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Information provision and consumer behavior: A natural experiment in billing frequency

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ABSTRACT

In this study, I estimate a causal effect of increased billing frequency on consumer behavior. I exploit a natural experiment in which residential water customers switched exogenously from bimonthly to monthly billing. Customers increase consumption by 3.5–5% in response to more frequent information. This result is reconciled in models of price and quantity uncertainty, where increases in billing frequency reduce the distortion in consumer perceptions. Using treatment effects as sufficient statistics, I calculate consumer welfare gains equivalent to 0.5–1% of annual water expenditures. Heterogeneous treatment effects suggest increases in outdoor water use.

1. Introduction

Conventional economic wisdom implies that more information is typically better. For many consumer goods and services, however, the decision to consume an economic good is disconnected from its purchase price. In these contexts, providing consumers with more information may affect their behavior. For consumption of water or electricity, for example, information on consumption costs is limited because billing is infrequent. If this source of limited information distorts the signal that consumers use to make decisions, then improving the clarity of this signal has implications for consumer welfare and management of scarce resources.

Whether and how imperfect perception of prices and quantities affects consumer behavior is an empirical question of growing interest. A recent vein of literature suggests that consumers tend to underestimate prices, taxes, and quantities consumed that are transmitted opaquely or allow for customer inattention (Chetty et al., 2009; Grubb and Osborne, 2015). Empirical examples range from behavioral responses to tax-inclusive prices for retail goods to improving the salience of consumption information through text-message reminders for cell-phone use. A parallel literature on consumer behavior in environmental policy considers the impact of social norms (Allcott, 2011; Ferraro and Price, 2013) and information provision (Jessoe and Rapson, 2014) and shows that informative

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interventions can reduce consumption and thus serve as an instrument of conservation.

With few exceptions, previous research suggests that various information treatments can be utilized to reduce consumption of economic goods that impose external costs on society. Despite lacking firm theoretical grounding, empirical evidence, so far, is aligned with the stylized notion that inattentive consumers tend to under-perceive price signals. Thus, policies designed to improve the salience of these signals can be cost-effective conservation strategies, particularly in regulated markets for electricity and water where prices may be politically difficult to change.

In this paper, I uncover causal estimates of consumer behavior that is at odds with improved salience being beneficial for resource conservation. I take advantage of a natural experiment in which residential water customers are exposed to exogenous increases in billing frequency within a single water provider's service area in the southeastern United States. I find strong empirical evidence that the provision of more frequent information increases water consumption in the short run. This result stands in stark contrast to findings of previous work and has significant implications for efficient management of scarce environmental resources.

Beginning in 2011, the City of Durham's Department of Water Management in North Carolina transitioned residential customers in geographically differentiated billing districts from bimonthly to monthly billing over the course of two-and-a-half years.[1] By exploiting the assignment of monthly billing, I estimate an average treatment effect on water consumption due to increased billing frequency at the household level. The primary result is that households billed monthly consume 3.5–5% more water than households billed bimonthly. I show that this effect is robust to unobserved neighborhood effects by examining household consumption before and after the change in frequency within 500 ft of common billing group boundaries. I find that inattentive consumers do not respond to the change in billing frequency, casting doubt on the notion that the increase in consumption is due to changes in metering technology. I also find important heterogeneity among baseline water use, lot size, and assessed home value.

My empirical results necessitate a closer examination of the mechanism driving consumer behavior in response to more frequent information. To that effect, I develop conceptual models of imperfect price and quantity perception that reconcile my empirical findings with the current literature on salience and inattention. Based on the notion that consumers are receiving more frequent information about the price and consumption of water with the receipt of monthly (versus bimonthly) bills, the information "treatment" allows consumers to update their perception of price or quantity consumed. This framework is general enough to accommodate the findings of previous research because more frequent information nudges consumers closer to the neoclassical ideal of decision-making under perfect information. As a motivating example, a consumer who initially under-perceives the price of electricity can be modeled similarly to a consumer who over-perceives the price of water, since more frequent billing will reduce the wedge between her perceived price and the actual price.

Further, I develop a transparent welfare framework using treatment effects as sufficient statistics for consumer demand. Because a consumer who misperceives price (quantity), and thus consumes suboptimally from her perfectly informed self, will be better off upon the receipt of new information, there are welfare gains from the provision of more frequent information. Consumer surplus measures suggest a welfare gain of approximately 0.5 to 1% of annual household expenditures on water that are attributable to the change in billing frequency. Other plausible mechanisms and their policy implications are discussed.

From a policy perspective, informative signals are being used increasingly as a regulatory instrument in the context of electricity and water conservation. The findings of this paper suggest that increases in billing frequency can have the perverse effect of increasing consumption. This result is particularly poignant because the efficient price for residential water is its long-run marginal cost of provision (Timmins, 2002; Olmstead and Stavins, 2009). However, because the market price is likely set below its efficient level (Mansur and Olmstead, 2012), the demand response to more frequent information may exacerbate the wedge between privately and socially optimal consumption levels.

1.1. Conceptual background

Consider the choice setting in which a consumer is deciding how much water to use in a given billing period.[2] Gilbert and Graff Zivin (2014), Harding and Hsiaw (2014), and Wichman (2014), for example, posit models of behavior based on prices, quantities consumed, and behavior in previous periods as heuristics for making consumptive decisions for electricity and water. Because utility bills are received periodically, the arrival of billing information offers consumers an opportunity to update their consumption in response to external feedback regarding their behavior. A change in the frequency of billing information is particularly relevant in the intermittent choice setting for water use because consumers generally do not know how much water they are using at any point in time, nor how much water an appliance uses and its associated variable costs (Attari, 2014). Thus, more frequent billing allows a consumer to better align market signals directly with the usage of appliances or water-intensive behavior.

With a fuzzy link between water consumption and the receipt of a water bill, however, the consumer may not have perfect information about prices and consumption that neoclassical models of consumer demand require. Several papers have documented this behavior theoretically and empirically in different markets. Studies show that (1) obtaining the relevant information to make perfectly informed decisions is costly (Shin, 1985; Sallee, 2014; Caplin and Dean, 2015); (2) consumers may be inattentive to or unaware of (changes in) prices or taxes (Sexton, 2015; Chetty et al., 2009; Finkelstein, 2009; Li et al., 2014; Houde, 2014); (3) inattention could be a function of attributes that are "shrouded" from consumers (Gabaix and Laibson, 2006); (4) consumers may use heuristics for decision-making when price and quantity information is opaque or uncertain (Ito, 2014; Wichman, 2014); or (5) consumers may have biased perceptions of prices, expenditures, and consumption (Allcott et al., 2014; Allcott, 2013; Grubb and Osborne, 2015; Bollinger et al., 2011; Byrne et al., 2014). Thus, relaxing the notion that consumers respond with perfect information for water use should not be met with much criticism. But the question remains: how are consumers using price and quantity information to make decisions in intermittent choice settings?

Many researchers examine this question in framed field experiments in the context of water and electricity demand to examine quantity reminders, social norms, and other forms of informative interventions (Allcott, 2011; Ferraro and Price, 2013; Kahn and Wolak, 2013; Jessoe and Rapson, 2014; Brent et al., 2015; Byrne et al., 2014). But, no studies have focused on an information treatment as simple as more frequent billing, which is arguably the easiest form of an intervention to implement as policy. In this paper, the consumer

[1] Bimonthly bills are those received every two months.

[2] While the model presented in this paper is generalizable to many choice settings in which consumption of the economic good and payment for consumption are separated temporally (e.g., cell phone usage, credit card purchases, and electricity demand), the discussion henceforth will consider water consumption to coincide with the empirical setting.

is provided with an information shock—the receipt of a utility bill. The bill allows the consumer to learn about her past usage and prices paid for water and update her consumption habits accordingly.[3]

In this framework, the customer's bill serves as a familiar mechanism for receiving information, but provides new price and quantity information to the consumer when it arrives. This treatment mechanism contrasts with that of many recent field experiments in which consumers were given a foreign source of information about their consumption (e.g., social comparisons, educational materials on complicated rate schedules, or informative signals on the variable costs of durable goods). Because consumers are familiar with their typical utility bill, it is perhaps more likely that they will simply update their behavior along an existing margin, rather than constructing a new consumption rule in response to a foreign information intervention. Thus, any prevailing misperceptions within a consumer's decision-making process are plausibly mitigated with more frequent information of the same type.

In the limit, increasing the frequency of information provided to consumers (i.e., real-time feedback) may tend towards the neoclassical ideal of perfect information. This notion corresponds to a "pure nudge", in the parlance of Allcott and Taubinsky (2015), that corrects the informational failure completely. With less frequent information (e.g., periodic utility bills), however, consumers are more likely to base their consumptive decisions on imperfect information. So, if a consumer receives a more frequent signal about her consumption, she may change her behavior in such a way that aligns more closely, but not perfectly, with standard models of consumer demand.[4] This example provides the groundwork for the conceptual setting in which water customers alter consumption in direct response to an increase in the frequency of bills.

2. Empirical setting

Beginning in December 2011, the City of Durham's Department of Water Management in North Carolina (henceforth, "Durham") transitioned individual billing districts from bimonthly to monthly billing at different points in time. Primary reasons for the transition include cost saving from fewer delinquent payments, early leak detection, improving customer service, and reducing administrative costs. In addition, the change in billing frequency was enabled by district-wide installation of automated meters. Customers were notified of the transition to monthly billing by mail approximately six weeks before the transition.[5]

To make a cost-saving argument to the city council (see Online Appendix Fig. 2), the water utility used a single billing district as a pilot group to measure changes in administrative costs before and after the transition to monthly billing cycles. After that, billing districts were switched to monthly billing sequentially. The order of districts for monthly billing was chosen to work around billing cycles and other administrative constraints. According to utility officials, no consideration of billing history, income base of neighborhood, or any other socioeconomic indicator was taken into account when choosing which districts to transition or when.

Given these details, the assignment of monthly billing is plausibly exogenous to the household, conditional on residing within a particular billing district. This assertion is explored in greater detail empirically. Within the study period, 12 of 17 billing districts were transitioned according to the timing in Table 1. The first district transitioned received its first monthly bill on December 1, 2011. Fig. 1 presents a map of the billing districts to transition to monthly billing by the end of each year of the sample. The entire service area is represented by the union of all billing districts outlined in bold. In Fig. 2, I present a magnified view of billing district boundaries within neighborhoods. This figure illustrates that the district boundaries are designated in such a manner that neighbors could be consuming water concurrently, but may be billed at different frequencies. This design allows for the exploitation of geographic discontinuities to minimize the concern that (changes in) unobservable differences in neighborhood characteristics might bias results.

2.1. Data

The primary data used in this analysis are residential billing records for Durham water customers. Included in these data are (bi-)monthly water and sewer use, fixed service fees and volumetric consumption rates, the address of the customer, billing district, and whether a customer has her water bill automatically deducted from a bank account. The billing data were matched by address with geocoded tax assessor data, containing structural characteristics of the home, obtained from Durham County. Each matched residential address was spatially linked to its 2010 Census block as well as billing district polygons provided by Durham. For each household, I determine the nearest billing district, as well as the linear distance from the centroid of the tax parcel to its nearest district boundary. Key demographic variables from the 2010 SF1 Census are matched to each household's Census block. Residential premises that changed water billing accounts within the timeframe of the study are removed from the sample—this strategy reduces the impact of renters, who may not pay water bills explicitly. Further, this avoids econometric identification problems when relying on variation within a household over time.[6]

The final sample consists of roughly 59,000 individual household accounts with water bills from February 2009 through June 2014, which produces slightly less than 1.7 million household-by-bimonthly unique observations. Summary statistics for variables of interest are presented in Table 1. The first four columns decompose household characteristics and details on water use by the year in which households transitioned from bimonthly to monthly billing. Summary statistics in the final column are for the entire sample. All of the treatment waves are relatively similar across demographic, water use, and housing characteristics, and similar to the sample mean, with the exception of households that transitioned in 2013 along several dimensions. For this group, home value (a proxy for wealth) is notably larger than that of all other groups. Further, these households tend to have larger homes on larger lots, and are more likely to be located in a Census block with fewer renters and a higher proportion of white residents. Water consumption, however, is similar across all groups. For the typical household in the sample, the mean assessed home value is approximately \$186,000 with a standard deviation of \$126,000. The average home is 34 years old, roughly 1800 ft^2, contains three bedrooms, and is located on one-third of an acre. Within the final sample, households reside in Census blocks in which approximately one-quarter of all homes are renter-occupied. Fifty-three percent of the sample is white and the average household size is between two

[3] An example of a utility bill, which serves as the information "treatment" in this paper, is included as Fig. A.1 in the Appendix.

[4] Consumers in this setting, however, may choose to be rationally inattentive to price signals in the sense of Sallee (2014), such that the costs of effort to synthesize price information from bimonthly, monthly, or real-time feedback exceed the benefits of doing so. If consumer inattention is orthogonal to information provision, then more frequent price signals should have no effect on demand. Conversely, if information provision changes consumption patterns, then one could assert that inattention itself is affected by the frequency of billing and can be modeled accordingly.

[5] A copy of the mailer distributed to customers is included in the online Appendix.

[6] Renters may cause problems for identification if they do not receive a water utility bill. However, this effect would tend to pull any estimated treatment effect towards zero so long as renters did not change their behavior at the exact time of the change in billing frequency.

