used it as a proxy for a leak. These leakages are only limited to residential pipelines, and do not include system-wide leakage values within the system. It is also important to note that given that only a small substrata of the household's experience leak notices, the number of households analyzed for the leak event study was reduced to just 78 households.[14]

4. Empirical Strategy

I use two complementary approaches to identify the average households' demand responses to AMR installation. I start with a differences-in-differences design that uses within-neighborhood variation. The design leverages the roll-out of the installations to compare short-run water use impacts of the new billing structure on households' water use. I then turn to an event study design, that uses within-household variation in water use centered at the timing of the new billing infrastructure.

4.1 Difference-in-Differences

I start with a two-way fixed effects difference-in-differences model. The model relies on some key assumptions, which include stable unit treatment value (Imbens and Rubin, 2015), specific parallel trend assumptions (Marcus and Sant'Anna, 2020), and homogeneous treatment effects across groups and periods (De Chaisemartin and D'Haultfoeuille, 2020). I estimate the following equation:

$$\ln(w_{it}) = \beta_0 + \beta_1[Install]_{it} + \delta_q + \pi_y + \rho_t + \alpha_n + X'\Gamma + \epsilon_{it} \qquad (1)$$

[14] Among the households, we see a variation in consecutive leak notices, number of leaks during the 2008-2015 period, and the timing of these leaks. This also suggests that we analyze more than 78 leaks as there are some households that had more than one leak during the period.

Where (w_{it})is household i's log water consumption in year-quarter t. *Install* is a dummy variable that equals 1 after household i's meter was installed. To account for seasonality, and trends in water consumption, I include fixed effects for year (π_y) and quarter cycle (δ_q).[15] I include the interaction of quarter and cycle time fixed effects due to differences in billing cycles. I also include neighborhood fixed effects α_n, which is defined by the census tract, to account for unobservable neighborhood-specific characteristics. I also include additional household characteristics control variables (X') which include lot size, house age, and house market value, which is used as a proxy for wealth. To account for different weather conditions (ρ_t), I also control for the aggregate quarterly precipitation, quarterly average temperature, and quarterly snow precipitation. Finally, it is the residual error term that will capture unobservable water consumption characteristics such as heterogeneity between high and low users, heterogeneity between different billing cycles, and other omitted variables.

The difference-in-difference approach uses neighborhood fixed effects over household level fixed effects to understand the variation within neighborhood. If we use household level fixed effects, there is risk that we might cut the limited variation in consumption across our study. Most importantly we would have trouble identifying long-run effects of the change in information policy if we used household fixed effects due to its limited variation. By evaluating both neighborhood level and household level fixed effects using the event study we are also able to identify potential issues in our two-way fixed effects controls if the estimates are not aligned/resemble similarity. As an alternative to household level fixed effects, I include baseline household consumption in some difference-in-differences as a way to control for differential average quarter consumption patterns across consumers. When regressing with a baseline consumption, our study is modified to only include years from 2010 -2015 as the baseline will include quarterly averages for each household from 2008-2010.

4.2 Event Study

I use a complementary event study approach that estimates within household variation in water use before and after treatment. I compare the event study estimates to the results in the difference-in-differences approach. I estimate an event study analysis of the following form:

[15] Quarter cycle is an indicator between the quarter and cycle combination. We have 12 different quarter cycles, as seen in the Appendix.

$$\ln(w_{it}) = \alpha_i + \sum_{j=-\tau}^{\tau} Install_{\mathrm{j}}\, 1[t = j] + \delta_q + \alpha_n + \rho_t + X'\Gamma + \epsilon_{it} \quad (2)$$

I restrict the event study timeframe to 2 years (8 quarters) before and after treatment, and I include the same controls as our specifications in equation (1). I allow for differential treatment effects by event-quarter, β_j. The event study includes neighborhood, cycle-quarter, and year fixed effects.

4.3 Leak Event Study

Last, I use an event study to understand the effects of leak notices on water consumption. I estimate the impact of leak notices 4 quarters (1 year) before and after households receive leak notices,[16] for a total event time window of 8 periods (2 years). I estimate the following model:

$$\ln(w_{it}) = \alpha_i + \sum_{j=-\tau}^{\tau} LeakNotice_{\mathrm{j}}\, 1[t = j] + \delta_q + \alpha_n + \rho_t + X'\Gamma + \epsilon_{it} \quad (3)$$

Equation (3) includes the same controls as our preferred specifications in equation (2). Compared to the equation (2) I normalize the coefficients to be relative to β_{-4}, the coefficient on 1[t = -4]. This allows me to compare water consumption to a "normal/baseline" set of consumption values instead of the value at β_0 which is an unusual consumption value.

