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Imperfect Procedural Knowledge: Evidence from a Field Experiment to Encourage Water Conservation

Sebastian Tonke*

Individuals often desire to achieve certain outcomes, but potentially lack the procedural knowledge on how to do so. This study provides causal evidence that imperfect procedural knowledge is a severe obstacle to efficient behavior, but can be overcome by providing low-cost information. I conduct a large-scale field experiment with a public water utility to encourage water conservation during a drought. Providing mass-targeted conservation strategies via text message decreases consumption by 5.2 percent. Additional treatments encouraging individuals to develop own strategies are ineffective and rule out alternative explanations such as reminders, awareness of water scarcity, or being asked to reduce consumption.

Keywords: Field experiment; information provision; resource conservation

JEL Classifications: C93, D91, Q25

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1. Introduction

In domains such as health, education, work and resource consumption, the underlying production function might be unknown. Individuals may lack knowledge about how the input factors relate to the outcomes because learning is cognitively costly (Foster and Rosenzweig, 1995; Hanna et al., 2014). This may pose an obstacle to efficient behavior as some individuals desire to achieve certain outcomes, but potentially lack the procedural knowledge on how to do so. In this paper, I study whether imperfect procedural knowledge is an obstacle to efficient behavior and whether this obstacle can be overcome by providing simple, low-cost information. A related strand of literature has demonstrated the importance of specific management practices within firms (e.g., Bloom et al., 2013; Bruhn et al., 2018; Gosnell et al., 2019; Manthei et al., 2019).

I conduct a large-scale field experiment among 14,796 individuals to test whether they need to be provided with specific strategies about how to reduce resource consumption or whether they know or are able to develop their own, potentially more effective strategies. Previous literature does not provide an answer to this question. Most studies bundle conservation strategies (saving tips) with other intervention features (Abrahamse et al., 2005; Andor and Fels, 2018). The few experimental studies that allow identification focus on social-norm interventions rather than being specifically designed to improve knowledge (Ferraro and Price, 2013; Dolan and Metcalfe, 2015).¹ Moreover, most interventions communicate procedural knowledge ineffectively. Conservation strategies are often provided as byproducts (e.g., printed on the back of the invoice) and use long lists, which may overwhelm and confuse people, instead of short and targeted tips (Gardner and Stern, 2008). These conceptual and methodological limitations may have led to the view that low-cost knowledge provision might be ineffective (Delmas et al., 2013).²

To provide clean evidence on the role of procedural knowledge provision, I conduct a natural field experiment in cooperation with the Namibian water utility (*NamWater*) to address residential water demand during severe water scarcity. In addition, I present evidence from a pre-intervention survey that measures procedural knowledge, intentions to reduce consumption and socio-demographics, to discuss the intervention and the potential mechanisms. The intervention is implemented as a one-shot text message on customers' mobile phones. All messages are personalized, inform about current water scarcity and ask the customer to take action. This allows me to control for salience effects and being asked to reduce water consumption by the water utility. I then randomly provide customers with a short list of targeted, specified strategies or encourage them to contribute with their own knowledge on how to reduce water consumption by providing specifiable tips. In total, three treatments vary by the degree

¹ Ferraro and Price (2013) write that it is unlikely that the saving tips provided new information, since the saving tips were already widely available prior to their intervention. Dolan and Metcalfe (2015) write that their information was very basic in terms of consumer energy knowledge, and it is information that customers may have already seen.

² Schultz (2002) and Abrahamse et al. (2005) argue that information campaigns increase knowledge, but that there is no clear evidence that increased knowledge leads to changes in behavior.

of involvement in the strategy development process. The degree of involvement in the idea generation process is inversely related to the degree of specificity of the treatments. In the *specified* treatment, customers receive three already specified strategies (e.g., reduce showering time by a minute). In the *semi-specifiable* treatment, they are partly involved in the strategy-development process. They receive three suggestions in a specified domain (e.g., avoid running water in the bathroom), but need to specify the water-saving activities otherwise. The *specifiable* treatment has high involvement in the strategy-development process and encourages customers to find three strategies of their own. The treatment provides specific instructions on how to save water by staying alert, by observing where too much water is used and by breaking current habits to save water “their own way”.

There are two pre-registered and contradicting hypotheses with respect to the effectiveness of specified and specifiable treatments. The *specified* treatment improves procedural knowledge by providing concrete strategies on how to reduce water consumption. This reduces the effort costs of knowledge acquisition. However, they might be inadequate to a particular household and undermine its autonomy and intrinsic motivation (Ryan and Deci, 2000; Fehr and Falk, 2002; Bénabou and Tirole, 2003). In contrast, the specifiable treatments could lead to individually more adequate ways to save water, since households have better knowledge of their own household and water-consuming activities. Further, prior research suggests that individuals overvalue their own input to products and ideas, making them more likely to engage and invest in them (Norton, Mochon and Ariely, 2012; Hooshangi and Loewenstein, 2016). Yet, the specifiable treatments depend on the customer’s knowledge or ability to develop effective strategies.

Two additional features of my study beyond the central research question make it distinct from previous literature. First, in addition to my experimental sample, I collect a large administrative data set to estimate price elasticity of water consumption. This allows me to benchmark the experimental treatment effects against the effectiveness of pecuniary strategies from the same setting. The administrative data set comprises 11 years (2006-2016) of monthly consumption data leading to a sample of 1,003,273 customer-month observations. The data set contains rich tempo-spatial price variation, with 27 different price changes in the range of 2.58% to 32.9%, which were implemented at seven distinct points in time. This leads to a substantial variation in prices beyond inflation adjustments, which allow the identification of price elasticities. To the best of my knowledge, this leads to one of the most comprehensive comparisons of non-pecuniary and pecuniary interventions within the same setting.

Second, this paper provides novel evidence on a fundamental issue that might occur whenever customers are charged per unit of consumption. Reductions in consumption mechanically lower what the utility can charge customers (the billable amount), which might affect their payment behavior. In a setting where all customers pay 100% of their invoice, a successful conservation campaign may translate into severe revenue losses. Such a perfect collection efficiency is rare, however, especially in low- and middle-income countries (e.g., Szabó and Ujhelyi, 2015; Jack and Smith, 2019). Most customers typically pay less than 100% of their invoice and accumulate debt over time. Among my experimental

sample, the majority of customers have debts on their account resulting from persistent non-payment of their bill. Non-payment remains a problem, since sanctioning, for example through disconnections, is extremely difficult, as water is a basic human right (Rockenbach et al., 2019). Whether and to which degree an effective conservation intervention may affect the customers' payment behavior and therefore the utility's revenues is still an unanswered question. Understanding spillovers is not only interesting from a behavioral perspective (Tiefenbeck et al., 2013; Truelove et al., 2014); it is particularly important from the utility's cost recovery perspective (high fixed cost infrastructure), which could be threatened by such negative externalities and might be a particular concern when the water utility is already struggling with non-payments. Measuring such second-order effects is important, as economists increasingly help governments to design new policies and regulations.