Table 1
Demographic and water use characteristics among households that transitioned to monthly billing at different points in time.

	Summary statistics for households that received first monthly bill in:				
	2011–2012	2013	2014	>2014	Total
Tax assessor records:					
Assessed value of home	161,248	226,557	179,055	169,726	185,998
	(103,633)	(162,985)	(80,776)	(123,219)	(126,453)
Lot size (acres)	0.32	0.39	0.25	0.31	0.32
	(0.43)	(0.53)	(0.41)	(0.31)	(0.43)
Age of home (years since 2014)	33.81	29.72	28.73	44.88	34.47
	(22.85)	(19.98)	(24.63)	(28.02)	(25.1)
Size of home (square feet)	1639.5	2005.2	1777.6	1708.9	1793.3
	(766.08)	(893.5)	(641.24)	(780.04)	(808.98)
Number of bedrooms	3.02	3.25	3.11	3.04	3.10
	(0.73)	(0.76)	(0.72)	(0.80)	(0.78)
Number of bathrooms	1.77	2.05	1.94	1.74	1.87
	(0.61)	(0.65)	(0.57)	(0.70)	(0.65)
2010 Census (block):					
Percent renters	0.27	0.17	0.23	0.33	0.25
	(0.23)	(0.20)	(0.23)	(0.28)	(0.24)
Percent white	0.46	0.61	0.50	0.47	0.53
	(0.28)	(0.31)	(0.29)	(0.37)	(0.31)
Household size	2.52	2.50	2.51	2.48	2.48
	(0.48)	(0.46)	(0.52)	(0.54)	(0.51)
Billing records:					
Total bimonthly water bill	81.96	91.21	89.02	84.13	84.62
($/ccf)	(36.54)	(44.76)	(41.99)	(38.91)	(39.67)
Full sample bimonthly	977.46	1033.81	986.89	978.50	985.24
water use (cf)	(520.35)	(551.99)	(489.66)	(542.51)	(528.03)
2009–2010 bimonthly	997.83	1066.01	1004.7	1014.96	1018.17
water use (cf)	(600.74)	(651.73)	(578.80)	(635.39)	(622.24)
Number of households:	18,042	15,415	10,589	14,215	58,965
Number of billing districts:	5	4	3	5	17
Date of first monthly bill:	12/1/11	1/29/13	1/30/14		
	7/13/12	2/12/13	4/18/14		
	10/25/12	3/30/13	5/15/14		
	11/14/12	11/22/13			
	12/29/12				

Note: Means and standard deviations (in parentheses) are presented. The first billing district to transition to monthly billing occurred on December 1, 2011, so this district is grouped jointly with districts that transitioned in 2012. The 2010 Census (SF1) data is assigned to the Census block in which the household resides. 2009–2010 bimonthly water use is used to provide a sense of average consumption among each group prior to the transition to monthly billing (2009–2010 refers to consumption that occurred in the full calendar years of 2009 and 2010).

and three people. Average bimonthly water bills for all time periods in the sample are $85 for consumption of 985 ft^3 of water.

I also include weather covariates obtained from the North Carolina State Climate Office. The key variables used are mean maximum temperature and the sum of rainfall (in inches) for a 60-day rolling window that is backwards-looking from the date each individual bill was mailed. Lastly, I pool households into two-month cycles corresponding to the date in which bills are received, but allow for each district to retain accurate measures of weather fluctuations within their use period. As such, there are 32 distinct time periods in the study that correspond to two-month windows between February 2009 and June 2014.

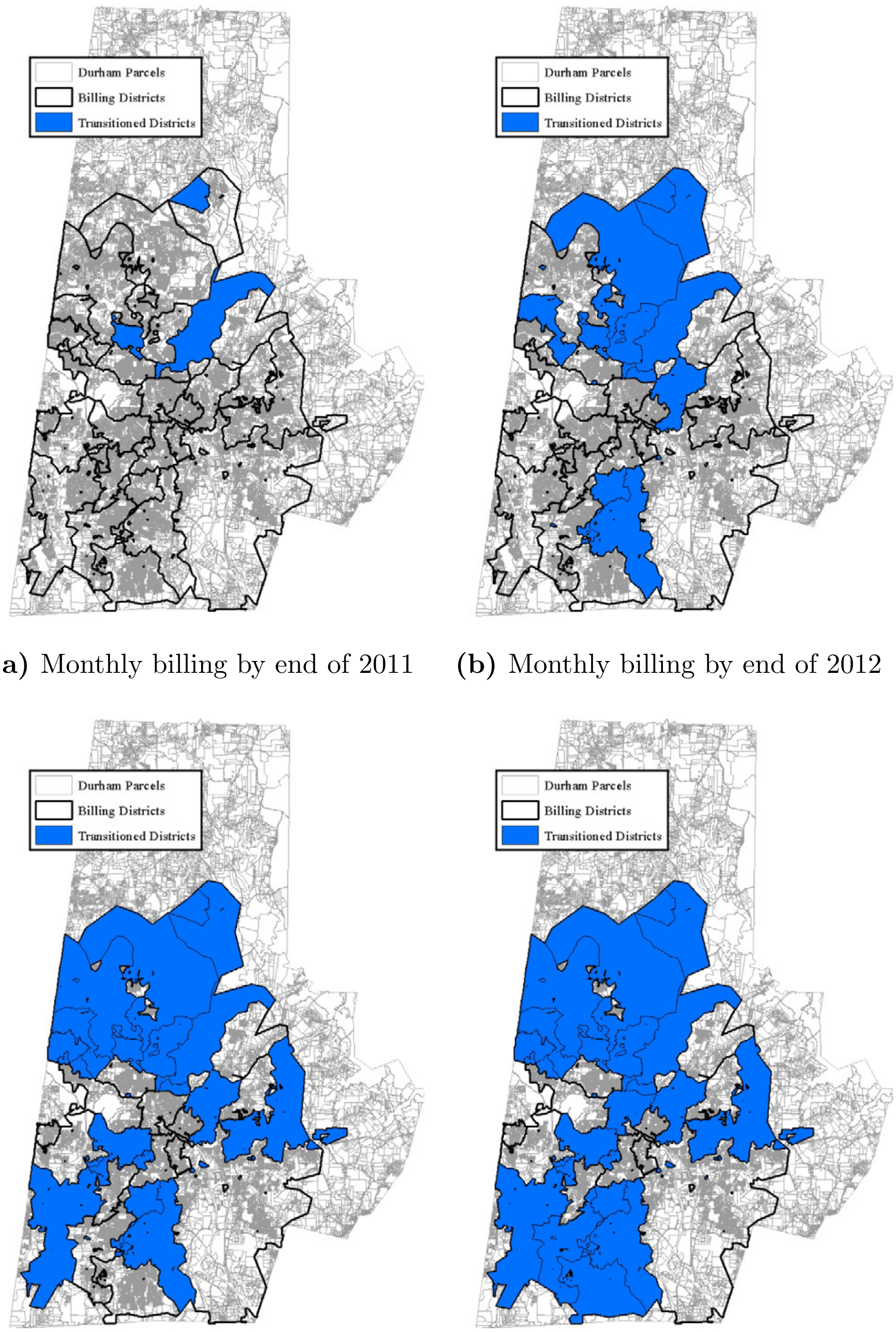
2.2. *Confronting confounding factors*

The transition of households to monthly billing provides a unique natural experiment to identify a causal effect of more frequent information on consumer behavior so long as other factors are not changing at the same time. When households were transitioned from bimonthly to monthly billing, two additional things occurred: (1) the nonlinear rate structure changed to account for the shorter billing period, and (2) new meters were installed around the same time as the switch to monthly billing. I discuss each of these potential confounding factors in this section, and I interpret all results in light of these potential threats to causal identification.

2.2.1. *Prices*

At the same time household were switched to monthly billing, fixed water and sewer service fees were halved and volumetric block cut-offs in the tiered water rate structure were halved as well. Marginal volumetric rates for consumption remained constant across billing frequencies. Sewer usage has a constant marginal price. Fig. A.2 illustrates the change in the rate structure for monthly and bimonthly billing. The solid line is the increasing block rate structure used to calculate bimonthly bills, while the dotted line is used to calculate monthly bills for the 2012–2013 fiscal year. As shown, the marginal prices for consumption do not change between monthly and bimonthly rate structures, but the quantity blocks for consumption are halved for each price tier.

This structure was adopted to ensure that customers transitioned to monthly billing were charged at the same rate as bimonthly customers. Thus, for the same level of consumption, two monthly bills are equivalent to one bimonthly bill in dollar amounts. This is a mechanical interpretation, however, and the change in the block endpoints could affect consumer behavior. To see this, consider an extreme version of the average water customer. She is extreme because she consumes no water in the first month and 10 ccf in the second month. Under bimonthly billing, her total bill is $82.12. Under monthly billing her first monthly bill is $12.05 (i.e., fixed service fees only) and her second bill is $74.80, totaling $86.85 for the two-month period, an *increase* in expenditures on water. The difference in the



(a) Monthly billing by end of 2011 (b) Monthly billing by end of 2012

(c) Monthly billing by end of 2013 (d) Monthly billing by end of sample

Fig. 1. Billing districts transitioned to monthly billing over time.

billed amounts for the same quantity consumed is a result of the nonlinear rate schedule: highly variable month-to-month consumption results in larger inframarginal price changes. The percent change in the average price of water for this extreme customer is $+5.6\%$. If we assume a common elasticity of -0.3, we would expect this change in average price to *reduce* consumption by 1.6% (or, 2.4% if we look only at changes in average volumetric prices). These percentages tend towards zero as the monthly consumption levels converge. This exercise shows that the nonlinear rate schedule can have an effect on price signals, although they work in work in the opposite direction as the treatments effects identified below. Further, the likelihood of this type of behavior being representative for Durham water customers is virtually zero.

Of course, the extent to which this bias exists also depends on whether consumers know and use the tiered rate information to make decisions. Because the water utility bill includes no information about

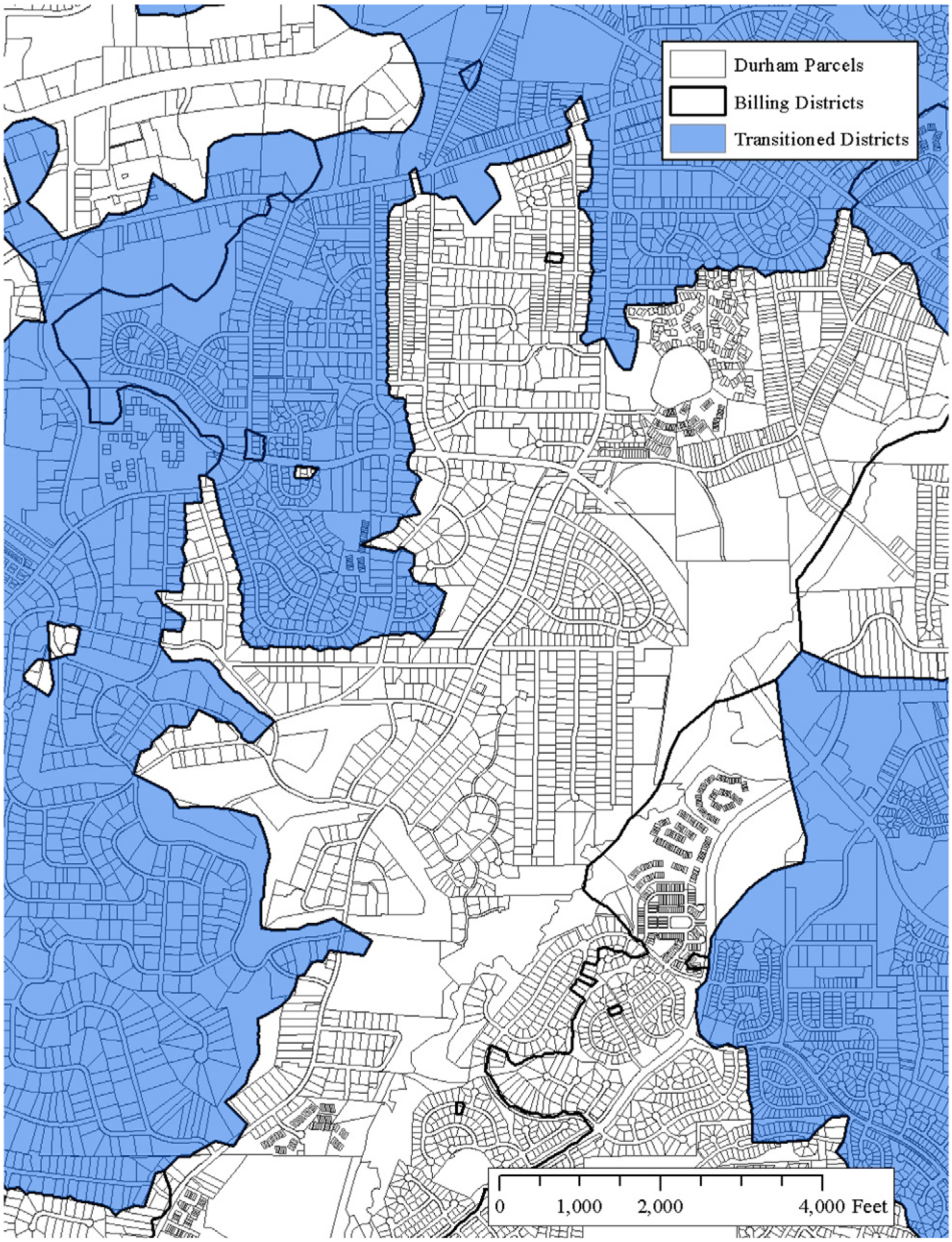


Fig. 2. Snapshot of billing group boundaries within neighborhoods.

the block rate structure (see Fig. A.1), it is unlikely that consumers are responding to changes in the rate structure itself.[7] Further, Wichman (2014) and Ito (2014) show that water and electricity customers, respectively, exhibit behavior that corresponds to changes in average price, or the total bill, when facing increasing block rates.