5. Results

5.1 New water bill information and water consumption

Table 2 presents average treatment effects of the updated billing format using my difference-in-differences model. The results show that, when regressions do not account for seasonality, estimates show that receiving new AMR bills reduces consumption by 7%. But as seen in Figure 2, households increase consumption during the summer as households' water their lawn and make use of higher intensity water activities (swimming, water sports). Therefore, such cyclical pattern needs to be controlled to better understand the effects of the new water bills. When I control for the year either through fixed effects or using it as a controlling variable, we see that consumers see their consumption increase after receiving new bills. These variables control for unobservables that may bias the average treatment effect estimate such as technological improvements in irrigation and water efficient machinery that have occurred across

[16] In the dataset there are households that have consecutive leak notices. Therefore, for the purpose of this study, event zero can include more than one period as it is the label for all periods (singular or consecutive) with a leak event notice.

the years. When I include these controls, we see that households have an insignificant increase in their water consumption after receiving new water billing information.

Table 2: Difference-in-Difference Results (ATE: Average Treatment Effect of new water bill information)[17]

	Regression			
	(1)	(2)	(3)	(4)
New Water Bill (ATE)	-0.0779***	-0.135***	0.0212**	0.0448***
	(0.00313)	(0.0032)	(0.00694)	(0.00753)
Controls				
Household Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Leaks Removed	Yes	Yes	Yes	Yes
Year + Year^2	No	No	Yes	No
Baseline Consumption	No	No	Yes	Yes
Fixed Effects				
Neighborhood FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	Yes
Cycle Quarter FE	No	Yes	Yes	Yes
Adj R-squared	0.118	0.153	0.433	0.433

As expected, there is a significant increase in our adjusted R-square estimates when we use baseline consumption as part of our model, as we insert individual consumption patterns as part of the regression. Once included, we see that ATE are not significantly altered compared to the ATE of other regressions estimates without baseline consumption as part of the regression setting.

The difference-in-difference approach estimates a potential increase in consumption of 2.1- 4.4% in water consumption after the introduction of AMR bills. These average treatment effects may obscure important heterogeneity among households. I, therefore, also explore

[17] *, **, *** denote significance at the 10%, 5% and 1% level. Standard Errors in parentheses.

whether the new billing format had heterogeneous impacts across households based on whether they were high- versus low-baseline users.

Table 3 presents my results. High-baseline households tend to be more responsive to the new bill format than low-baseline households by 2% to 4%. Similar to other empirical studies (Schultz, 2007; Ferraro and Price, 2013), I find that information effects have heterogeneous treatment effects depending on the type of household. Similarly, to Ferraro and Price, high consumption households tend to have a comparatively greater consumption decrease. Table 3 shows that consumption from high users drops to 1.7% to 4%, while consumption from low users increases by 4-6%. These differential treatment effects further provide evidence of potential benefits of selective messaging. If the utility would like to decrease household consumption levels, they might want to primarily target high-baseline consumption users.

Table 3: Heterogeneity (ATE: Average Treatment Effect of new water bill information)[18]

	Regression	
	(1)	(2)
ATE for High Consumption Users	-0.0404***	-0.0169*
	(0.00792)	(0.00844)
ATE for Low Consumption Users	0.0460***	0.0697***
	(0.00711)	(0.00768)
Controls		
Household Controls	Yes	Yes
Weather Controls	Yes	Yes
Leaks Removed	Yes	Yes
Year + Year^2	Yes	No
Baseline Consumption	Yes	Yes
Fixed Effects		
Neighborhood FE	Yes	Yes
Year FE	No	Yes
Cycle Quarter FE	Yes	Yes
Adj R-squared	0.434	0.434

[18] *, **, *** denote significance at the 10%, 5% and 1% level. Standard Errors in parentheses.

Figure 3 presents results from the event study model. As a reminder, the event study model relies on within household variation, comparing average water consumption in the quarters before and after the new billing format in event time. Unlike the difference-in-differences results, Figure 3 shows little evidence of a change in average water consumption after households switched to the new billing format. The Figure shows a general downward trend in water consumption, and there is little change in consumption in the quarter after households started receiving the new billing format.