This study provides several insights into human behavior and has direct policy implications: First, the *specified* treatment is the most effective and decreases water usage by 5.2 percent. The point estimate of the *semi-specifiable* treatment suggests a reduction of 2.2 percent; yet, it is not statistically different from zero. The *specifiable* treatment is ineffective. Mechanisms like reminders, awareness of water scarcity or being personally asked and reminded to save water by the water utility are unlikely to be the mechanism behind the effectiveness of the *specified* treatment, since they are held constant among all treatments. Instead, the rank ordering of the treatment coefficients is predicted by the hypothesis that the effectiveness decreases with higher involvement in the strategy development process, since customers lack strategies on how to save water effectively. This finding is corroborated by survey evidence, as around 92% of the interviewed customers struggle to name more than one strategy to save water. This shows that imperfect procedural knowledge is a severe obstacle to efficient behavior, but can be overcome by providing simple, low-cost information.

Beyond helping to understand the role of procedural knowledge for important economic decisions among individuals, this paper adds to the literature on resource management through non-pecuniary interventions. Targeted procedural knowledge provision might bear a lot of untapped potential. Much of the previous literature focuses on social-norm interventions, inspired by a study of Schultz et al. (2007). These interventions provide information of one's own usage in comparison to other households (Ferraro and Price, 2011; Ferraro and Miranda, 2013; Brent et al., 2015).³ The treatments in these large-scale experiments reduce water consumption between 4.8 to 5.6 percent. Outside the United States, comparable social-norm interventions to curb water demand have been conducted in Costa Rica (Datta et al., 2015) and Colombia (Torres and Carlson, 2018) with similar results.

There is a surprising paucity of experimental evidence from severely water stressed countries, however, as most previous studies are not conducted in drought stricken regions.⁴ In contrast, this experiment is conducted in Namibia. Namibia is an ideal experimental setting to study resource

³ Social-norm experiments in the electricity domain yield treatment effects that are smaller, ranging from 0.7 to 3.3 percent (Allcott, 2011; Allcott and Rogers, 2014; Costa and Kahn, 2013; Ayres et al., 2013; Andor et al., 2019).

⁴ To the best of my knowledge, the most comparable study is provided by Brick et al. (2018), who document the effectiveness of a battery of behavioral interventions to curb water consumption in Cape Town.

management, since it is a typical country facing water scarcity because of low, seasonal and unpredictable rainfall (Lu et al., 2016). At the time of the intervention (August 2017), Namibia was threatened by a drought due to limited rainfall in past years. Since two thirds of the world's population already experiences severe water scarcity for at least one month a year (Mekonnen and Hoekstra, 2016), the findings of this study might be of high practical relevance for a large group of people.

Second, I estimate treatment effects beyond the immediate short-term effect. Measuring treatment effects over time is critical, since short-term and long-term effects might differ substantially. For example, treatment effects could quickly fade out or show rebound effects over time, resulting in a zero-sum effect. Moreover, understanding long-term effects is critical when estimating the return-of-investment of policy interventions. Yet, many studies do not do estimate treatment effects over time (Thaler, 2018; Czibor et al., 2019). I follow customers over the span of a year and find that treatment effects persist over eight months. They do not wane until the rain season sets in (March 2018), which replenishes water resources. This suggests that customers adjust their behavior as long as water scarcity persists. The waning of treatment effects after the rain season is not surprising since the text message asked customers to use less water because of the prevailing water scarcity. The water scarcity is relieved when rain season sets in. The study provides rare evidence on the medium-term effects of a single-shot intervention and adds to the growing literature studying the persistence of behavioral interventions (Bernedo et al., 2011; Frey and Rogers, 2014; Allcott and Rogers, 2014; Brandon et al., 2017).

Comparing this to the long-term price elasticity estimates, the treatment effect of the specified treatment corresponds to a price increase of 10.2 percent. The short-term price elasticities, however, are about half the size. The short-run effect size of the specified treatment corresponds to a price increase of 21.1 percent. This implies that short-term price changes need to be large in order to reduce water demand substantially. However, such short-term price increases may lack political acceptance, for example, because of unequal distributional effects among poorer households and the fact that access to clean water is a basic human right. This study suggests a complementarity of pecuniary and non-pecuniary strategies. Pecuniary strategies are more effective in the long run than in the short run. In contrast, non-pecuniary interventions show an immediate effect on water consumption, but do not persist in the long term. Non-pecuniary strategies are particularly important when environmental disasters are imminent or unforeseen because they are usually easier to implement than price changes (Katz et al., 2016) and cheaper than technological solutions like smart-metering (Tiefenbeck et al., 2018). These findings add large-scale field-experimental evidence to the literature comparing the relative importance of non-pecuniary and pecuniary incentives (Gneezy and List, 2006; Gneezy et al., 2011; Ito et al., 2018).

Third, I find strong heterogeneity in treatment effects. The treatment effects are driven entirely by customers with above-median usage (high users). I provide survey evidence suggesting that low and high users are not statistically significantly different from each other with respect to socio-demographics, knowledge, or intentions to reduce water consumption. Instead, the findings support a “slack” interpretation (Allcott, 2011; Tiefenbeck et al., 2018). High users seem to have lower cost to

conserve water, whereas the consumption levels of low users are close to subsistence levels, leaving little room to improve on. Future interventions should target customers with higher consumption levels.

Fourth, payments do not decrease despite the large reduction in monthly billable amounts (through decreased consumption). This means that the intervention creates positive externalities for the utility, as customers accumulate less debt and pay a higher fraction of their invoice. These novel insights might help to mitigate conflicts of interest between the utility's revenue collection and demand reduction strategies. There are several potential explanations that can explain why the reduction in billed amounts did not cause a decline in payments. First, the monthly-billed amounts correlate little with monthly payments and thus seems to be a relatively unimportant factor for the customer's payment decision. Instead, customers make bulk payments about three to four times a year. Second, a large fraction of customers do not understand or receive the invoice properly (Rockenbach et al., 2019) and therefore might not even notice changes in the billed amount. Third, some customers might be too poor to pay their full bill anyway and might merely pay what they can afford.

Lastly, the intervention costs only 0.04 USD per customer and is delivered in a large geographical area (about the size of Austria or the United Arab Emirates). Even policy-makers with limited money and time could implement this type of intervention at scale. While concerns about the scalability and generalizability are always warranted (Allcott, 2015; Al-Ubaydli et al., 2017; Banerjee et al., 2017), they might be reduced here, since the implementation quality does not depend on personal interaction. Over the span of a year, the intervention reduced water consumption by about 30 million liters at cost of around 800 USD. This amount corresponds to roughly 3,382 months of the average household consumption. Had everyone in the sample received the *specified* treatment, the campaign would have saved about 75 million liters.

The remainder of the paper is as follows: in Section 2, I describe the experimental sample. Section 3 presents the treatment messages and Section 4 the hypotheses. In Section 5, I describe the empirical strategy and the results on water consumption. Section 6 studies potential externalities on payment behavior. Section 7 estimates price elasticity, and Section 8 concludes.