2.2.2. Meters

Durham installed automated meter reading (AMR) technology prior to switching billing districts to monthly billing. Based on conversations with utility representatives, the order of districts was chosen for new meter installation based on geographic convenience (see, e.g., Panel B of Fig. 1), difficulty of reading meters, district size, and working around the odd-even billing schedule. Once a district reached 90% saturation with new meters, the district was ready to be switched to monthly billing.

The new meters allow for consumption levels to be obtained via radio frequency such that the costs to read meters manually were reduced. Meters were installed for each billing district and, once the installations were completed, the entire district was transitioned to monthly billing. In the water industry, meters may fail to register all water that passes through them over time. Meter replacement offers an avenue through which consumption could increase mechanically; that is, the treatment effect may also include the increase in accuracy of the meter. This "mechanical efficiency" improvement depends on the degree of inaccuracy of the meter being replaced, water pressure, appropriate meter sizing, and a host of other factors that are, at present, unobservable. Although manufacturers often tout the benefits of improved meter reading accuracy, there is mixed evidence of

[7] As further evidence, I present the empirical density of consumption in Fig. A.3 in the Appendix. In this figure, there is no evidence of bunching at the block rate cut-offs for consumption in the calendar year prior to treatment.

this effect in the industry and engineering literature (see, e.g., Boyle et al., 2013; Lovely, 2010; Barfuss et al., 2011; Criminisi et al., 2009; Arregui et al., 2006).

Many of the frequently cited benefits of smarter water meters for utilities are captured by Ritchie (2011), "… utilities across the US are proving that AMI can drive down costs in unaccounted water, plus other important areas, such as energy, labor, conservation, capital investment, forecasting, billing, and customer service." Unaccounted-for water is a common metric of lost revenue. A case study in Leesburg, VA, found that system-wide meter replacement helped reduce unaccounted-for water from upwards of 23% down to $<$ 5% (Shoemaker, 2009). They also found that the older meters were under-registering water consumption for households. But age of the meter is not the only factor that matters for efficiency. In McKinney, TX, a utility-wide installation of new AMR meters revealed that many of the newly installed residential meters were undersized for their purpose and only registering a fraction of actual water use (Dobbie et al., 2003). Further, Britton et al. (2013) suggest that "there is still limited understanding of meter accuracy when considering the starting or minimum registrations levels (Qs), therefore water with a flow rate that is below the Qs flow rate of the meter cannot be measured." All of this is to suggest that although meter accuracy potentially changed for Durham households within the study period, there is not a clear direction of this bias, nor is the potential bias a static issue.

Further, the City of Durham's primary goals for installing AMR meters included reduced payment delinquency, earlier leak detection, and reduced administrative costs from manual meter reading. No mention of improved meter accuracy was cited in publicly available documents, which arguably would be a boon in city council deliberations for a revenue-conscious municipal water utility.[8]

Regardless, improved mechanical efficiency is the primary concern for attributing the change in consumption after the switch to monthly billing to changes in consumer behavior. I evaluate this potential threat in several ways. First, I present in Fig. 3 several water utility statistics. In Panel A, I plot system efficiency defined as the total amount of water billed each month divided by the total amount of water treated and distributed for consumption. A value of 80%, for example, means that 20% of distributed water never made it onto a customer's bill. Although this measure of system efficiency is aggregate and lacks statistical power, a technical efficiency gain from metering technology should display an increasing trend as older meters are replaced. As shown, there is no discernible increase in system efficiency after the rolling introduction of monthly bills begins in 2011. So, the relatively flat trend observed after the introduction of the new meters provides some indication that the purported technical efficiency improvement of meters does not confound the treatment effect.

Additionally, in Panel B of Fig. 3, I present the total amount of water billed to residential accounts. During the study period, there is a decreasing trend that appears to flatten out near the time when the first district was transitioned to monthly billing. The changes in consumption mirror the time series of system efficiency in Panel A. Although there is no obvious increase in residential use after 2011, it is unclear what counterfactual consumption would have been. To get a sense of this counterfactual, in Panel C I present total revenue, adjusted for inflation, from water and sewer sales for Durham and two nearby water utilities of similar albeit slightly smaller size, servicing Chapel Hill, NC, and Greensboro, NC.[9] The trend for Durham is relatively constant but increasing slightly relative to the other utilities that faced similar exogenous demand shocks but did not initiate a system-wide meter replacement program. Turning to the statistics, a difference-in-difference estimate of the relative change in revenue for Durham during the study period for Durham suggests a \$3.8 million increase, a roughly 5% increase relative to pre-2011 levels. This increase in revenue, of course, includes the effect of any changes in consumption due to billing frequency. Given the small sample and inability to control for other confounders, however, this estimate lacks meaningful statistical confidence. Although only suggestive, this suite of graphical tests provides mild evidence that improved meter accuracy did not improve system efficiency.

In addition to this discussion, I interpret the results and provide checks of robustness in the following sections in light of this concern. Several alternative data-driven tests provide a broad foundation of evidence that rule out the likelihood that metering efficiency is the driver of the treatment effect.

3. Empirical strategy

The empirical approach I take in this paper identifies consumption responses to an increase in billing frequency using quasi-experimental techniques. I regard the transition from bimonthly to monthly billing as the treatment, whereas households that, at any point in time, are billed on a bimonthly basis serve as a comparison group.

3.1. Event study

Prior to estimating average effects, I employ an event study that illustrates the time profile of treatment effects to better focus the empirical analysis. The event study plots coefficients from the following regression,

$$\text{Daily use}_{ijt} = \sum_{s=-12}^{s=12} \beta_s 1[\Delta_{ijt} = s]_{ijt} + C_t'\gamma_C + X_i'\gamma_X + \alpha_j + \tau_t + \varepsilon_{ijt} \quad (1)$$

where Daily use$_{ijt}$ is household i's daily water consumption in billing district j at time t; C_t is a vector of weather controls; X_i is a vector of household characteristics; α_j and τ_t are district and time fixed effects; and Δ_{ijt} denotes the distance, in time, from when a billing district was transitioned to monthly billing, with $\Delta_{ijt} = 0$ denoting the period in which monthly billing was enacted. Normalizing our dependent variable to daily consumption accounts for the fact that bimonthly and monthly billing periods account for different durations of usage. Standard errors are clustered at the district level.

The set of β_s coefficients and 95 percent confidence intervals are plotted for a year before/after treatment in Fig. 4. As shown, the time fixed effects appear to control well for seasonality. The pre-treatment trend is not significantly different from zero, and there is an apparent break in the trend at the time of the treatment. This effect is an approximately 1.5 cf/day increase in water consumption, or around a 9% increase relative to a pre-treatment mean of 16 cf/day. This initial increase is sustained for the following twelve months, although its magnitude declines slightly towards the end of the period and the error bars begin to widen. Overall, this exercise provides visual evidence that water consumption increased after the switch to monthly billing. Further, this profile of treatment effects is maintained when Eq. (1) is estimated on a subsample of households proximate to billing district boundaries (see Fig. A.4).

[8] See, e.g., a city council memo included in Online Appendix Fig. 2, https://durhamnc.gov/ArchiveCenter/ViewFile/Item/1203, and https://durhamnc.gov/2983/Water-Meter-Replacement-Automated-Meter-.

[9] I also considered the water utilities of Charlotte, Raleigh, Fayetteville, and Winston-Salem, although all had very different pre-treatment trends in revenue than Durham.

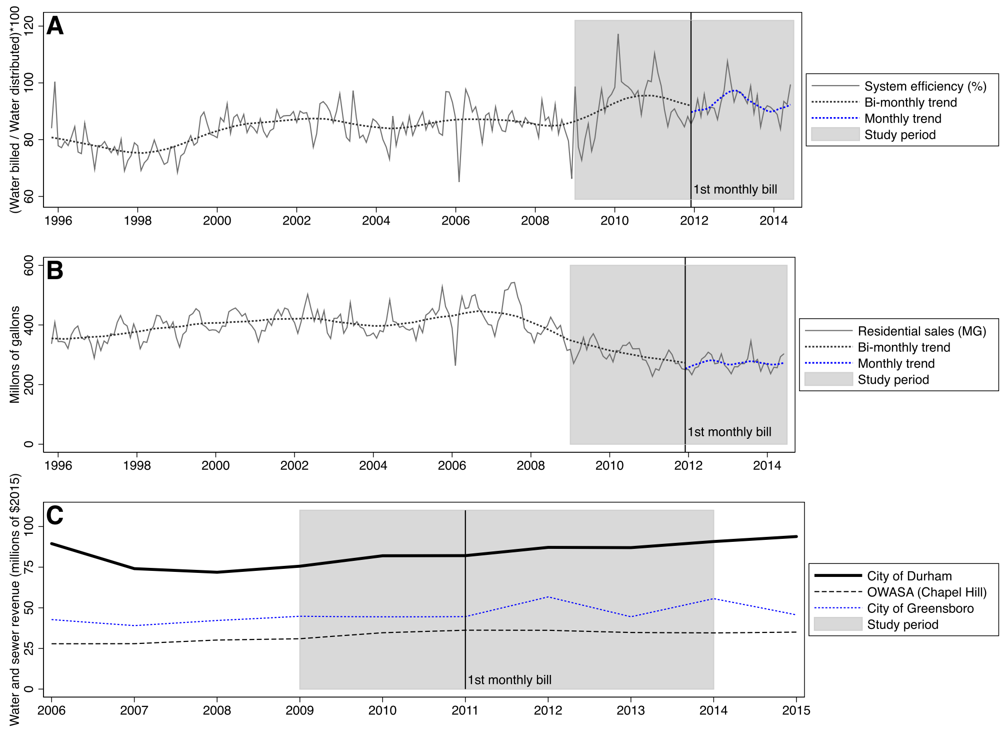


Fig. 3. In Panel A, the quantity of water billed to all accounts divided by the quantity of water treated and distributed (times 100) is presented over time. In Panel B, the total quantity of water billed to residential customers is presented over time. In Panel C, water and sewer revenue for three geographically similar utilities (Durham, Orange Water and Sewer Authority (Chapel Hill), and the City of Greensboro) is presented in 2015 dollars. In all panels, the shaded area is the study period, and the vertical line in December 2011 indicates when the first district transitioned to monthly billing.
Sources: (A)–(B) City of Durham; (C) Comprehensive Annual Financial Reports for each municipality.

Further, new meters were installed in the months leading up to the treatment within a billing district. So, if technical efficiency improvements were driving the treatment effect, we would expect to see an increase in consumption before the transition to monthly billing. In the event study (Fig. 4), there is no discernible change in consumption prior to the switch to monthly billing. Thus, the consumer response appears to be the dominant driver of the treatment effect.

3.2. Average effects and identification

To estimate an average treatment effect (ATE) of the change in billing frequency empirically, the following log-linear equation is specified,

$$\ln\left(w_{ijt}\right) = \beta \mathrm{BF}_{jt} + C_t'\gamma_C + X_i'\gamma_X + \alpha_{ij} + \tau_t + \varepsilon_{ijt}, \tag{2}$$

where w_{ijt} is bimonthly water use for household i in district j at time t; BF_{jt} equals one if district j is billed monthly at time t and zero otherwise; X_i is a vector of household and demographic characteristics described in Table 1;α_{ij} are spatial fixed effects at either the district or household level; and τ_t is a vector of time controls including some combination of time fixed effects, a linear time trend, and seasonal indicators. All else is the same as in Eq. (1). The α_{ij} term absorbs time-invariant unobservable characteristics that may influence water demand at the household or district level, such as preferences for the environment, water-intensive durable goods, and landscape features.