Figure 3: Event Study Water Consumption over Time

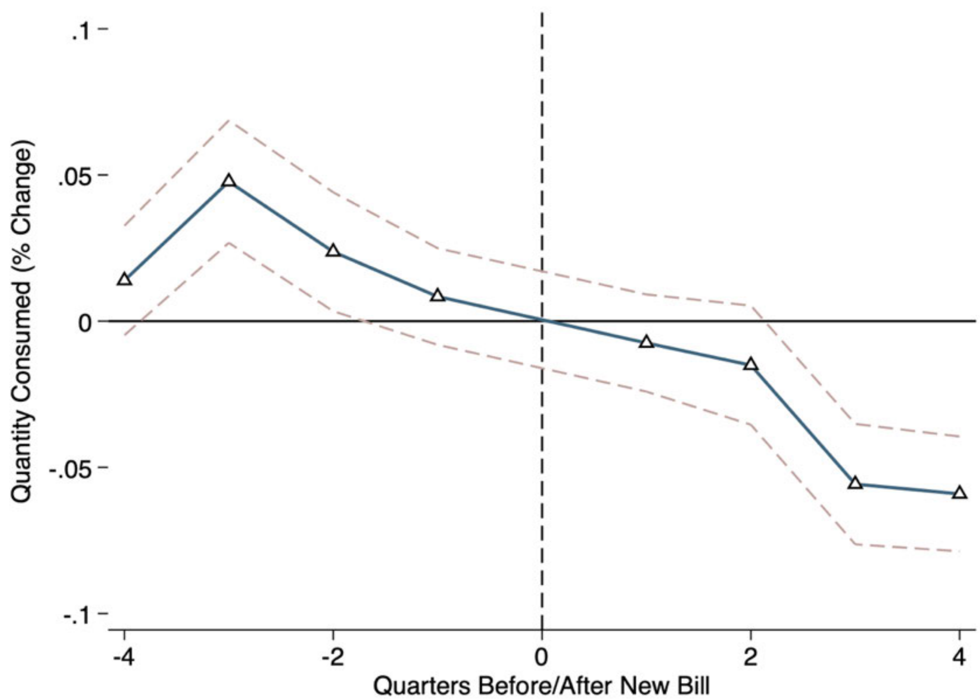
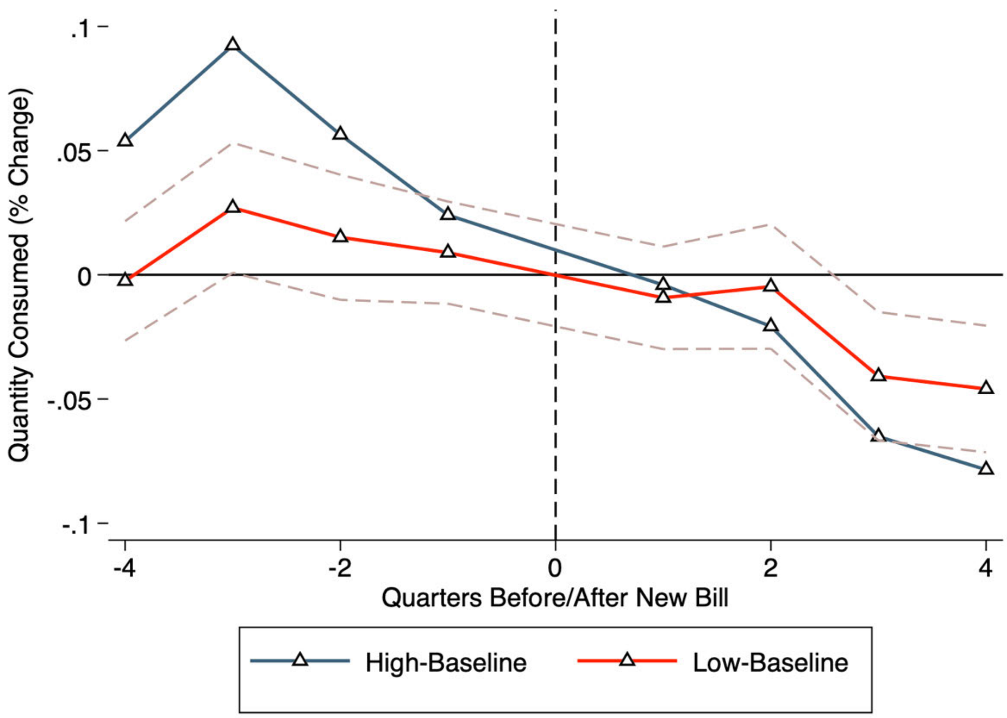


Figure 4 presents results from a similar exercise exploring heterogeneous impacts of the new billing format across high- and low-baseline water consumers. Low baseline consumers show limited effects of new information provision. Like Figure 3, high-baseline consumers exhibit a strong, unabated downward trend in consumption before and after the new billing format, again suggesting limited to no impact of the new information. Overall, the results suggest the bill had no impact on average consumption for any households, conflicting with the difference in differences model. However, standard errors are large, and I cannot rule out small impacts.