2. Experimental Sample and Data

The experiment is conducted among *NamWater's* residential customers in northern Namibia in an area of 84,610 square kilometers. The sample contains all active accounts that provide a mobile phone number at the time of the intervention, which corresponds to 71.2% of the total number of customers in that region. The sample is highly heterogeneous, containing both small rural households and larger more urbanized households. According to the pre-intervention survey, the average monthly household income is about 347 USD, has seven members and consumes around 9,000 liters monthly. Water is predominantly used for cleaning, bathing and cooking (for details see table 5).

NamWater provides monthly administrative data. To randomize, the sample is split into four approximately equally sized groups and balanced via the min-max t-stat method, stratified by a geographical location proxy with 1,000 redraws to balance on water consumption, debt and payment behavior. The invoice and payment data is heavily right-skewed, with some extreme outliers and erratic data.⁵ I use Grubbs' outlier test (Grubbs, 1969) to exclude 376 households with a 99.9% confidence level that have unusual and extreme water usages of more than 200,000 liters (2,782 N\$) in a single month. This amount approximately corresponds to the volume of a large public swimming pool and is potentially due to extreme leakages, faulty accounting data or commercial usage.⁶ Additionally, 59 households are excluded because of attrition and inactivity (zero annual consumption), for example due to moving and vacancy.

Table 1 provides summary statistics for the experimental sample of 14,796 customers and balance checks between the treatments and the untreated group. I provide estimates on water consumption for the inverse hyperbolic sine (IHS) of water consumption, since the consumption data contains zeros and, unlike the log transformation, the inverse hyperbolic sine is defined for zero values (Burbidge et al., 1988; MacKinnon and Magee, 1990).⁷ For large samples, the inverse hyperbolic sine can be interpreted in the same way as the traditional log transformation. McKenzie (2017), for example, uses the inverse hyperbolic sine transformation for profit data of entrepreneurs in Nigeria. A robustness check using top-coded data can be found in Appendix A2. The results remain unchanged.

The sample is well balanced with no statistically significant differences among observables. The messages were sent out on two consecutive days in August 2017 in English and the local language Oshiwambo. Back-and-forth translations ensured that the content was identical in both languages.

⁵ *NamWater* enters the majority of data manually into the system. Clear guidelines for quality checks of data and a consistent notation of data correction were missing at the time of the study.

⁶ Appendix A1 provides several alternative cut-off rules that do not change the results.

⁷ The inverse hyperbolic sine is defined as $\ln(y+(y^2+1)^{0.5})$.

Table 1. Baseline Summary Statistics and Test of Balance

	Mean	SD	P25	Median	P75	Mean diff. to Control	P-value
Untreated Control (N=3,656)							
Water consumption in kl	8.49	13.82	1.98	4.00	8.90		
IHS(Water consumption in kl)	2.15	1.17	1.44	2.09	2.88	-	-
Water consumption in N\$	111.63	181.84	26.00	52.40	117.00	-	-
Debt in N\$	712.59	1481.02	46.26	195.20	752.26	-	-
Payment amount in N\$	89.26	218.43	0.00	0.00	70.00	-	-
Payment propensity (binary)	0.32	0.47	0.00	0.00	1.00	-	-
Specified (N=3,722)							
Water consumption in kl	8.80	14.20	2.00	4.05	9.00	0.312	0.177
IHS(Water consumption in kl)	2.17	1.18	1.44	2.11	2.89	0.025	0.197
Water consumption in N\$	115.77	186.87	26.00	56.60	117.00	4.143	0.174
Debt in N\$	750.63	1556.51	49.47	204.84	754.51	38.03	0.283
Payment amount in N\$	89.10	219.26	0.00	0.00	70.22	-0.163	0.955
Payment propensity (binary)	0.32	0.47	0.00	0.00	1.00	-0.001	0.972
Semi-specifiable (N=3,688)							
Water consumption in kl	8.70	14.11	2.00	4.00	8.90	0.209	0.365
IHS(Water consumption in kl)	2.17	1.17	1.44	2.09	2.88	0.021	0.293
Water consumption in N\$	114.42	185.79	26.00	52.80	117.00	2.793	0.358
Debt in N\$	743.07	1567.28	51.10	196.07	725.13	30.47	0.392
Payment amount in N\$	90.90	220.94	0.00	0.00	76.00	1.643	0.565
Payment propensity (binary)	0.31	0.46	0.00	0.00	1.00	-0.004	0.441
Specifiable (N=3,730)							
Water consumption in kl	8.76	14.42	1.98	4.00	8.90	0.269	0.252
IHS(Water consumption in kl)	2.15	1.19	1.43	2.09	2.88	0.007	0.719
Water consumption in N\$	115.24	190.06	26.00	52.80	117.00	3.609	0.243
Debt in N\$	717.89	1476.35	49.37	202.18	745.11	5.300	0.877
Payment amount in N\$	93.36	226.60	0.00	0.00	80.00	4.097	0.152
Payment propensity (binary)	0.32	0.47	0.00	0.00	1.00	-0.003	0.597

Notes: The table reports pre-intervention summary statistics for the experimental sample. The table provides mean, standard error, 25th percentile, median and 75th percentile. Water consumption, debt, and payment amount are top-coded at the 99th percentile. IHS stands for inverse hyperbolic sine. Kl stands for kiloliters. For a subsample of customers, the average price (13.15 N\$ per cubic meter) is used to compute consumption in kl, since administrative price information was unavailable at the time of the study. The last two Regressions test for pre-treatment differences in means between control and treatments, using a pooled OLS regression with treatment dummies and standard errors clustered at the customer level. I report the regression coefficients and p-values of the treatments in comparison to the untreated control group.

3. Treatment Messages

Customers receive randomly either specified, semi-specifiable or fully specifiable tips on their mobile phones or are assigned to an untreated control group. All messages are personalized, inform customers about the current water scarcity and include a call to action (“You need to start acting today. Please use less water”). Table 2 shows the exact content of the three types of messages. The *specified* treatment contains three specified strategies to save water. The *semi-specifiable* treatment partially involves customers in the strategy development process. The treatment provides the same domain as the *specified* treatment (bathing, cooking and cleaning) over a range semi-specific activities (avoid, re-use), but the actual activity to reduce water needs to be concretized by the customer. The *specifiable* treatment fully involves customers in the strategy development process. The treatment encourages customers to find three own strategies to save water in the household. The message gives specific instructions on how find own ways to save water.