Treatment status is assigned to households if they reside in a billing district that is billed monthly at time t. In this specification, β will capture a causal effect of the change in billing frequency on water consumption, conditional on standard exogeneity assumptions, as well as avoiding the following major threats to identification, which are analyzed subsequently: (1) differential trends

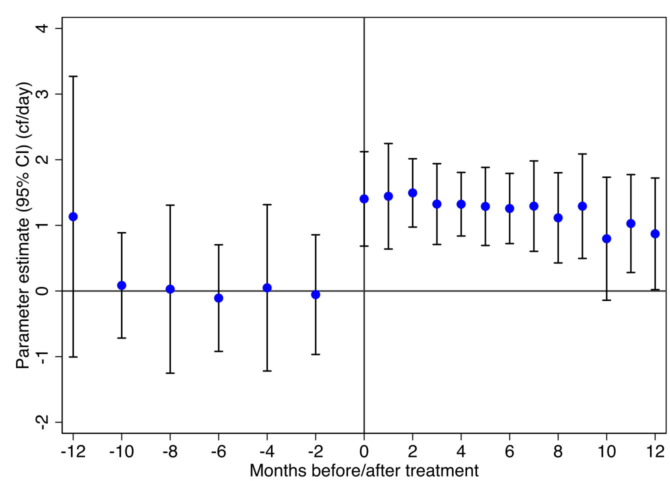


Fig. 4. Event study of monthly billing transition on residential water usage for full sample. Figure presents estimated coefficients and 95% confidence bands for Eq. (1). Standard errors are clustered at the billing district level. Two-month intervals before treatment reflect bi-monthly billing, whereas monthly intervals after treatment reflect monthly billing.

between treatment and comparison groups, (2) selection, and (3) other confounding factors.[10]

To analyze common trends, I first note that treatment and comparison households reside in a relatively small geographic area, and sometimes within the same neighborhood (see Fig. 1). So, there is no reason, a priori, to think that consumption would exhibit different trends, or even different levels, because all households are exposed to common weather, annual rate increases, and other exogenous utility-wide shocks. Further, most comparison households eventually become treatment households within the study. Regardless, I explore pre-treatment mean consumption levels and differences graphically for all households that eventually transitioned to monthly billing relative to households that never transitioned to monthly billing within the study. Fig. 5 compares mean usage for both treatment and comparison groups in each time period. The comparison households (dashed trend line) track the treated households (solid trend line) closely before the first monthly bill in December 2011. I also plot the difference between treatment and comparison consumption against the right axis in Fig. 5, which shows small differences between these groups. There appears to be some fluctuation over time, but no deterministic patterns emerge. The differences also remain small (within 50 ft^3) for all pre-treatment periods.

Second, there are two primary channels through which selection could violate the conditional exogeneity assumption: (1) the water utility must not have selected the order of billing districts based on observable characteristics of the households; and (2) the differences in observable characteristics across treatment and comparison groups must be orthogonal to treatment assignment.[11]

Discussions with utility representatives revealed that the order of monthly billing districts was chosen primarily for geographical convenience. That choice did not take into consideration the billing history of the district, the income base of the neighborhood, or any other financial indicator. Of course, socioeconomic characteristics are not distributed randomly across space, so 'geographical convenience' may indeed be correlated with other things that affect water use. To support this notion, in Table 2 I present statistical differences in observable covariates for each district, in the order they switched to monthly billing, relative to all other districts that had not yet switched at that time. I present two-sided t-tests and Kolmogorov-Smirnov equality-of-distribution tests.[12] For almost all socioeconomic characteristics for all districts there are statistical differences ($p = 0.01$). Notably, there are fewer differences in water use and total bill size among these households, and households nearby district boundaries are more similar.[13]

To put slightly more structure on this problem, in Table 3 I present regression results that predict the likelihood of a billing district to be transitioned from bimonthly to monthly billing based on observable household characteristics. In particular, I consider the first district to transition in a probit model, as well as the sequential transition of routes in an ordered probit framework. I present nominal coefficients and for each variable whether the marginal effect, evaluated at

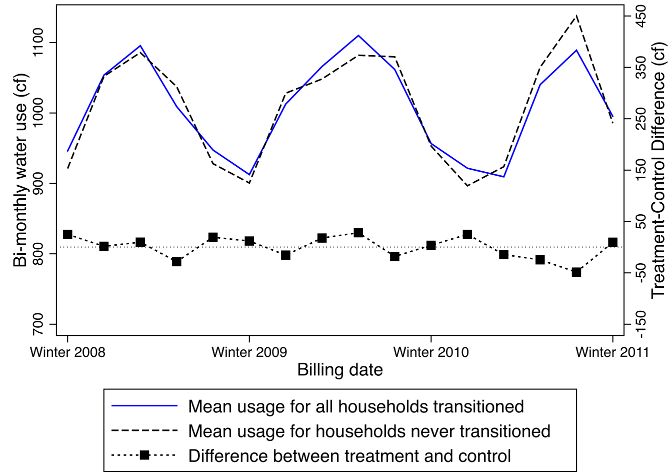


Fig. 5. Mean bimonthly consumption over time for households that transitioned to monthly billing and households that never transitioned to monthly billing.

its mean, is statistically significant at the $p = 0.1$ level.[14] The former suggests that lot size, household size, and the number of bedrooms increased the latent propensity of the pilot group being chosen, while the square footage of the home and number of bathrooms decreased that propensity. There is also evidence that these pilot households have larger summer water use. Importantly, none of the average marginal effects are significantly different from zero. If we restrict the sample to households only within 500 ft of billing district boundaries, thus making the sample more observationally similar by design, we retain statistical differences in the nominal coefficients for the first district's propensity to be chosen for monthly billing. Beyond the pilot group, an ordered probit in columns(4) through (8) in Table 3 suggests that there is only one weakly significant predictor: age of the home. Once I limit the sample to households on either side of billing district boundaries, however, I fail to find any significant coefficients or average marginal effects. This exercise suggests that although the selection of the billing districts to switch to monthly billing is nonrandom, controlling for observable characteristics parametrically (i.e., with observable variables or fixed effects) and by design (i.e., limiting the sample to household within a fixed distance from a shared district boundary) makes the conditional exogeneity of treatment timing more plausible.

Third, the primary confounding factors (i.e., changes to the rate schedule and the installation of new metering technology) are discussed preemptively in preceding section, and all results are interpreted with respect to these concerns.

3.3. Exploiting billing district boundaries

To extend the robustness of the difference-in-difference estimates, I estimate treatment effects within a narrow window on either side of the billing district boundaries. I consider households within 2000, 1000, and 500 ft of district boundaries. I first estimate Eq. (2) in a pooled cross-sectional framework because differencing out unobservables is unnecessary for identification of a local average treatment effect (LATE) in a regression discontinuity framework (Lee and Lemieux, 2010). However, I also estimate the fixed effects model in this framework because there may be unobservables biasing results in the pooled cross-section. The latter specification, dubbed "differe nce-in-discontinuity", takes account

[10] The panel models also require strict exogeneity and conditional independence of the household-specific intercepts. The latter assumption indicates that treatment status cannot be correlated with any unobservable, time-varying factors at the household level.

[11] Additionally, self-selection into (or out of) treatment is unlikely to occur because it would require households to move premises with the intention of sorting along billing district boundaries that are not publicly observable.

[12] I also present results for the same tests using households nearby billing district boundaries in Table A.1.

[13] These tests come with the caveat that sample balance is a function of sample size and, thus, should not be based on statistical significance alone (Wichman and Ferraro, 2017).

[14] For the ordered probit, I consider significance of the average marginal effects for each variable at the mean of each transitioned district.

Table 2
Statistical differences in observable variables by order of transition relative to districts not yet transitioned.

	Order of district transition											
	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th
Home value (in $10,000)	*+	*+	*+	*+	*+	*+	*+	*+	*+	*+	*+	*+
Lot size (acres)	+	*+	*+	+	+	+	*+	*+	+	*+	*+	+
House age (in years)	*+	*+	*+	*+	*+	*+	*+	*+	*+	*+	*+	*+
Square feet (in 100 ft)	*+	*+	+	*+	*+		*+	*+	*+	*+	*+	*+
No. bedrooms	*+	*+	+	*+	*+	*+	*+	+	+	*+	*+	*+
No. bathrooms	*+	*+	*+	*+	*+		*+	*+	*+	*+	*+	+
Pct. renters	*+	*+	+	*+	+	+	*+	+	*+	*+	*+	*+
Pct. white	*+	*+	*+	*+	*+	*+	*+	*+	*+	*+	+	*+
Household size	*+	*+	*+	+	*+	*+	*+	*+	*+	*+	+	*+
Total bill ($)	*+		*		*+					+	+	*+
Pre-treatment use	*+				*+		*+	*	*+	+		*+

Note: This table presents symbolic results for a mean comparison for each listed covariate between the *n*th district to transition to monthly billing relative to all other districts that have not yet transitioned at that time. * indicates a two-sided *t*-test returns a *p*-value < 0.01. + indicates a two-sample Kolmogorov-Smirnov equality-of-distributions test returns a *p*-value < 0.01.

of the differences over time both within households and across treatment/comparison groups, while simultaneously limiting the set of included household observations based on distance from the nearest billing district boundaries (Grembi et al., 2016). The intuition behind the identification of a LATE in this scenario is that as one approaches the billing district boundary households become more similar, thus avoiding potential confounding factors in the difference-in-difference framework. Additionally, because there are comparison households on either side of a given district threshold at some point in time, the LATE identifies the relative difference of a treated household in the same "neighborhood" as a comparison household over time. The main benefit of this approach is that it is robust to changes in unobservable neighborhood characteristics over time, such as local economic growth and development.

To explore the appropriateness of these methods, I plot mean consumption in 40 foot bins within 1000 ft of billing district boundaries for three different time periods—two pre-treatment and one post-treatment. In Panels A and B of Fig. 6, treatment households are those residing in districts that transitioned to monthly billing at some point within the study, whereas comparison households are all other households. Panel A summarizes consumption from January 2009 through January 2010, whereas Panel B summarizes consumption from August 2010 through August 2011. In Panel C, post-treatment consumption is shown for households that transitioned to monthly billing between January 2012 and January 2013, relative to comparison households. As shown, there is a clear discontinuity in the quadratic trend at the billing district boundary for the post-treatment observations.[15] This series of cross-sectional figures provides further graphical evidence of a treatment effect arising from monthly billing at geographic discontinuities, in addition to temporal deviations in the event study.

3.4. Heterogeneous responses to information provision

I conclude the empirical analysis with an examination of heterogeneity in the estimated treatment effects. In particular, I focus on heterogeneity arising from subpopulations that may respond differentially to more frequent information. Formally, I estimate conditional average treatment effects (CATE) similar to Allcott (2011), Ferraro and Miranda (2013), and Abrevaya et al. (2015) by interacting covariates of interest with the treatment indicator. Specifically, I consider indicators for quintiles of each of the following covariates: pre-treatment mean (summer) consumption in 2009 and 2010, assessed home value as a proxy for wealth (Ferraro and Miranda, 2013), lot size as a proxy for irrigation intensity (Mansur and Olmstead, 2012; Renwick and Green, 2000). I restrict the sample to observations beginning in January 2011 for models that explore heterogeneity based on 2009 and 2010 water use. The conditioning variables chosen to estimate CATEs represent either key drivers of residential water demand or serve as a proxy for preferences that may influence demand responses. As such, evidence of heterogeneous treatment effects along established margins allows for probing the mechanism through which consumers may be responding.

Finally, I explore the responsiveness of households who are enrolled in automatic bill payment (ABP) throughout the transition to monthly billing. These households provide two useful functions. First, under the notion that ABP customers are less attentive to changes in prices and, correspondingly, billing frequency (Sexton, 2015), a null treatment effect would instill confidence that the empirical results are identifying a response to the information treatment. Relatedly, if these households do not display a response to the treatment, then it provides additional evidence that the ATE is not confounded by an improvement in efficiency of the metering technology.

4. Empirical results and discussion

In this section, I present results that correspond to the empirical models outlined in the previous section. First, Table 4 presents primary estimates of Eq. (2). In columns (1) through (4), I add additional controls successively and analyze the coefficient on BF, the indicator for billing frequency. In each column, I present coefficients and robust standard errors clustered at the household level, as well as the billing district level, to account for serial correlation (Bertrand et al., 2004). The former accounts for the fact that water consumption is serially correlated within a household, whereas the latter acknowledges that the variation in treatment status arises at the billing district level. For all estimated ATEs, the sign is positive and each coefficient is significant at conventional levels. All other covariates have expected signs and significance. Collectively, the results imply that the transition to monthly billing increased consumer demand between 4 and 9%. The preferred specification, however, is the panel

[15] In Fig. A.5, I present mean household characteristics for treated and comparison households as a function of distance from district boundaries. If there were notable discontinuities in these distributions, it would raise concerns for the regression discontinuity design. As shown, the majority of the structural and demographic characteristics of the homes move relatively smoothly across the district boundaries. There is some deviation at the boundary for lot size (Panel B) and proportion of white residents (Panel H), however these effects are relatively small in magnitude.