Figure 4: Event Study Water Consumption Low vs High Baseline consumers



Results from the event study model are consistent with Geller, et.al (1983) and Brent, et.al (2015), who show that own-consumption messages provide limited effects on water consumption, with significant heterogeneity across the distribution of baseline water use.[19] Consistent with earlier studies, we find that treatment is most effective on high baseline water users (Alcott, 2011; Ferraro and Miranda, 2013; Ferraro and Price, 2013). These studies argue that conservation policies should be targeted to subgroups that are more responsive to reduce the costs of such implementations. Yet the decreasing consumption trend shown by high-baseline consumers in Figure 4 indicates that there may be other pre-treatment trends (before billing statement switch) that are producing this decrease in consumption. Potential drivers of this decrease might be the development of more water efficient irrigation technologies, changes in landscaping, or the development of other water efficient products which seem to have a greater effect on higher baseline users. [20]

Results from our event study are consistent with (Geller, et.al, 1983; Brent, et.al 2015) which show that own-consumption messages provide limited effects on water consumption, with significant heterogeneity across the distribution of baseline water use.[21] Consistent with earlier

[19] The study looks at three different cities in California randomizing households into treatment.
[20] Other water efficient products include showerheads, toilets, dishwashers, washing machines.
[21] The study looks at three different cities in California randomizing households into treatment.

studies, we find that treatment is most effective on high baseline water users (Alcott, 2011; Ferraro and Miranda, 2013; Ferraro and Price, 2013). These studies argue that conservation policies should be targeted to subgroups that are more responsive to reduce the costs of such implementations. Yet the decreasing consumption trend shown by high-baseline consumers in Figure 4 indicates that there may be other pre-treatment trends (before billing statement switch) that are producing this decrease in consumption. Potential drivers of this decrease might be the development of more water efficient irrigation technologies, changes in landscaping, or the development of other water efficient products which seem to have a greater effect on higher baseline users. [22]

Higher consumption users and Low consumption users to a lesser extent may violate the parallel pre-trends assumptions, and the decreases in consumption cannot be solely attributed on the introduction of social norms billing information, particularly to the high-consumption subgroup. Negative pre-trends show that there is not enough evidence to suggest that high-baseline consumers are more responsive to these policies.

5.2 Leaks and consumer response

Figure 5 presents my results for the impact of high-consumption, or leak, notices on average household water usage. As a reminder, the coefficient four quarters before the leak notice is normalized to zero. Consistent with the utility definition of a residential leak, households with high-consumption alerts increase water consumption 15% to 50%, with an average of 33.3% increase compared to their baseline levels, in the quarter the leak notice is delivered. Importantly, households respond quickly to the notices. Consumption for most households decreases by 19% to 26% relative to to baseline levels, a significant decrease in consumption. These reductions are sustained for at least two quarters, with baseline levels after three quarters.