Table 2. Content of Treatment Messages

Specified	<p>Dear [Name],</p> <p>Our nation is low on water supply. You need to start acting today. Please use less water.</p> <p>Please consider the following tips:</p> <p>Shorten the time you spend in the shower by a minute or two.</p> <p>Re-use water from cooking and cleaning food to water plants.</p> <p>Use a broom instead of water to clean floors in and around your house.</p>
Semi-specifiable	<p>Dear [Name],</p> <p>Our nation is low on water supply. You need to start acting today. Please use less water.</p> <p>Please consider the following ideas:</p> <p>When can you keep the water tap closed and avoid running water (for example in the bathroom)?</p> <p>How can you re-use water in your household (for example from the kitchen)?</p> <p>How can you avoid unnecessary water usage (for example outside the house)?</p>
Specifiable	<p>Dear [Name],</p> <p>Our nation is low on water supply. You need to start acting today. Please use less water.</p> <p>Please take a couple of minutes to find three ways to use less water in your household.</p> <p>Be alert and observe where you use too much water.</p> <p>What can you personally change to use less water and to break your habits?</p> <p>Save water and do it your own way!</p>

4. Hypotheses

There are two pre-registered and contradicting hypotheses with respect to the effectiveness of the treatments (AEARCTR-0002280).

Hypothesis 1: Specification of strategies increases the effectiveness of the treatment.

Customers may have imperfect knowledge of their production function and may not know which input factors to change in order to reduce resource consumption. They may lack this knowledge because of limited attention and limited cognitive capacity (Hanna et al., 2014; Steg, 2016). Specified strategies overcome this obstacle by providing procedural knowledge. Survey studies indicate that procedural knowledge correlates with ecological attitudes and behavior (Kaiser and Fuhrer, 2003). Interventions that reduce cognitive effort and complexity are effective behavioral interventions (Thaler and Sunstein, 2008) and might be particularly important when cognitive capacity is impeded by being poor itself (Shah et al., 2012). Drexler et al. (2014), for example, show that a simplified training course among micro-entrepreneurs leads to better management practices than standard accounting training, in particular for less sophisticated individuals. This hypothesis predicts an increasing rank ordering of treatment effects as one moves from the *specifiable* to the *semi-specifiable* to the *specified* treatment.

Hypothesis 2: Specification of strategies decreases the effectiveness of the treatment.

Specified strategies might propose inapplicable actions (e.g., “don’t wash your car with a water hose” when one does not own a car) or types of behavior that have already been acted upon (Abrahamse et al., 2005). Customers might also be more motivated to act upon their own ideas. Attempts to restrict specific kinds of behavior could undermine intrinsic motivation and autonomy (Deci and Ryan, 2000; Fehr and Falk, 2002; Bénabou and Tirole, 2003) or even lead to psychological reactance (Brehm, 1966; Kronrod et al., 2012). The specifiable treatments might be more effective because customers have better knowledge of their household characteristics and water consumption activities. They might be able to develop their own, potentially more effective strategies. A strand of literature argues that individuals overvalue their own input into ideas and products. Hooshangi and Loewenstein (2016) find that individuals are overconfident about the value of, and overly likely to invest in their own entrepreneurial idea. On the other hand, when investing in another person’s idea, they are underconfident about the value of, and insufficiently likely to invest in it. Along these lines, the “IKEA-effect” (Norton et al., 2012) describes the phenomenon that individuals have a higher valuation of self-made products. Franke et al. (2010) show that involving customers in the specification and design process of products increases their willingness to pay for these products. Involvement of individuals in pro-environmental campaigns improves the acceptability of pro-environmental strategies (Steg, 2016). All these strands of literature argue that if customers know or are able to develop effective strategies, then the specifiable treatments should be more effective. This hypothesis predicts a decreasing rank ordering of treatment effects as one moves from the *specifiable* to the *semi-specifiable* to the *specified* treatment.

5. Estimation Strategy and Results

In this section, I test whether customers need specified saving tips or whether they know or are able to develop their own, potentially more effective strategies to conserve water. The treatment effects are estimated using administrative monthly data from *NamWater* over the span of a year.

5.1 Treatment effects on water consumption

Table 3 provides difference-in-difference regressions on monthly water consumption using month-year fixed effects and customer fixed effects. Standard errors are clustered at the customer level (Bertrand et al., 2004). I use the following difference-in-difference estimator to estimate treatment effects for the treatment periods before and after the rain season sets in:

$$Y_{it} = \beta^1 D^1_{it} + \beta^2 D^2_{it} + \beta^3 D^3_{it} + \gamma^1 R^1_{it} + \gamma^2 R^2_{it} + \gamma^3 R^3_{it} + \tau_t + \alpha_i + \varepsilon_{it}$$

Y_{it} is the inverse hyperbolic sine (IHS) of water consumption in kiloliters (kl) in month t of customer i . D^1_{it} is a treatment indicator that is equal to one if a customer is treated and in the *specified* treatment group at time t before the rain season sets in (August 2017 to March 2018) and zero otherwise. Equivalently, D^2_{it} is a treatment indicator for the *semi-specified* treatment and D^3_{it} is a treatment indicator for the *specifiable* treatment. R^1_{it} is a treatment indicator that is equal to one if a customer is treated and in the *specified* treatment group at time t after rain season sets in (April 2018 to July 2018) and zero otherwise. Equivalently, R^2_{it} is a treatment indicator for the *semi-specified* treatment and R^3_{it} is a treatment indicator for the *specifiable* treatment for the time t after rain season sets in. Month-year fixed effects are denoted τ_t , customer fixed effects are denoted α_i and ε_{it} is an error term.

Regression (1) of table 3 shows the intention-to-treat effects (ITT) on water usage among the full sample (232,495 customer months). Regressions (2) and (3) of table 3 present the ITT effects separately for below-median users (low users) and above-median users (high users) according to their baseline consumption.

Table 3. ITT Treatment Effects in Comparison to Control Group

	(1) All - IHS (Consumption in kl)	(2) Low Users - IHS (Consumption in kl)	(3) High Users - IHS (Consumption in kl)
<i>Specified (August-March)</i>	-0.052*** (0.018)	-0.012 (0.020)	-0.074*** (0.029)
<i>Semi-specifiable (August-March)</i>	-0.022 (0.018)	-0.004 (0.020)	-0.039 (0.028)
<i>Specifiable (August-March)</i>	0.008 (0.018)	0.016 (0.020)	0.005 (0.028)
<i>Specified (April-July)</i>	-0.016 (0.021)	0.007 (0.024)	-0.020 (0.033)
<i>Semi-specifiable (April- July)</i>	-0.005 (0.021)	0.022 (0.024)	-0.031 (0.033)
<i>Specifiable (April- July)</i>	0.021 (0.021)	0.031 (0.024)	0.017 (0.033)
Comparison Mean in kl	9.107	5.536	12.769
Observations	232,495	116,286	116,209
R-squared	0.074	0.106	0.077
Number of customers	14,796	7,391	7,405
Customer FE	YES	YES	YES
Year-month FE	YES	YES	YES

Notes: The table shows the ITT estimates from a difference-in-difference regression including month-year and customer fixed effects on water consumption in kl, in comparison to the untreated group. The outcome variable is transformed using the inverse hyperbolic sine (IHS) of monthly water consumption in kl, which can be interpreted as the log transformation. The first three rows show treatment effects until March 2018 (peak of rain season) and the following three rows show the treatment effects for the months after the rain season (April to July 2018). Standard errors (in parentheses) are clustered on the customer level. *** $p < 0.01$

Result 1: *The specified treatment decreases consumption by 5.2 percent (ITT). The specifiable tips are ineffective in reducing water consumption.*

The *specified* treatment reduces water consumption by about 5.2 percent ($p=0.004$) per customer per month, in comparison to the untreated group. The result is robust to multiple hypothesis adjustments using the conservative Bonferroni correction ($p^{adj}=0.012$) for three treatment arms (Savin, 1980). The effect translates into a reduction of about 520 liters per month per customer (Table A2, data winsorized at 99th percentile). This amount corresponds, for example, to reducing showering time by one to two minutes per day.⁸ This suggests that each customer saves on average 4,160 liters over the span of the 8 months until the rain season sets in.