Table 3
Predicting the likelihood of billing districts to be transitioned from bimonthly to monthly billing based on observable household characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Probit for first district				Ordered probit for all districts			
		dy/dx sig.?		dy/dx sig.?		dy/dx sig.?		dy/dx sig.?
			<500 ft				<500 ft	
Home value (in \$10,000)	0.008	–	−0.001	–	−0.011	–	−0.002	–
	(0.005)		(0.007)		(0.010)		(0.006)	
Lot size (acres)	0.109*	–	−0.008	–	0.076	–	0.061	–
	(0.061)		(0.128)		(0.137)		(0.198)	
House age (in years)	0.005*	–	0.010***	–	−0.011*	–	−0.008	–
	(0.003)		(0.003)		(0.007)		(0.006)	
Square feet (in 100 ft)	−0.029***	–	−0.028***	–	0.011	–	0.004	–
	(0.006)		(0.008)		(0.010)		(0.008)	
No. bedrooms	0.044**	–	0.078***	–	−0.023	–	−0.074	–
	(0.018)		(0.024)		(0.036)		(0.046)	
No. bathrooms	−0.252***	–	−0.215***	–	0.008	–	0.077	–
	(0.049)		(0.043)		(0.086)		(0.069)	
Pct. renters	−0.163	–	0.266	–	−0.290	–	0.066	–
	(0.172)		(0.167)		(0.305)		(0.362)	
Pct. white	−0.405	–	1.074***	–	0.489	–	0.150	–
	(0.270)		(0.324)		(0.467)		(0.593)	
Household size	0.311***	–	0.022	–	−0.004	–	0.036	–
	(0.101)		(0.079)		(0.130)		(0.123)	
Total bill (\$/100)	−0.157	–	−0.046	–	0.117	–	−0.042	–
	(0.110)		(0.088)		(0.160)		(0.121)	
Pre-treatment use (100 cf)	−0.003	–	−0.018**	–	−0.012	–	−0.003	–
	(0.007)		(0.008)		(0.013)		(0.011)	
Pre-treatment summer use (100 cf)	0.014***	–	0.017***	–	0.002	–	0.002	–
	(0.004)		(0.006)		(0.007)		(0.008)	
Log pseudolikelihood	−10,808.7		−2441.6		−131,294.1		−33,631.7	
Pseudo R-sq.	0.077		0.124		0.020		0.009	
Observations	55,322		14,547		55,322		14,547	

Note: Robust standard errors in parentheses clustered at the district level. Nominal regression coefficients are presented in columns (1), (3), (5), and (7); significance (at $p = 0.10$) of average marginal effects for each model evaluated at the mean of each variable (within each district) are presented in columns (2), (4), (6), and (8). The first 4 columns predict the likelihood of the first district being chosen to transition from monthly billing. The last 4 columns predict the order in which billing districts were transitioned from bimonthly to monthly billing. The sample is restricted to households within 500 ft of a billing district in columns (3)–(4) and (7)–(8).
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

model, which estimates the ATE as a 4.6 percent increase in consumption in response to the increase in billing frequency.[16] Notably, the progressive decrease in the ATE estimate suggests that the panel framework with the inclusion of a rich set of time controls reduces the positive impact of unobserved heterogeneity.

In terms of economic significance, this estimate is approximately one-half of the magnitude of water reductions called for during moderate to severe droughts in North Carolina (Wichman et al., 2016). Additionally, my point estimate of 4.6% contrasts with the results of Ferraro and Price (2013), who find that strong social comparisons *reduce* water consumption by approximately 5.6%—a similar magnitude in the opposite direction. Brent et al. (2015) also find a roughly 5 percent reduction in response to social comparisons for two water utilities in their sample, with substantial heterogeneity in the treatment effects. Accordingly, although a 5 percent increase in consumption in response to more frequent billing may appear large in magnitude, social comparisons and restrictions can affect consumption by approximately the same magnitude and there are arguably fewer margins on which to reduce consumption than there are to increase consumption.

To examine whether there are unobservable changes in neighborhood characteristics that may bias the preferred ATE, I present regression discontinuity (RD) estimates (for the pooled cross-section) and difference-in-discontinuity (for the panel) estimates in Table 5. In Panel A of Table 5, pooled cross-section models are estimated for the set of households within 2000, 1000, and 500 ft of billing district boundaries. The LATE remains stable as the window shrinks, and is nearly identical to that of the ATE in Table 4.[17] Further, I present results from the preferred fixed effects model, and similarly restrict the sample to the same households within 2000, 1000, and 500 ft of billing district boundaries in Panel B of Table 5. The estimates decrease monotonically moving from columns(1) to (3), while standard errors increase, but the results remain statistically similar under the more conservative standard errors. The LATE estimate within 500 ft of billing district boundaries indicates a 3.5 percent effect of billing frequency on water demand that is robust to unobservable time-varying factors at the neighborhood level. This result suggests that controlling for neighborhood unobservables in the boundary discontinuity models accounts for an additional one percentage point decrease in the local treatment effect relative to the ATE in Table 4.

[16] For this estimate, a block bootstrap of t-statistics (with 200 draws) was performed at both the household and billing district levels to account for serial correlation with a small number of treatment districts, as suggested by Bertrand et al. (2004). Inference on the coefficient of interest does not change. Results are available upon request.

[17] The inclusion of a flexible polynomial for distance from the boundary cut-off (up to degree 3) has no effect on the treatment estimate or the fit of the model. These results are available upon request.

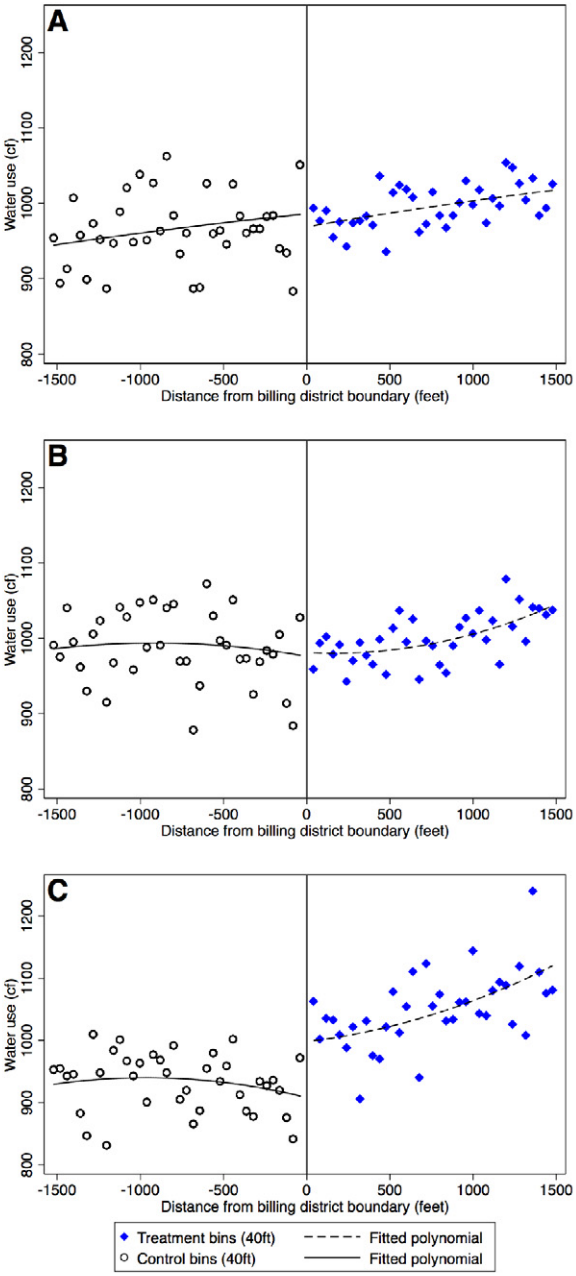


Fig. 6. Mean consumption in 40-foot bins as a function of distance from district boundaries for consumption during different calendar years. Panel A presents pre-treatment consumption in 2009. Panel B presents pre-treatment consumption in 2010/2011. Panel C presents post-treatment consumption in 2012. Treated households are those that were transitioned to monthly billing within the study, while comparison households are all other districts.

Table 4
Primary difference-in-difference regression results.

Dependent variable:				
$\ln(w_{ijt})$	(1)	(2)	(3)	(4)
BF	0.090	0.066	0.050	0.046
	(0.006)***	(0.007)***	(0.005)***	(0.005)***
	[0.024]***	[0.023]**	[0.021]**	[0.017]**
Rain	−0.003	−0.003	−0.003	−0.004
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
	[0.001]**	[0.001]**	[0.001]**	[0.001]***
Max. temp.	0.004	0.005	0.005	0.005
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
	[0.000]***	[0.001]***	[0.001]***	[0.001]***
Home value (in $10,000)	0.003	0.003	0.003	
	(0.001)***	(0.001)***	(0.001)***	
	[0.001]**	[0.001]**	[0.001]***	
Lot size (acres)	0.021	0.021	0.025	
	(0.009)**	(0.009)**	(0.009)***	
	[0.014]	[0.014]	[0.014]	
Square feet (in 100 ft)	0.007	0.007	0.007	
	(0.001)***	(0.001)***	(0.001)***	
	[0.001]***	[0.001]***	[0.001]***	
Pct. renters	0.013	0.013	0.001	
	(0.018)	(0.018)	(0.019)	
	[0.033]	[0.034]	[0.031]	
Pct. white	0.057	0.058	0.028	
	(0.014)***	(0.014)***	(0.016)*	
	[0.031]*	[0.032]*	[0.026]	
House age (in years)	−0.001	−0.001	−0.001	
	(0.000)***	(0.000)***	(0.000)***	
	[0.001]**	[0.001]**	[0.001]**	
No. residents	0.212	0.213	0.211	
	(0.008)***	(0.008)***	(0.009)***	
	[0.015]***	[0.015]***	[0.016]***	
No. bathrooms	0.054	0.053	0.049	
	(0.008)***	(0.008)***	(0.008)***	
	[0.013]***	[0.012]***	[0.012]***	
No. bedrooms	0.093	0.093	0.094	
	(0.007)***	(0.007)***	(0.007)***	
	[0.011]***	[0.011]***	[0.011]***	
Observations	1,684,025	1,684,025	1,684,025	1,694,859
Number of households				58,965
Adj. R-sq.	0.039	0.040	0.042	0.006
Additional controls:				
Time trend	Y	–	–	–
Season fixed effects	Y	–	–	–
Month-of-sample fixed effects	–	Y	Y	Y
Billing district fixed effects	–	–	Y	–
Household fixed effects	–	–	–	Y

Note: Robust standard errors clustered at the household level in parentheses. Robust standard errors clustered at the billing district in square brackets. Estimation results in (1)–(4) are from OLS regressions with the log consumption as the dependent variable; results in (5) are from a linear fixed effects model with log consumption as the dependent variable. Constant term omitted.

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

4.1. Heterogeneous treatment effects

I estimate heterogeneous treatment effects for two reasons—first, to explore any policy relevant heterogeneity in response to information provision, and second, to examine the mechanism through which billing frequency affects behavior.

First, I examine the CATE of baseline water consumption. I create indicators for households that reside in each quintile of the consumption distribution for 2009 and 2010 (as well as the distribution of 2009 and 2010 summer consumption) and interact each of these with the treatment indicator. These results are presented graphically in Fig. 7. As shown in Panel A, there is significant heterogeneity in responsiveness to billing frequency across the consumption distribution. I find a strong decreasing trend in the CATE as pre-treatment consumption increases. Households in the lowest 20th percentile of water consumption exhibit the largest CATE, while households in the highest 20th percentile exhibit a negative response to billing frequency. A similar relationship is observed in Panel B for the distribution of summer consumption as well, though CATE estimates remain positive for all subgroups.

These relationships are consistent with Mansur and Olmstead (2012), Wichman et al. (2016), and Klaiber et al. (2014), who show that low-use households are more sensitive to price changes.

Table 5
Local average treatment effect estimates.

Dependent variable:	(1)	(2)	(3)
$\ln(w_{ijt})$	Within 2000 ft	Within 1000 ft	Within 500 ft
Panel A: pooled cross-section regression-discontinuity results			
BF	0.049	0.044	0.047
	(0.005)***	(0.008)***	(0.011)***
	[0.021]**	[0.022]*	[0.024]*
Observations	1,334,147	812,965	436,377
Adj. R-sq.	0.040	0.039	0.037
Panel B: fixed effects difference-in-discontinuity results			
BF	0.045	0.040	0.035
	(0.006)***	(0.007)***	(0.010)***
	[0.018]**	[0.018]**	[0.021]
Number of households	46,645	28,632	15,462
Observations	1,341,595	816,643	437,730
Within R-sq.	0.006	0.006	0.005

Note: Robust standard errors clustered at the household level in parentheses. Robust standard errors clustered at the billing district in square brackets. Results are from local linear (panel) estimators with log consumption as the dependent variable. Each column represents a limited sample of households within 2000, 1000, and 500ftof a billing district boundary, respectively. In Panel A, all models include full demographic covariates, weather variables, time effects, and billing district fixed effects. In Panel B, all models include weather variables, time effects, and household fixed effects.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

However, the negative effect observed in Panel A suggests that informative interventions work differently for different subpopulations. The implications that arise from these effects on baseline usage suggest that lower users of water increase consumption by more (in percentage terms) than large users of water. Upon receiving monthly bills, low water users may realize that water is less expensive than they previously thought and increase consumption accordingly. Additionally, the within-sample heterogeneity indicating both a positive and a negative response to the same information treatment emphasizes the importance of reconsidering the mechanism through which consumers assimilate and use information in intermittent choice settings.

Additionally in Fig. 7, I consider the assessed value of a home as a proxy for a consumer's wealth, as well as lot size as a proxy for preferences for outdoor water use. As shown in Panel C, households in the highest 20th percentile of "wealth" exhibit no significant response to the treatment. High-income households generally have a greater willingness-to-pay for water and, thus, are likely to be less sensitive about changes to their water bill. Because low-income households are more sensitive to price (Mansur and Olmstead, 2012; Wichman et al., 2016), the heterogeneity among income classes is consistent with the notion that consumers are responding to the change in frequency similarly as they would to a change in price.

In Panel D of Fig. 7, I present the CATEs for quintiles of a household's lot size as a proxy for outdoor water use preferences (Renwick and Archibald, 1998; Mansur and Olmstead, 2012). As shown, there is a decreasing trend in the estimated CATE as lot size increases, though all estimates remain positive and significant. This relationship can be interpreted similarly to the effect of summer water use—more frequent reminders might attenuate the effect for large users of water, while low users of water may their usage more in response to the same information.