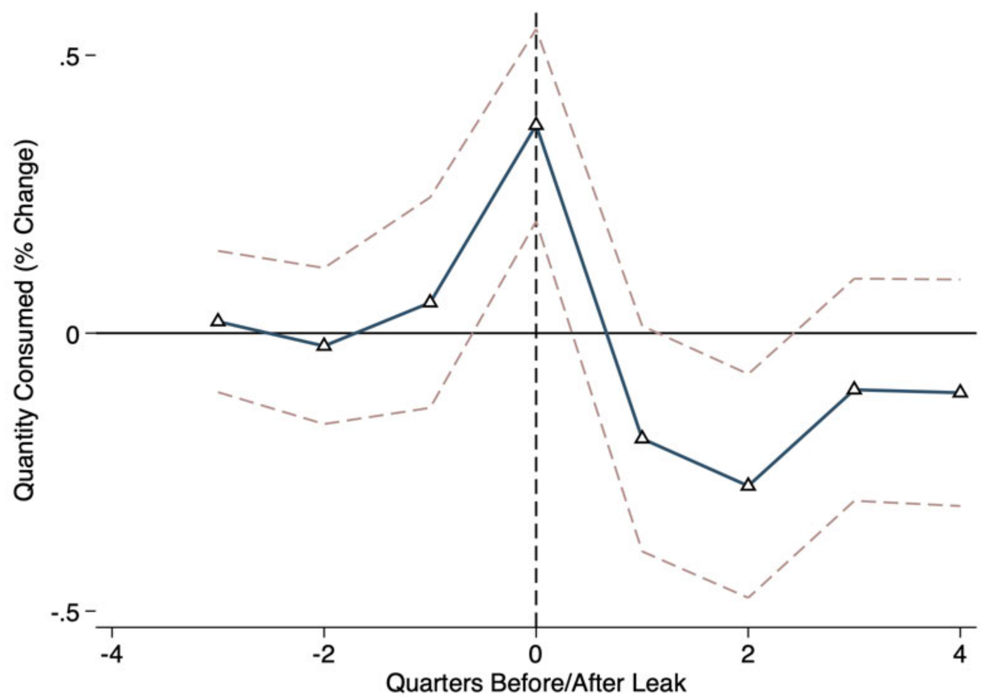
The results suggest that the shock of high bill statements causes consumers to over-correct, reducing consumption below their baseline usage levels temporarily. In other words, it is possible that leaks serve as a shock intervention to consumers changing their perceptions about water conservation. It is important to note that the shock is not sustained as consumers return to

[22] Other water efficient products include showerheads, toilets, dishwashers, washing machines.

their baseline levels of consumption, as consumers forget about their conservation goals, which is in par with Gilbert and Zivin (2014), where one-time interventions have shown to wane over time.

The current data frequency does not allow me to definitively assess the benefits of faster leak detection. However, my results suggest households respond quickly to such notices. If this result holds for shorter time steps (e.g., weekly or daily consumption after receiving a leak notice), then AMR systems may have the additional conservation benefit of allowing utilities to respond to abnormally high-water usage among residential consumers more quickly.

Figure 5: Leak Event Study Water Consumption over Time



6. Conclusion

This paper evaluates whether increased billing information affects residential water use. The literature provides varying results for the effects of different types of information on household water consumption. Our study shows limited evidence of an effect of own-consumption information on household water use. Complementary methodologies provide contrasting results. Our difference and difference methodology that looks at within-neighborhood variation suggests that billing led to an increase in consumption, while our event study that looks at within household variation shows limited effect of this new information provision.

Our estimates concur with other studies such as Ferraro and Miranda, (2013); Jessoe, et.al (2017); Kažukauskas, et.al (2017) that show limited effect of information policies on consumption. This does not suggest that information policies, which are easier to implement after the installation of AMR/AMI meters, are not an effective water demand management tool. Other informational policies such as social norms messaging have shown to effectively decrease consumption, particularly during droughts (Ferraro and Price, 2013; Bernedo, et.al, 2013; Bolsen and Ferraro, 2014)

Additionally, my estimates on the effects on consumption via new billing information might be limited due to the low frequency of the information. We are unable to capture much of the effects of receiving such notices as consumers tend to react right after receiving billing information, but their conservation efforts are not persistent as they return to baseline levels (Schultz, 2007). There is a possibility households do react right after receiving a water bill, but unfortunately due to limitations on the frequency of the data, our study could not explore such effects.

When evaluating consumer behavior during leaks, our results show that consumers decrease consumption below baseline level after fixing their leaks. Consumption for most households decreases by 17-25% compared to baseline levels. And such decreases are sustained for at least 2 quarters but for most households, consumption returns back to normal after 3 quarters. This provides evidence that consumers do react to some information nudges by changing their behavior, but they are unable to persist as consumer's attention is malleable and non-durable. And although we are unable to compare the benefits of leak detection due to the frequency of data, our results on consumption patterns after a high consumption or leak notices suggests that the response is immediate. Assuming that these consumption patterns remain true even to a higher frequency there can be additional benefits of quicker leak notices, which is possible with the new AMR infrastructure.