The point estimate of the *semi-specifiable* treatment suggests a reduction of 2.2 percent, but is statistically insignificantly different from zero ($p=0.231$). The *specifiable* treatment has a positive point estimate of 0.8 percent ($p=0.655$) and is therefore ineffective in reducing water consumption. A Wald

⁸ Water-efficient showerheads have a flow rate of around 6-8 liters per minute, whereas standard showerheads can use more than twice that amount.

test shows that the *specified* treatment is also significantly more effective than the *specifiable* treatment ($p=0.001$).⁹ A nonparametric Jonckheree-Terpstra testing for trends in total water usage indicates a significant trend ($p=0.012$), as one moves from the *specified* to the *semi-specifiable* to the *specifiable* treatment. This rank ordering of the treatment effects is predicted by Hypothesis 1.

Result 2: *The treatment effect is driven by high users.*

Regressions (2) and (3) show treatment effects for the subsamples of low and high users. Among low users, all coefficients are statistically insignificantly different from zero. Regression (3) shows large effects for high users in the *specified* treatment. The *specified* treatment reduces water consumption by 7.4 percent ($p=0.010$). The *semi-specifiable* treatment reduces water consumption among the high users by 3.9 percent, but is not statistically different from zero ($p=0.166$). The *specifiable* treatment has a statistically insignificant effect of 0.5 percent ($p=0.856$). Panel A in Figure 2 plots the treatment coefficients with 95% confidence intervals.

Result 3: *Treatment effects persist over eight months and then wane after the rain season replenishes the water supply.*

After the end of the rain season (April-June), none of the coefficients is statistically significantly different from zero in comparison to the control group. While treatment effects do not persist beyond this point, they do not rebound either, for example through moral licensing effects (Merritt et al., 2010). Instead, they are insignificantly different from to the level of the untreated group. The results suggest that customers adjust their behavior during a time of water scarcity, rather than investing in more water-efficient technology. The waning of treatment effects after the rain season is not surprising since the text message asked customers to use less water because of prevailing water scarcity, which is resolved when rain season sets in.¹⁰ Panel B in Figure 2 plots the treatment coefficients with 95% confidence intervals.

⁹ The *specified* treatment is statistically significantly different from the *semi-specifiable* treatment at the 10% level ($p=0.098$).

¹⁰ The pre-registered end date is the 31st of December 2017. The end date was chosen since the first seasonal rainfalls typically arrive around January. In 2018, the rain season arrived later than usually and peaked in March. In table A3, I provide a difference-in-difference regression using the pre-registered end date.¹⁰ The results do not change.

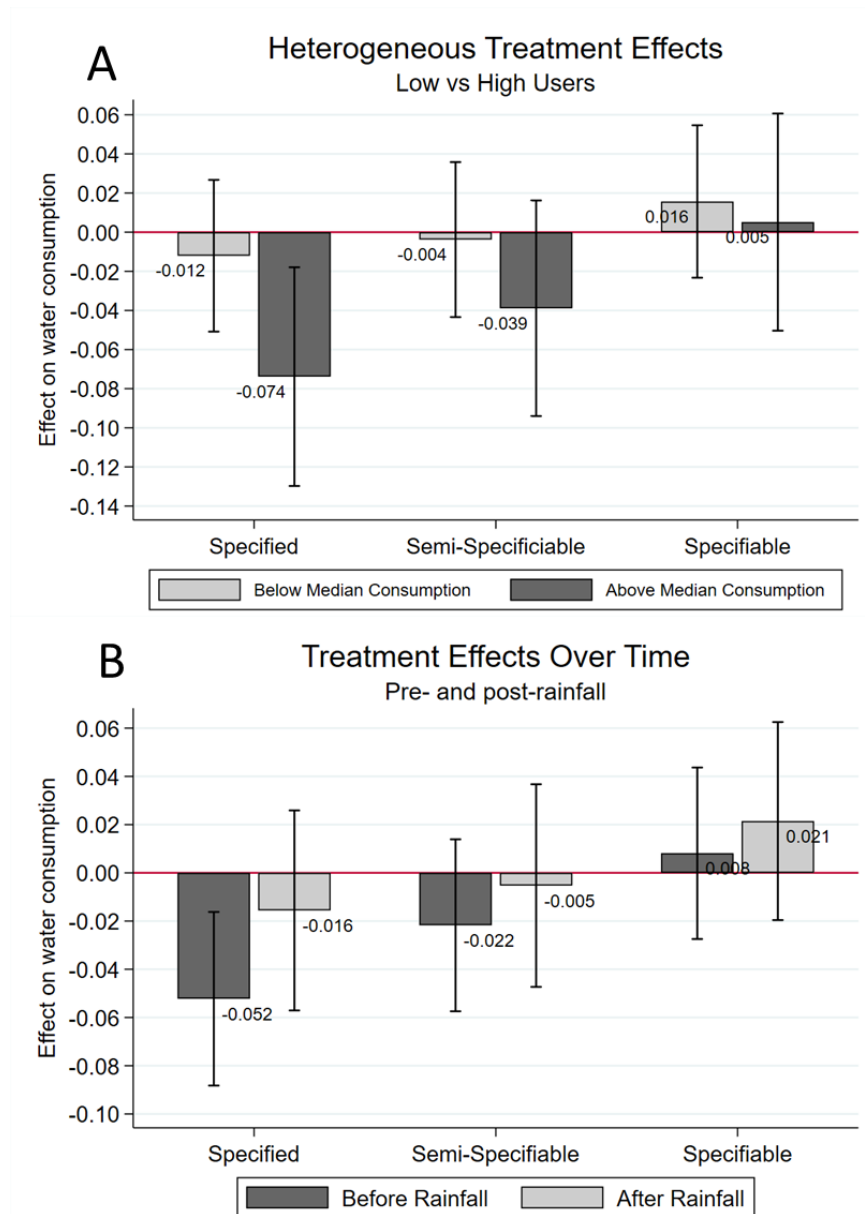


Figure 1: The figures show treatment effects (ITT) on water consumption with 95% confidence intervals, in comparison to the untreated group. The upper panel (A) shows heterogeneous treatment effects with respect to high and low users before the rain season sets in. The lower panel (B) shows treatment effects for the full sample before and after the rain season sets in.