Collectively, these results suggest that there is substantial heterogeneity in response to treatment and, for large baseline consumers, more frequent provision of consumption information can incur a negative response. For the majority of other conditioning covariates, a positive treatment effect is the predominant result despite within-sample heterogeneity. The results are consistent with several stylized facts about water consumption in response to changes in price and non-pecuniary instruments, suggesting that price misperception may be driving the ATE, particularly for low-use households. This conclusion, however, is speculative. Further research on the mechanism driving these results is needed.

4.2. Robustness

To assess the meter accuracy argument from a different angle, I examine the effect of automatic bill payment on the primary

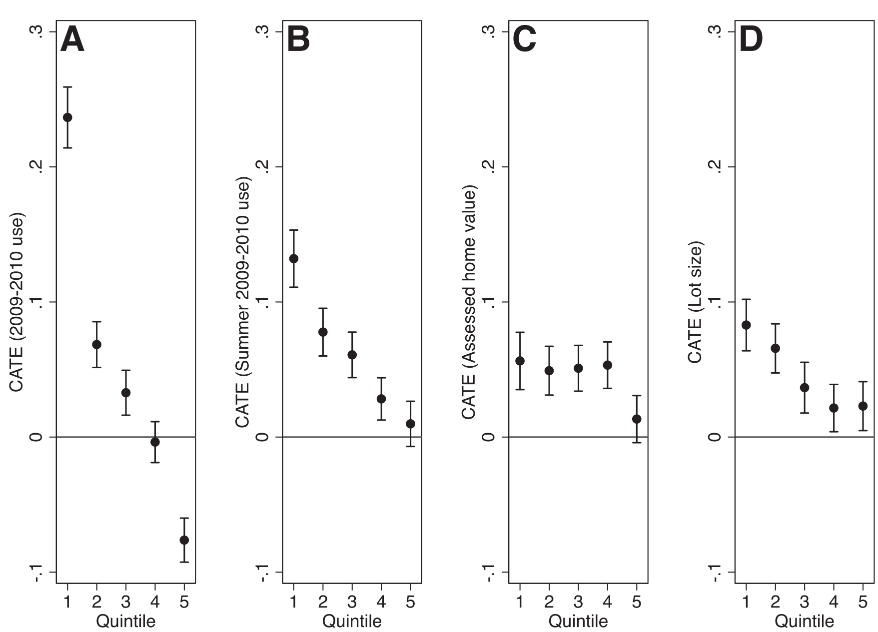


Fig. 7. Conditional average treatment effects for: (A) pre-treatment baseline consumption, (B) pre-treatment summer consumption, (C) assessed value of the home, and (D) lot size in acres. The figure depicts estimated coefficients (dots) and 95 percent confidence intervals (whiskers).

Table 6
Heterogeneous treatment effects among automatic bill payment customers.

Dependent variable:	(1)	(2)	(3)	(4)
$\ln(w_{ijt})$	Full sample	Within 2000 ft	Within 1000 ft	Within 500 ft
BF	0.049	0.048	0.042	0.038
	(0.005)***	(0.006)***	(0.008)***	(0.011)***
	[0.018]**	[0.019]**	[0.018]**	[0.022]
BF × ABP	−0.064	−0.061	−0.053	−0.051
	(0.015)***	(0.017)***	(0.023)**	(0.034)
	[0.020]***	[0.020]***	[0.018]***	[0.022]**
Total effect for ABP customers	−0.015	−0.014	−0.010	−0.013
	(0.015)	(0.017)	(0.022)	(0.033)
	[0.021]	[0.022]	[0.024]	[0.018]

Note: Robust standard errors clustered at the household level in parentheses. Robust standard errors clustered at the billing district in square brackets. Coefficients correspond to interactions with BF from linear panel data estimators with log consumption as the dependent variable and household and time fixed effects. All models include weather covariates and household and time fixed effects.
*** $p < 0.01$.
** $p < 0.05$.

empirical results. In Table 6, I show that the effect of an interaction of the treatment indicator and automatic bill payment (ABP) works in the opposite direction from the treatment effect. This provides an empirical test for whether customers who are inattentive to prices and water bills observe the change in billing frequency (Sexton, 2015). The net response of customers enrolled in ABP throughout the transition to monthly billing is negative but not statistically different from zero—indicating a null response among this subgroup of customers. As this result pertains to rationally inattentive consumers (Sallee, 2014), those who enrolled in automatic bill payment made an active choice to be inattentive in this setting, whereas the other customers did not. To the extent that ABP proxies for rational inattentiveness, the divergence in behavior of these types of consumers suggests that the average non-ABP consumer is aware of the change in billing frequency and adjusts her behavior accordingly. This result instills confidence that the preferred specifications are indeed identifying a response to the change in billing frequency. The lack of a positive effect also lends credence to the notion that the preferred ATE in previous models is not an artifact of mechanical efficiency of the new meters. Due to selection into ABP, however, these results should be interpreted with caution.

As a final piece of evidence against the meter accuracy argument. I take advantage of a peculiarity in the roll out of monthly billing for a single district. According to Durham, District 11 did not transition directly to monthly billing after the installation of new meters due to an increase in the number of accounts in that district. It was thus switched to monthly billing at the end of the schedule, with its first monthly bill mailed on May 15, 2014. The district that was switched to monthly billing prior to this was on April 18, 2014.[18] By restricting the sample to these two districts and estimating the treatment effect from Eq. (2), we can isolate the demand response from the confounding change in meters. Results are presented in Table 7. As shown, the estimated treatment effects are virtually identical to the primary effects for the full sample and for households within 500 ft of district boundaries.

5. Conceptual framework, welfare, and alternative mechanisms

This paper, so far, has provided strong evidence that water customers increased consumption in response to more frequent billing. In this section, I attempt to shed light on the question: Why? I develop two complementary models of consumer behavior—misperceived price and misperceived quantity—in which a consumer who receives more frequent information may choose to consume more or less water since she has a more accurate perception of water prices or her consumption in each billing period. Finkelstein (2009), Li et al. (2014), and Sexton (2015) find that consumers tend to misperceive (changes in) prices or taxes that are not salient. Thus, more frequent billing is a plausible mechanism to increase the salience of water prices and consumption. Consequently, if consumers are making more informed consumption choices with more frequent billing, there are calculable welfare gains from these actions. I develop transparent welfare estimates for behavior commensurate with both price and quantity misperception.

5.1. Price misperception

Consider a consumer with utility over water consumption (w) and a composite good (x):

$$u = x + aw^{1/\gamma+1} \tag{3}$$

where utility is quasilinear in x and preferences over w exhibit constant elasticity of demand. The consumer observes the budget constraint $M = x + \tilde{p}w$, where her wealth (M) equals expenditures on x with its price normalized to unity and her perceived expendi-

Table 7
Confounding change in metering technology.

Dependent variable:	(1)	(2)
$\ln(w_{ijt})$	Full sample	Within 500 ft
BF	0.040	0.046
	(0.015)***	(0.032)
	[0.018]*	[0.022]*

Note: Robust standard errors clustered at the household level in parentheses. Robust standard errors clustered at the billing district in square brackets. Sample is restricted to two billing districts as described in the text. All models include weather covariates and household and time fixed effects.
*** $p < 0.01$.
* $p < 0.1$.

[18] Unfortunately, information on the timing of meter replacement is not available.

tures on water. The budget constraint is satisfied with equality since any residual consumption is allocated to the composite good. The price a consumer perceives for her consumption of w is defined as $\tilde{p} = \theta p$ where p is the true price and θ is a perception parameter that specifies the degree to which she over- or underestimates the true price, which is defined as a function of billing frequency for this analysis. A consumer with perfect information is represented by $\theta = 1$. While previous research bounds this parameter from above at unity, I allow for misperceptions to deviate above and below the true price since there is no good theoretical foundation for why an inattentive consumer would always under-perceive prices.

As empirical support, the average versus marginal price debate (e.g., Ito, 2014; Wichman, 2014; Nataraj and Hanemann, 2011) provides strong evidence that consumers may not perceive prices correctly. Specifically, if a water bill includes fixed services fees, then the average price a consumer faces may be mechanically larger than the marginal price of water consumption. Within this context, it is easy to argue that consumers over-perceive the true price of water.

As a useful, and plausible, assumption, I restrict information to be weakly welfare improving:

Assumption 1. More frequent billing information can never make anyone worse off.

That information is welfare improving simply means that consumers can always choose to be ignorant, and that there are no cognitive costs to ignoring new information. There may, in fact, be cognitive costs to processing this information, but the consumer will only undertake such an action if its benefits exceed costs at the margin. For $\theta > 1$, increases in BF exhibit a negative effect on θ such that increasing billing frequency reduces the distortion between the true price and perceived price. However, I do not restrict θ to be greater than one. For $\theta < 1$, the predicted response to changes in BF is reversed, allowing for increases in information to decrease the wedge between the true price and the perceived price regardless of the direction of price misperception. Because θ is unknown to the researcher, it is unclear a priori whether a consumer perceives a price that is higher or lower than the true price p. Hence, the demand response to an increase in the frequency of billing information is ambiguous and depends on the initial degree of price misperception. Further, the direction of the demand response ($\partial w/\partial \mathrm{BF}$) reveals consumers' initial misperceptions of price.

5.1.1. Welfare effects from price misperception

Since the misperception of prices from infrequent billing drives a wedge between the actions of a perfectly informed consumer and an inattentive consumer, there are welfare gains from information provision. Consider an increase in the frequency of information, represented by θ_0 to θ_1, that corresponds to a change in perceived price from $\tilde{p}_0$ to $\tilde{p}_1$. Assumption 1 allows us to remain agnostic about the initial misperception of price since a positive demand response to an increase in information implies that consumers display $\theta > 1$, as well as the converse. Under the notion that perceived price tends towards the true price with an increase in billing frequency, I make the following assumption as a useful benchmark:

Assumption 2. Under the more frequent billing regime, ex post perceived prices are proportional to the true price.

While strong, this assumption allows the researcher to back out perceived prices from observable changes in demand. Assumption 2 is reflective of the pure nudge assertion in Allcott and Taubinsky (2015) and Chetty et al. (2009), in which the informational treatment is fully corrective; ex post proportionality to the true price weakens this assumption. With respect to real-time feedback through smart-metering technology, it is possible that consumers do in fact know the marginal price they are paying at any point within the billing cycle. Strong and Goemans (2014) and Kahn and Wolak (2013), for example, show that consumers tend to optimize "better" under block rate structures when provided with real-time consumption feedback and educational treatments on how their bill is calculated, respectively. In any case, monthly billing provides an opportunity for price misperception to prevail after the change in billing frequency.

To derive an empirically tractable measure of θ, we can define the constant elasticity of demand with respect to perceived price as $\eta^P = \%\Delta w(\tilde{p})/\%\Delta\tilde{p}$. The percent change in perceived price can be used to obtain an empirical measure of the change in the perception parameter by observing a change in quantity demanded. In particular, we can write, $\%\Delta\tilde{p} = \tilde{p_0}/\tilde{p_1} - 1 = \theta_0 p/\theta_1 p - 1 = \%\Delta\theta$, since the market price does not change. Combining this expression with the definition of η^P, rearranging, and multiplying through by $\tilde{p_1}$ provides,

$$\Delta\tilde{p} = \Delta\theta\tilde{p_1} = \left(\frac{\%\Delta w(\tilde{p})}{\eta^P}\right)\tilde{p_1}, \tag{4}$$

where $\tilde{p_1}$ is the ex post perceived price that is proportional to p, that is $\tilde{p_1} = \alpha p$ with α being the degree of ex post misperception via Assumption 2. Eq. (4) states that a change in perceived price is simply a function of the market price, the perceived price elasticity, and the corresponding demand response. This expression is convenient since η^P can be estimated or inferred from other studies and the change in water consumption can be estimated using quasi-experimental techniques. Since Eq. (4) describes the change in perceptions of price due to a change in an unobserved parameter, I utilize Assumption 2 to provide a reference point (i.e., the observable price) to obtain a price-equivalent, in dollars per unit of water consumption, of the consumer's perceived price.

Using this measure of the consumer's ex post perceived price, consumer surplus can be calculated by integrating the demand function between the initial price perceived, $\tilde{p_0}$, and the price perceived after the change in billing frequency, $\tilde{p_1}$,

$$\Delta CS^P = \int_{\tilde{p_1}}^{\tilde{p_0}} w(\tilde{p})\mathrm{d}\tilde{p} \cong -\frac{1}{2}\Delta\theta\tilde{p_1}\frac{\partial w}{\partial \mathrm{BF}}, \tag{5}$$

which is analogous to the Harberger (1964) approximation for deadweight loss since the data in the experiment are not sufficient to estimate a true demand function. Under the assumptions made so far, the treatment effect ($\partial w/\partial \mathrm{BF}$) and the perceived price elasticity of demand (η^P) serve as sufficient statistics for calculating changes in welfare due to a change in billing frequency.

5.2. Billing frequency and quantity misperception

In the previous subsection, I motivated a model in which changes in the frequency of billing induce better price perception. Because a water utility bill contains both price and quantity information, a consumer could be fully aware of the market price, but uncertain about her quantity consumed each period. This precise sort of quantity uncertainty for water consumption is documented in Strong and Goemans (2014). The uncertainty considered within this mechanism is interpreted as quantity salience in the sense that a water customer has imprecise knowledge and imperfect control over her water use within a billing period. In this framework, a consumer who receives more frequent information about her consumption habits may alter her water use since she has a better sense of how much water, and for what purpose, she is using in each billing period.