Our results show that the benefits of AMR installation come mostly from the utility operations side, as the utility benefits from labor savings and potentially better leak detection. And this is no surprise as the utility carried out AMR infrastructure restructuring plan for operational purposes. And although our study might show that information has limited effect on consumption, these findings do not carry over to AMI or other information provision methods such as social norms. Literature shows that social norms policy can be used as an effective water demand management tool. Edina does provide an interesting case to evaluate social norms messaging in the future particularly due to its affluent nature, non-pecuniary measures might be more effective as a water demand management tool as prices and water bills are just a very small proportion of their income. Also, the utility did not change their frequency of billing after the introduction of AMR meters, and it is possible that the effects of the new bill might not be as pronounced as conservation efforts wane out. This means that billing systems such AMI which allow for real-time communication with consumers might see beneficial conservation efforts as consumers will receive more consistent reminders on their consumption levels, potentially promoting conservation habits.

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8. Appendix

Table 4: Composition of Billing Cycles

1. CYCLE 01:
    - Q1 = January, February, March aggregated estimates
    - Q2 = April, May, June aggregated estimates
    - Q3 = July, August, September aggregated estimates
    - Q4 = October + November + December aggregated estimates
2. CYCLE 02:
    - Q1 = November, December, January aggregated estimates
    - Q2 = February, March, April aggregated estimates
    - Q3 = May, June, July aggregated estimates
    - Q4 = August, September, October aggregated estimates
3. CYCLE 03:
    - Q1 = December, January, February aggregated estimates
    - Q2 = March, April, May aggregated estimates
    - Q3 = June, July, August aggregated estimates
    - Q4 = September, October, November aggregated estimates

Table 5: Explanation of Different Variables and Controls used in the Modeling Process

Controls	**Explanation**
Household Controls	
House Market Value	Measured in Dollars
Age of House as of 2008	(in years)
Size of Parcel Area	Measured in squared feet
Weather Controls	
Quarterly Precipitation	Total Quarterly precipitation
Quarterly Average Temperature (F)	Average Temperature for the Quarter
Quarterly PDSI	Palmer Drought Severity Index is a standardized index that measures relative dryness
Drought Level 1 (D1)	If more than 50% of the soil in Hennepin County experiences Moderate Drought (Water Shortages Common and Water Restrictions Imposed). Levels are defined by the US Drought Monitor
Drought Level 2 (D2)	If more than 50% of the soil in Hennepin County experiences Extreme Drought (Widespread Water Shortages). Levels are defined by the US Drought Monitor
Quarterly Snow	Quarterly Aggregate Snow Fall (inches)

Figure 6: Sample Bill

City of Edina Utility Billing
4801 West 50th Street
Edina, MN 55424-1330

00088941 0341581005 03/10/2021

$265.77

Pre-authorized payment of 265.77 will be drawn from your bank on 03/10/21

AUTOMATIC PAYMENT-DO NOT PAY

034158100500088941000026577

[redacted]

CITY OF EDINA
PO BOX 860586
MINNEAPOLIS, MN 55486-0586

00088941034158100570000265771

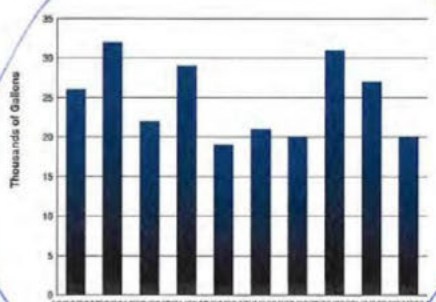
SERVICE ADDRESS: [redacted]

BILLING DATE: 02/10/2021

00088941	0341581005	11/03/2020 to 01/27/2021	$265.77	03/10/2021

SERVICE ADDRESS: [redacted]

52514308	01/27/2021	682008	702482	20



NEW -
PAST USAGE
GRAPH

BILLING		276.73
PAYMENT - THANK YOU		276.73CR
BALANCE FORWARD:		**0.00**
3/4" WATER METER - FIXED CHARGE		23.54
MN STATE WATER TESTING FEE		2.43
WATER - TIER 1	20 gallons x 2.58	51.60
SEWER	20 gallons x 6.00	120.00
STORM DRAINAGE		40.60
RECYCLING		11.10
RECYCLING ORGANIC CHARGES		16.50
TOTAL CURRENT CHARGES:		**265.77**
TOTAL AMOUNT DUE:		**265.77**

A 5% PENALTY ON THE TOTAL OUTSTANDING BALANCE IS APPLIED IF PAYMENT IS NOT RECEIVED IN OUR OFFICE BY 4:30PM ON THE DUE DATE.

When you pay by check the City of Edina will present your check for payment to your bank electronically. Your original check will be destroyed once processed and you will not receive your cancelled check back.