5.2 Corroborating survey evidence shows imperfect procedural knowledge

Result 1 shows that the *specified* treatment is the most effective treatment and significantly more effective than the *specifiable* treatments in reducing water consumption. Mechanisms like reminders, awareness of water scarcity or being asked to reduce consumption by the water utility can be ruled out, since they are held constant across treatments. Instead, the rank ordering of the treatment effects is predicted by Hypothesis 1, which argues that customers lack procedural knowledge because knowledge acquisition is costly. In the following, I present corroborating survey evidence in favor of this hypothesis.

Why did the *specifiable* treatment fail to decrease water consumption? To shed light on that question, I provide evidence from a pre-intervention survey (N=285) that was conducted via phone among a randomly drawn sample of *NamWater* customers. The interviews were conducted with the person responsible for water payments in the household. The survey was carried out by a team of local students, who introduced themselves as a part of a research team of the *University of Cologne*. Most importantly, the survey asks for customers' intentions to reduce consumption, to name some concrete steps to reduce water consumption, where most water is used, perceptions on payments and measures sociodemographics.

About 70.3% state that they plan to reduce water consumption. However, the survey shows that customers have difficulties to name specific and effective strategies to save water. Panel A in Figure 2 shows that, conditional on planning to reduce water, around 25.4% are unable to mention any specific steps and 92% cannot mention more than one strategy.¹¹

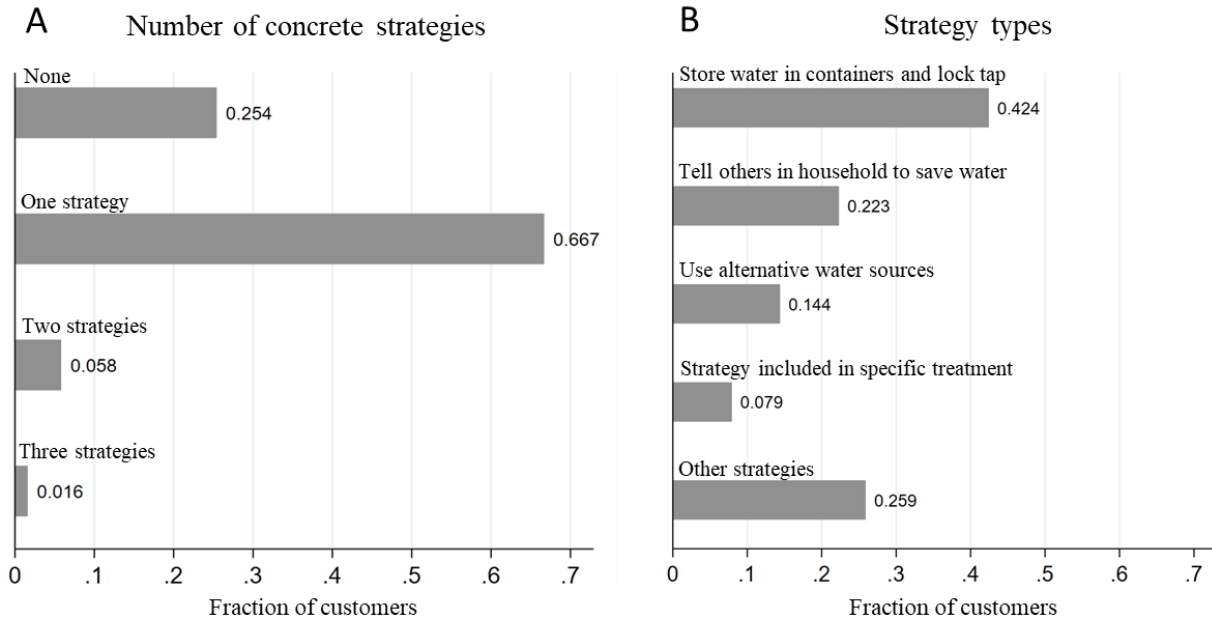


Figure 2: The figure shows knowledge of conservation strategies. Panel A shows the number of mentioned strategies when asked for specific steps to decrease water consumption. Panel B shows the categorized strategies conditional on mentioning a strategy (multiple answers possible).

Next, I analyze the type of strategies suggested by customers, which are displayed in panel B (multiple answers possible). The most common strategy (42.4%) is to store water in containers and to lock the water tap. The idea behind this strategy is visibly to monitor one's consumption and to commit to a restricted amount of water. To be effectively used as a commitment device, customers would need to fill their containers to a smaller amount in comparison to what they would have used otherwise, which is a very challenging task. Even if they manage to do so, they still would need to find an actual activity that reduces their consumption. The second-most common strategy (22.3%) is to tell others (like kids

¹¹ Summary statistics including tests for differences between high and low users are provided in Table A4.

and other household members) to reduce their water consumption by wasting less water. Given how difficult it is to come up with concrete strategies for the interviewees themselves, it is questionable whether the other household members are more knowledgeable. The third-most commonly given answer (14.4%) is the use of alternative water sources. Among those, around 66% suggest harvesting rain water during the rain season, which is not feasible during an ongoing drought. Taken together, the survey evidence suggests that the majority of customers lacks actionable information on how to reduce consumption, which explains why the *specifiable* treatment is ineffective.

What makes the *specified* treatment so effective? The *specified* treatment overcomes the lack of knowledge by providing new strategies on how to curb water demand. Customers do not need to invest cognitive effort to acquire this knowledge. Strategies are new in the sense that only few customers mention such strategies when asked how to save water. Among those planning and proposing a concrete strategy, only 7.9% of interviewees state one of the three strategies included in the *specified* treatment. This means that almost everyone receives two or three new strategies to save water, since the vast majority can name at most one strategy. In addition, the *specified* treatment targets the three most commonly mentioned main domains of water usage. These domains are cleaning, bathing and cooking, which are shown in Panel A in Table 5 (multiple answers possible).

5.3 Heterogeneous effects between low and high users

Result 2 shows that the treatment effect is entirely driven by high users. Heterogeneous effects among high and low users are common in the conservation literature and have been reported in social-norm interventions and in studies on real-time smart-meter feedback.¹² I provide suggestive survey evidence to understand how much of the heterogeneity can be explained by socioeconomic factors. I find no statistically significant differences among the survey items between high and low users.¹³ The sample is not underpowered to find a medium-sized effect. Given the sample size, a Chi-square test achieves a power of around 75% for a 10-percentage-point shift in proportions at a 5% significance level. The two-sided Wilcoxon rank sum test achieves a power of around 98%, assuming a medium effect size of 0.5 (Cohen's *d*). While this does not mean that there are no differences, it suggests that the measured survey items cannot explain the difference very well. Instead, I interpret the heterogeneous effects as higher levels of "slack" among high users, which the intervention helps to reduce. This interpretation follows Allcott (2011), who argues that high-users might have lower costs of reducing consumption. Similarly, Tiefenbeck et al. (2018) argue that high users might be more wasteful and therefore might have more room to improve on. When looking at descriptive statistics, the low users in the untreated group use, on average, 5,536 liters per month in the post-intervention period, which corresponds to about 25-40 liters per person per day in a typical household. This is close to subsistence

¹² Similar heterogeneous effects among high and low users are reported by Allcott (2011), Ayres et al., (2013), Ferraro and Price (2011), Brent et al., (2015), Datta et al. (2015) and Tiefenbeck et al. (2018).