Consider initial consumer utility provided in Eq. (3), assuming perfect information about prices, augmented by a quantity perception parameter (λ),

$$u = x + a(\lambda w)^{1/\gamma+1} \tag{6}$$

where λ, a function of BF, is a parameter that scales quantity demanded within a billing cycle similar to the perceived price parameter introduced in the previous subsection. A consumer maximizes Eq. (6) subject to a budget constraint, $M = x + \lambda pw$. In contrast to imperfect price perception, imperfect quantity perception affects consumer utility by scaling consumption by λ in both the utility function as well as the budget constraint through its effect on anticipated water expenditures.

A consumer's perceived demand can be written as

$$\tilde{w}(p) = Ap^{\frac{1-\gamma}{\gamma}}\lambda^{\frac{1-2\gamma}{\gamma}} = \lambda^{\eta^Q-1}w(p) \tag{7}$$

where $A \equiv \left(\frac{1+\gamma}{a}\right)^{\frac{1-\gamma}{\gamma}}$, $\eta^Q = (1-\gamma)/\gamma$ is the price elasticity of perceived demand, and $w(p)$ is consumer demand under perfect information. A derivation of demand functions under quantity misperception is presented in Appendix B. Eq. (7) illustrates that demand is scaled conveniently by the quantity misperception parameter.

By Assumption 1, we can interpret the marginal effects of billing frequency on perceived demand, $\partial\tilde{w}(p)/\partial\text{BF}$, similarly to that of the price parameter in that increasing quantity information allows a consumer to predict consumption closer to her true consumption. The implication here, then, is that the marginal effect of changes in billing frequency on consumer demand depends critically on the initial perception of quantities. Intuitively, this result implies that increasing the precision of the information with which consumers make decisions decreases the wedge between perceived quantity and the actual quantity consumed.

5.2.1. *Welfare effects from quantity misperception*

Similar to price misperception, quantity misperception allows for a divergence in the behavior of a consumer with perfect information and a consumer who misperceives her consumption. Thus, any policy that decreases the wedge between these two types of consumers will provide welfare gains to the consumer. An analytical calculation for this welfare change is obtained in a similar fashion to that of price misperception, though it is not necessary to estimate the change in λ empirically. Since λ scales consumption multiplicatively, and we observe the demand response directly in the experiment, all of the information necessary to calculate welfare is revealed through observable consumption. Effectively, we observe the movement in quantity demanded, trace out the demand function for a given price elasticity of perceived demand, and recover the prices that reflect different points of consumption along the demand curve.

Within the experiment, we observe an increase in information that moves a customer from a bimonthly billing regime to a monthly billing regime. To provide a calculable estimate of welfare changes from these changes in information, we can write the price elasticity of perceived demand as a function of the demand response and prices, $\eta^Q = \%\Delta\tilde{w}(p)/\%\Delta p$. Because we do not observe price changes, we can recover price changes that correspond to perceived quantity changes by rearranging the definition of η^Q and multiplying through by p,

$$\Delta p = \left(\frac{\%\Delta\tilde{w}(p)}{\eta^Q}\right)p. \tag{8}$$

Because the change in quantity demanded is observed in the experiment and η^Q can be estimated or inferred from other studies, Eq. (8) provides a price change that corresponds to the observed change in consumption attributable to changes in billing frequency under a quantity misperception mechanism. Within this framework, we can use the observable demand response to changes in billing frequency ($\partial\tilde{w}/\partial\text{BF}$) and the price elasticity (η^Q) to calculate consumer surplus in response to the change in billing frequency,

$$\Delta CS^Q = \int_{p_1}^{p_0}\tilde{w}(p)\mathrm{d}p = \lambda^{\eta^Q-1}\int_{p_1}^{p_0}w(p)\mathrm{d}p \cong -\frac{1}{2}\Delta p\frac{\partial\tilde{w}}{\partial\text{BF}}. \tag{9}$$

Thus, Eq. (9) provides an analytical formula from which we can use quasi-experimental estimates to calculate changes in economic welfare.

Notably, for a common price elasticity (i.e., $\eta^Q = \eta^P$) and perfect ex post price perception, the welfare changes in both the price (ΔCS^P) and quantity (ΔCS^Q) misperception scenarios are equivalent (see Wichman, 2015 for further discussion). Thus, under these conditions, the mechanism through which consumers respond to changes in information provision is immaterial for the calculation of welfare.

5.3. *Welfare estimates from price and quantity misperception*

Prior to interpreting the welfare calculations, I make several important caveats. First, the welfare analysis abstracts completely from economic costs and benefits borne by the water supplier and focuses entirely on changes in consumer surplus.[19] Second, there are many alternative mechanisms that align with empirical results and, accordingly, may produce different welfare effects. Finally, the preceding theoretical model was based on the notion that more frequent information nudges consumers in the direction of optimizing perfectly. My welfare analysis assumes that consumers respond to average prices under block rates (Wichman, 2014; Ito, 2014), as opposed to marginal prices in each tier of the rate structure in a discrete-continuous choice framework (Hewitt and Hanemann, 1995). Thus, the welfare estimates presented below are predicated on the notion that even with better information, consumers still use heuristics that minimize costs of effort to make consumptive decisions (Shin, 1985). As such, the welfare estimates are accurate to the degree that the average consumer bases water use on average price. These estimates, however, will mask any benefits (costs) arising from inattention to the utility's rate structure itself (Shin, 1985; Ito, 2014).

For the welfare analysis, I use results in line with the preferred ATE estimate. The change in consumption considered is a 4.5 per-

[19] Anecdotally, the switch to monthly billing benefited the water utility by reducing administrative costs through more efficient meter reading, earlier leak detection (i.e., less "non-revenue" water lost), and fewer delinquent payments, which outweighed the direct costs of printing and mailing twice as many water bills. So, my welfare estimates are likely more conservative than that of a comprehensive analysis.

Table 8
Changes in consumer surplus from an increase in billing frequency under different modeling assumptions.

Price elasticity (η)		−0.2	−0.3	−0.4	−0.5
Panel A: price mechanism for a 4.5% increase in water consumption					
$\tilde{p}_1 = 100\% \times p$	$\Delta\theta p$ ($/ccf)	−1.93	−1.29	−0.97	−0.77
	Δ consumer surplus ($)	0.43	0.28	0.21	0.17
	% monthly bill	1.01%	0.68%	0.51%	0.41%
$\tilde{p}_1 = 110\% \times p$	$\Delta\theta p$ ($/ccf)	−2.13	−1.42	−1.06	−0.85
	Δ consumer surplus ($)	0.47	0.31	0.23	0.19
	% monthly bill	1.11%	0.74%	0.56%	0.45%
$\tilde{p}_1 = 125\% \times p$	$\Delta\theta p$ ($/ccf)	−2.42	−1.61	−1.21	−0.97
	Δ consumer surplus ($)	0.53	0.35	0.27	0.21
	% monthly bill	1.27%	0.84%	0.63%	0.51%
$\tilde{p}_1 = 150\% \times p$	$\Delta\theta p$ ($/ccf)	−2.90	−1.93	−1.45	−1.16
	Δ consumer surplus ($)	0.64	0.43	0.32	0.26
	% monthly bill	1.52%	1.01%	0.76%	0.61%
Panel B: quantity mechanism for a 4.5% increase in water consumption					
$p(\lambda) = p$	Δp ($/ccf)	−1.93	−1.29	−0.97	−0.77
	Δ Consumer surplus ($)	0.43	0.28	0.21	0.17
	% monthly bill	1.01%	0.68%	0.51%	0.41%

Notes: $\tilde{p}_1$ is the baseline price after the change in billing frequency. The first row in Panel A reflects the pure nudge assumption in that perceived price is equated with the true price with increased billing frequency. Subsequent rows relax this assumption by allowing for misperception to be proportional to the true price. $\Delta\theta p$ is the change in price that reflects the demand response to billing frequency under the price mechanism for different assumptions on price elasticities. Panel B presents the analogous measurements for the quantity mechanism. Δp is the change in the true price corresponding to the demand response under a quantity mechanism. Consumer surplus is approximated according to Eqs. (5) and (9), respectively, for the relevant change in consumption. The true price used for all calculations is $8.60/ccf, which is the sample mean average price for households that never transitioned to monthly billing.

cent increase in water use in response to the change in billing frequency. Welfare estimates are calculated for a common range of short-run elasticities for residential water demand found in the literature that imply that residential water demand is generally inelastic, with modal estimates lying between −0.5 and −0.2 (Espey et al., 1997; Arbués et al., 2003). Additionally, I assume that the price relevant for consumer decision-making under block rate structures is the ex post average price, which is $8.60 per hundred cubic feet in the sample for households that never transitioned to monthly billing.

In Table 8, I present welfare statistics for a range of elasticities under different modeling assumptions. Particularly, I let the ex post perceived price vary from 100% to 150% of the true price. Allowing $\tilde{p_1} = p$ reflects the pure nudge assumption, while $\tilde{p_1} > p$ relaxes this assertion in line with Assumption 2. Although the price elasticity may indeed be different for consumers responding to perceived price and the true price, there is not sufficient variation in prices within the natural experiment to estimate these elasticities directly. As such, I present changes in consumer surplus as a function of the perceived price elasticity. Under the pure nudge assumption ($\tilde{p_1} = p$) in the price misperception model—or the quantity misperception model—with a price elasticity of −0.3, the welfare gain from increased information provision is approximately $0.28 per month. This amount reflects a $1.29 decrease in the perceived price of water and approximately 0.68% of the average consumer's monthly bill. Taken collectively, a conservative estimate of the change from bimonthly to monthly billing for Durham, NC, water customers resulted in an approximately $300,000 per annum increase in consumer welfare (that is, $5.11 per household).[20] This estimate of consumer welfare can be contrasted with expected costs of around *negative* $500,000 per year for the switch from bimonthly to monthly billing (see Online Appendix Fig. 2). That is, under the assumptions in this section, this welfare improvement came at a negative cost before accounting for any revenue impact borne by the utility. From a conservation perspective, however, the change in billing frequency resulted in an aggregate increase in water consumption of roughly 46 million ft^3 per year. This increase in consumption is roughly equivalent to the amount of water needed to fill 520 Olympic-size swimming pools.[21]

5.4. Alternative mechanisms

While the discussion thus far considered only price or quantity misperception in intermittent choice settings, it is possible that a number of other mechanisms could influence consumer behavior in response to a change in billing frequency.

A water utility bill contains both price and quantity information, as well as the total billed amount. If a consumer responds not to the price or quantity, but simply to the total bill, then the welfare framework put forth previously is invalid. Because the change in billing frequency lowered the total billed amounts mechanically, consumers might indeed respond to this initial 'scale effect' and this would work in the same direction as the treatment effects identified in this paper. In Fig. 4, there does appear to be a significant initial response that begins to wear off over time. Focusing on a long-term effect might shed more light on this issue but it is beyond the scope of the present analysis.

Additionally, the change in the absolute magnitude of the total bill could produce an 'expenditure effect'. That is, because total bills are smaller, customers might change consumption because they feel as if water is cheaper relative to other regular budgeted expenditures, such as monthly electricity and natural gas consumption. Wichman (2015) explores this directly in a demand system

[20] This back-of-the-envelope statistic is obtained by multiplying the average customer's welfare gain by the approximate number of households in the sample (60,000) by twelve to obtain an annual equivalent.

[21] The volume of an Olympic-size swimming pool is approximately 88,000 ft^3.

that can produce relatively larger price elasticities for a bimonthly billing scenario simply because the expenditure share of water in a bimonthly billing regime is larger. This mechanism, however, is notionally similar to one in which consumers misperceive water prices albeit for a different reason. As such, I contend that the policy implications of such a mechanism are consistent with the misperceived price model.

Another conceptual mechanism is that more frequent billing acts as a reminder to keep water use more on the 'top of the mind'. This framework is in line with Gilbert and Graff Zivin (2014), for example, who show that an electricity bill improves salience about consumption at the time it is received. The predictions from such a model, however, seem difficult to reconcile with the empirical results in this analysis since I find an increase in water use with more frequent billing. If, however, bringing water consumption to the forefront of the consumer's mind improves her ability to optimize according to her true preferences, then this model is largely consistent with a model of misperceived quantities.

Overall, both price and quantity misperception mechanisms provide plausible stories for why consumers may alter behavior in response to more frequent information and, importantly, they produce similar implications for consumer welfare. That the price or quantity of water consumption becomes more salient with more frequent billing aligns well with recent literature (e.g., Gilbert and Graff Zivin, 2014; Sexton, 2015; Chetty et al., 2009; Finkelstein, 2009), but it is certainly not the only explanation consistent with my results. Regardless of the mechanism, however, the empirical finding that increased billing frequency increases consumption is robust, and it contrasts the results of current literature on informational interventions in water and electricity demand that are, at times, based on equally ambiguous theoretical mechanisms.