¹³ This is also largely true for knowledge or intentions to reduce water consumption (Appendix A4).

levels and shows that low-user households indeed have little or no room to reduce water consumption. Future interventions should focus on customers with higher usage.

Table 5. Survey Results				
<i>Panel A: Main Purposes of Water Usage</i>	All	Low Users	High Users	p-value High=Low
Cleaning	0.712 (0.453)	0.704 (0.458)	0.720 (0.450)	0.765
Bathing	0.488 (0.501)	0.507 (0.502)	0.469 (0.501)	0.515
Cooking	0.393 (0.489)	0.401 (0.492)	0.385 (0.488)	0.772
Gardening	0.249 (0.433)	0.211 (0.410)	0.287 (0.454)	0.141
Animals	0.253 (0.435)	0.211 (0.410)	0.294 (0.457)	0.109
<i>Panel B: Socioeconomic Demographics</i>				
Employed	0.484 (0.501)	0.479 (0.501)	0.490 (0.502)	0.857
Female	0.505 (0.501)	0.556 (0.499)	0.457 (0.500)	0.103
Household earnings in N\$	4312.6 (6465.6)	3745.4 (5265.3)	4879.8 (7455.8)	0.985
People living in household	7.449 (4.346)	7.00 (3.894)	7.878 (4.713)	0.228
Has access to alternative water sources	0.376 (0.485)	0.368 (0.484)	0.384 (0.488)	0.779
Owens crop	0.263 (0.441)	0.232 (0.424)	0.294 (0.457)	0.240
Owens animals	0.211 (0.408)	0.190 (0.394)	0.231 (0.423)	0.400
<i>N</i>	285	142	143	

Notes: This table shows means and standard errors in parentheses. The last column shows the p-value of non-parametric tests testing for a difference between low and high users (median split of survey sample). Binary variables are tested using a two-sided Chi-square test. Other variables are tested using a two-sided Wilcoxon rank-sum test.

6. Externalities on Payment Behavior

Non-payment is a persistent problem in many low- and middle-income countries, as customers typically pay less than what they are being billed (Aguilar-Benitez and Saphores, 2008; Vásquez, 2015; Szabó and Ujhelyi, 2015). In my setting, the majority of customers are in debt and the pre-intervention median debt is 199 N\$, which corresponds to about four unpaid median water bills. Customers do not pay every month, but instead pay on average three to four times a year. According to the pre-intervention survey, around 95% percent of customers pay in cash and travel on average 25 km to the next payment point. The long commuting time justifies quarterly bulk payments instead of monthly payments. When customers pay, the payment amount correlates little with the amounts billed on a monthly basis. Figure 3 shows a scatter plot of payments and invoices for the whole data set (the simple correlation coefficient is 0.029). Dots on the 45-degree line would mark customers who exactly pay their current bill. Only 1.4% of the values lie on that line. Instead, many customers make bulk payments in multiples of 100 on average three to four times a year. These dots combine to horizontally dashed lines in Figure 3.

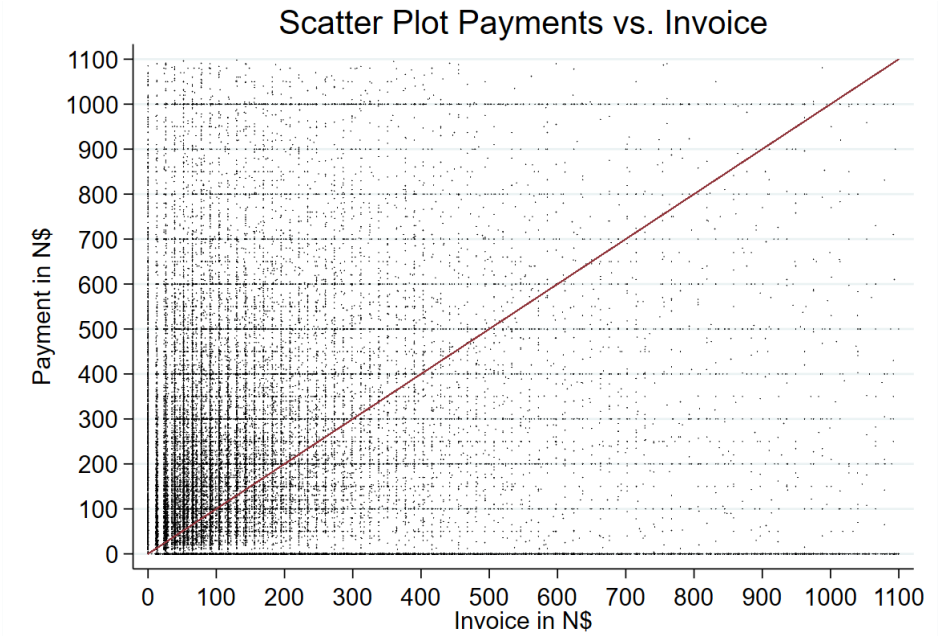


Figure 3: Monthly payment amounts correlate little with billed amounts.

Since customers do not pay 100% of their bill each month, it is unclear how reductions in the billed amount might affect payment behavior and therefore revenues of the water utility. In the following section, I estimate whether payment behavior is affected by the reductions in water consumption and whether this leads to negative externalities.

6.1 Treatment effects on payment behavior

Table 4 presents OLS estimates on aggregated payments, aggregated consumption, the fraction of the bill paid, and total debt, using robust standard errors. The regressions control for the pre-treatment values of variables and the strata used for randomization in the regression (Bruhn and McKenzie, 2009).