6. Conclusions

Information provision is a growing topic in markets both where expenditures are made intermittently and where price changes are politically challenging. In this paper, I make several contributions to this literature. Empirically, I take advantage of a natural experiment in which residential water customers are exposed to more frequent billing information for a water provider in the southeastern US. I find strong evidence that with the provision of more frequent information, consumers increase consumption of water by 3.5–5%, which is roughly half the magnitude of water reductions called for during moderate to severe drought in North Carolina. This result is the first documented causal increase in consumption in response to an increase in billing frequency within environmental and resource policy, which is a particularly pertinent result for drought-prone regions. Further, heterogeneous treatment effects suggest that the increase in consumption is driven by outdoor water use during the summer. I also posit a model of consumer misperception that is consistent with the observed demand response to more frequent billing. Within this framework, I develop a transparent analytical framework to measure economic welfare using limited empirical information.

In practical terms, many water utilities bill customers bimonthly, or even less frequently, despite growing empirical evidence that more frequent price and quantity signals can encourage conservation. This research provides a counterpoint to the existing empirical literature by identifying a robust positive demand response to an exogenous transition from bimonthly to monthly billing. This change in behavior is attributed to the fact that the consumers billed less frequently observe more opaque market signals, thus driving a wedge between perceived and actual billing information. Increasing the transparency of prices or quantity consumed through increased billing frequency results in welfare gains of approximately 0.5 to 1% of aggregate expenditures on water use. These economic gains, however, come at the cost of increased consumption of a scarce natural resource. Thus, future research seeking to use information provision as a tool of conservation needs to account for potential uncertainty in consumers' perceptions of prices and consumption. Further, this research provides an opportunity to rethink the billing information provided to consumers and its potential impact on consumption.

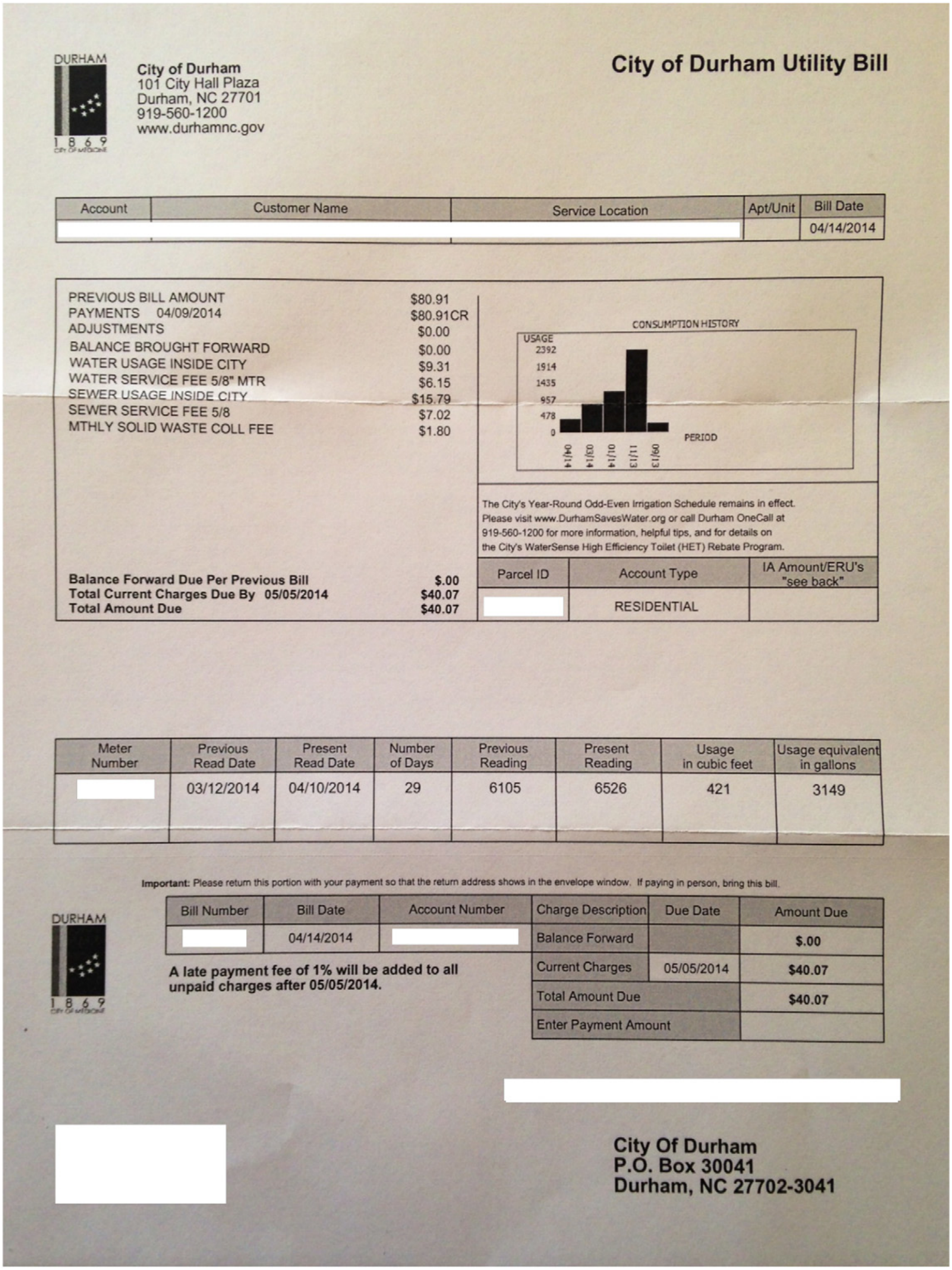
This research adds to the broader literature on intermittent billing and inattention for economic goods, and provides a topical counterpoint to mounting empirical evidence that informative interventions can serve as a cost-effective instrument of conservation. While this research sheds light on how consumers may react to a change in the frequency of familiar information, more research needs to be performed to understand the specific mechanism through which consumers assimilate and use information for decision-making in intermittent choice settings.

Appendix A. Additional figures and results

Table A.1
Statistical differences in observable variables by order of transition relative to districts not yet transitioned for households within 500ft of billing district boundary.

	Order of district transition											
	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th
Home value (in $10,000)	*+	+	*+			+			*+	*+		
Lot size (acres)							+					+
House age (in years)	*+	+	*+	*+	*+		+	*+	+	*+	*+	*+
Square feet (in 100 ft)	+		+	*+	*+			+	*+	*		+
No. bedrooms				+	+	*+	*+					+
No. bathrooms	*+				+*	*+	*+				+	+*
Pct. renters				*			+					
Pct. white	+		+	*+	*+	*	*	*+			+	
Household size	*		+			*		*+			+	*+
Total bill ($)	*+											
Pre-treatment use	*+								+			

Note: This table presents symbolic results for a mean comparison for each listed covariate between the nth district to transition to monthly billing relative to all other districts that have not yet transitioned at that time. * indicates a two-sided t-test returns a p-value < 0.01. + indicates a two-sample Kolmogorov-Smirnov equality-of-distributions test returns a p-value < 0.01.



DURHAM 1869 CITY OF MEDICINE

City of Durham
101 City Hall Plaza
Durham, NC 27701
919-560-1200
www.durhamnc.gov

City of Durham Utility Bill

Account	Customer Name	Service Location	Apt/Unit	Bill Date
[redacted]	[redacted]	[redacted]		04/14/2014

PREVIOUS BILL AMOUNT	$80.91
PAYMENTS 04/09/2014	$80.91CR
ADJUSTMENTS	$0.00
BALANCE BROUGHT FORWARD	$0.00
WATER USAGE INSIDE CITY	$9.31
WATER SERVICE FEE 5/8" MTR	$6.15
SEWER USAGE INSIDE CITY	$15.79
SEWER SERVICE FEE 5/8	$7.02
MTHLY SOLID WASTE COLL FEE	$1.80

CONSUMPTION HISTORY
USAGE
2392
1914
1435
957
478
0
04/14
03/14
01/14
11/13
09/13
PERIOD

The City's Year-Round Odd-Even Irrigation Schedule remains in effect. Please visit www.DurhamSavesWater.org or call Durham OneCall at 919-560-1200 for more information, helpful tips, and for details on the City's WaterSense High Efficiency Toilet (HET) Rebate Program.

Balance Forward Due Per Previous Bill	**$.00**
Total Current Charges Due By 05/05/2014	**$40.07**
Total Amount Due	**$40.07**

Parcel ID	Account Type	IA Amount/ERU's "see back"
[redacted]	RESIDENTIAL	

Meter Number	Previous Read Date	Present Read Date	Number of Days	Previous Reading	Present Reading	Usage in cubic feet	Usage equivalent in gallons
[redacted]	03/12/2014	04/10/2014	29	6105	6526	421	3149

Important: Please return this portion with your payment so that the return address shows in the envelope window. If paying in person, bring this bill.

DURHAM 1869 CITY OF MEDICINE

Bill Number	Bill Date	Account Number
[redacted]	04/14/2014	[redacted]

A late payment fee of 1% will be added to all unpaid charges after 05/05/2014.

Charge Description	Due Date	Amount Due
Balance Forward		**$.00**
Current Charges	05/05/2014	**$40.07**
Total Amount Due		**$40.07**
Enter Payment Amount		

[redacted]

[redacted]

City Of Durham
P.O. Box 30041
Durham, NC 27702-3041

Fig. A.1. Example of first monthly water bill for the City of Durham Water Utility.

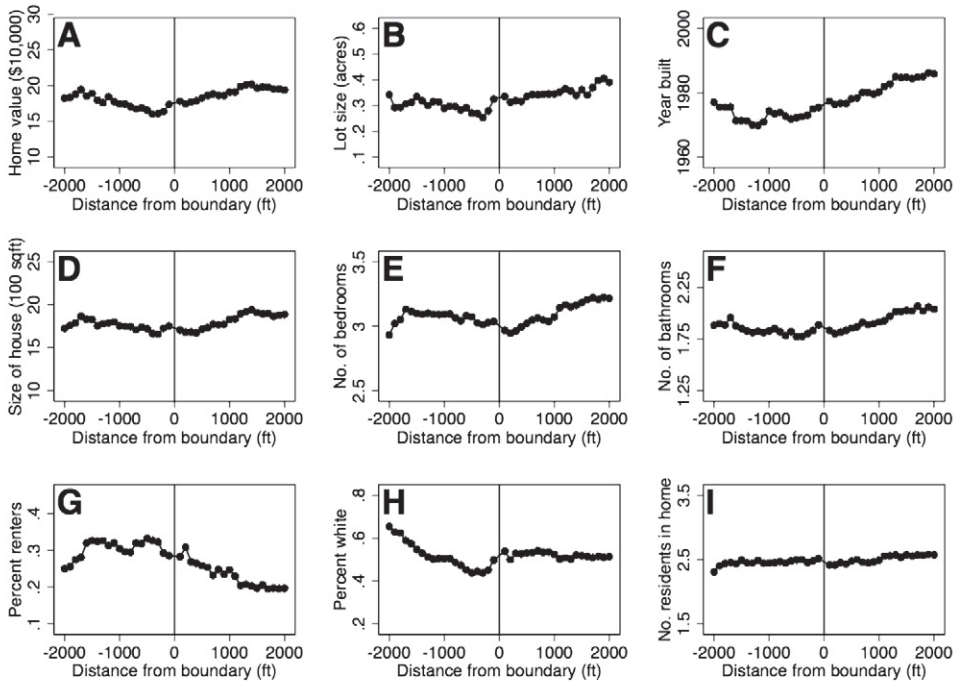


Fig. A.5. Distribution of observable structural and demographic characteristics at the household level as a function of distance from the nearest billing district boundary. Each dot represents the average value for all households within a common 100foot bin. The vertical line at zero in each panel represents an arbitrary district boundary. Positive values on the horizontal axis reflect households in treated districts, whereas negative values on the horizontal axis reflect households in the comparison districts.

Appendix B. Derivation of demand functions under quantity misperception

Under quantity misperception, the consumer's problem is

$$\max_{w} \left\{ x + a(\lambda w)^{1/\gamma+1} \right\} \text{ subject to } M = x + \lambda p w,$$

which provides the following necessary condition for an interior solution,

$$\left(\frac{a}{\gamma+1} \right) (\lambda w)^{-\gamma/\gamma+1} = \lambda p. \tag{B.1}$$

Eq. (B.1) can be rearranged to represent perceived demand as

$$\tilde{w}(p) = A p^{\frac{1-\gamma}{\gamma}} \lambda^{\frac{1-2\gamma}{\gamma}}, \text{where } A \equiv \left(\frac{1+\gamma}{a} \right)^{\frac{1-\gamma}{\gamma}}, \tag{B.2}$$

which shows that demand is scaled multiplicatively by a function of λ since $w(p) = Ap^{\frac{1-\gamma}{\gamma}}$. Thus, the perceived demand function can be written as $\lambda^{\frac{1-2\gamma}{\gamma}} w(p)$.

Further, we can derive the price elasticity of perceived demand,

$$\eta^Q = \frac{\partial \tilde{w}(p)}{\partial p} \frac{p}{\tilde{w}(p)} = \left(\frac{1-\gamma}{\gamma} \right) A p^{\frac{1-\gamma}{\gamma}-1} \lambda^{\frac{1-2\gamma}{\gamma}} \frac{p}{\tilde{w}(p)} = \frac{1-\gamma}{\gamma}, \tag{B.3}$$

which shows that elasticity is constant across prices and levels of λ.

Combining Eqs. (B.3) and (B.2) allows for perceived demand to be written succinctly,

$$\tilde{w}(p) = \lambda^{\frac{1-2\gamma}{\gamma}} w(p) = \lambda^{\eta^Q - 1} w(p).$$

Appendix C. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jpubeco.2017.05.004.

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