	(4) Total Consumption in N\$	(5) Total Payments in N\$	(6) Fraction of bill paid	(7) Debt in N\$
<i>Specified</i>	-48.288** (18.965)	-0.911 (21.394)	0.051** (0.024)	-46.667** (23.115)
<i>Semi-specifiable</i>	-17.767 (19.432)	12.144 (21.665)	0.021 (0.023)	-35.160 (22.452)
<i>Specifiable</i>	11.365 (19.451)	30.374 (21.458)	0.007 (0.023)	-12.827 (23.136)
Comparison value	1097.801	973.841	0.903 ^a	851.333
Observations	14,759	14,759	14,683	14,596
R-squared	0.323	0.337	0.051	0.624

Notes: Regressions (4-7) show the ITT estimates of an OLS regression in comparison to the untreated group on aggregate measures until March 2018. Regression (7) shows the debt in April 2018. I control for the pre-treatment values of variables and strata used for randomization as recommended by Bruhn and McKenzie (2009). The variables are top coded at the 99th percentile (winsorized).^a Here, I report the median fraction of bill paid, since the mean (1.004) is sensitive to outliers. The average price of water is 13.15 N\$ per kiloliter. Robust standard errors are shown in parentheses. ** $p < 0.05$

Result 4: *The intervention does not decrease payments. The fraction of the bill paid and debt improve in comparison to the control group.*

Regression (4) of Table 4 shows treatment effects on the total amount of water charged in N\$ until the rain season sets in. On average, customers in the *specified* treatment were charged 48.29N\$ (about 3.25 USD) less because of their reduced consumption ($p=0.011$). Next, I estimate treatment effects on the total amount of payments in Regression (5). The intervention does not negatively affect payment behavior. The coefficient of the *specified* treatment is not statistically significant ($p=0.872$). The point estimates of the *semi-specifiable* and *specifiable* treatment are even positive, but not statistically significant either ($p=0.579$ and $p=0.177$). The same analysis split by low and high users is provided in Appendix A5. A more detailed analysis of payment behavior across intensive and extensive margin is provided in Appendix A6, which does not yield substantially different results.

This suggests that the fraction of the bill paid (i.e., total payments divided by total consumption) improves. Regression (6) shows that the fraction of the bill paid in the *specified* treatment indeed increases by 5.1 percentage points ($p=0.034$). Accordingly, I find that customers in the *specified* treatment accumulate 46.67N\$ ($p=0.044$) less total debt in Regression (7).

There are several explanations that may help to explain why the reduction in billed amounts did not cause a decline in payments. First, as described above, the monthly-billed amount seems to be a relatively unimportant metric for customers' payment decision. Second, a large fraction of customers do not understand or receive the invoice properly (Rockenbach et al., 2019) and therefore might not even notice changes in the billed amount. Third, some customers might be too poor to pay their full bill anyway and might merely pay what they can afford. Lastly, there might be combination of effects that result in a zero sum effect. A potential negative effect of reduced billable amounts might be compensated through an improved payment morale stemming from an increased awareness of water scarcity. These payment patterns for public utility are certainly more typical for low- and middle-income countries (Aguilar-Benitez and Saphores, 2008; Vásquez, 2015; Szabó and Ujhelyi, 2015). To which extent such findings may translate to settings in which non-payment is less common or whether payment levels might change beyond the evaluated time horizon is a question for future research.

The key takeaway from the analysis of payment behavior is that, from the perspective of the water utility, the intervention does not create a trade-off between revenue collection and water demand reduction. Instead, the intervention causes positive externalities on the fraction of the bill paid and debt of customers.

7. Comparing Non-pecuniary and Pecuniary Strategies

The standard economic approach to curb resource demand is to increase prices. In this section, I benchmark the experimental treatment effects against pecuniary strategies by estimating price elasticities.

Comparing price elasticities across studies and contexts is difficult because meta-studies show that elasticities vary substantially across settings due to different regional contexts, price structures, econometric approaches and data quality. For example, Olmstead et al. (2007) use structural modeling and find price elasticities of residential water demand between -0.59 and -0.33. Arbués et al. (2003) report findings of 63 studies estimating reduced-form estimates with elasticities ranging from -1.63 to +0.33. The estimation of elasticities faces many econometric complexities stemming from block pricing or increasing and decreasing marginal price schedules (Arbués et al., 2003; Szabó, 2015). An advantage of my study in comparison to previous studies is that customers pay a fixed price per kl of water used. Further, my estimation exploits an unusually large panel data set, which allows me to control for customer and time-fixed effects, as well as region-specific seasonal variation. Nevertheless, price elasticity estimates typically rely on observational data and should be treated with caution, as estimates might be biased by customer-specific, time-varying omitted variables that are not controlled for by the fixed effects or other sources of endogeneity.

To compare non-pecuniary and pecuniary strategies in the same setting, I collect an administrative data set containing 11 years (2006-2016) of monthly data leading to a sample of 1,003,273 customer-month observations. The data set contains 27 price changes, implemented at seven distinct time points in the range of 2.58% to 32.9%. Price changes occur in no particular seasonal pattern. After being approved by the *Ministry of Agriculture, Water and Forestry*, price changes became effective in August 2006, February 2010, June 2011, October 2012, November 2014, September 2015 and May 2016.

I use the log of prices to estimate elasticity in terms of percentage changes. The following fixed-effects regression model is used with standard errors clustered at the customer level.

$$Y_{it} = \pi P_{it} + \tau_t + \alpha_i + \varepsilon_{it}$$

Y_{it} the inverse hyperbolic sine of water consumption in kl in month t of customer i . P_{it} is the log of water price per kl. Month-year fixed effects are denoted τ_t , customer fixed effects are denoted α_i and ε_{it} is an error term. In addition, regressions (9) and (10) control for region-specific seasonal patterns by including the interaction of a season indicator variable (coded 1-12 for each month of the year) and a geographic proxy (bulk pipeline location dummy). Regression (10) further interacts the price variable with a short-term indicator variable, that is coded one for the six months following a price change and zero otherwise. This interaction term allows me to estimate whether price elasticities differ within the first six months after a price change occurs.

Table 6. Price Elasticity			
	(8)	(9)	(10)
	IHS	IHS	IHS
	(Consumption in kl)	(Consumption in kl)	(Consumption in kl)
Log(price)	-0.549*** (0.129)	-0.507*** (0.132)	-0.726*** (0.146)
Log(price)*Short term			0.480*** (0.125)
Short term			-0.181 (0.283)
Observations	1,013,028	1,013,028	1,013,028
R-squared	0.062	0.072	0.072
Number of customers	17,398	17,398	17,398
Customer FE	YES	YES	YES
Year-month FE	YES	YES	YES
Season*geographic proxy	-	YES	YES

Notes: This shows estimates of a fixed effect regressions of prices on water consumption (price elasticity). The outcome variable is water consumption measured in kiloliters (kl) and is transformed using the inverse hyperbolic sine (IHS). Short term is an indicator variable, coded 1 for the six months following a price change. Season is a variable coded 1-12 for each month of the year. Standard errors are clustered at the customer level. *** $p < 0.01$

Regressions (8) and (9) suggest that a 10-percent price increase reduces water consumption by 5.1 to 5.5 percent ($p < 0.001$). However, price elasticity is significantly smaller ($p < 0.001$) within the first six months after a price change. In the short term, a 10-percent price increase reduces water consumption by about 2.4 percent (Regression 10).¹⁴ This is in line with meta-studies showing that price elasticity can be low in particular in the short term (e.g., Olmstead et al., 2007).

The short-run effect size of the *specified* treatment corresponds to a price increase of 21.1 percent. This is remarkable, as a simple one-shot message decreases consumption as much as a substantial price increase. Such large price increases, however, could lack political and ethical acceptance because of undesirable distributional effects among poorer households. In fact, governments often subsidize water and electricity to make them affordable to low-income households (McRae, 2015). According to my survey data, the median household would already have to pay 4.9% of its income for water if they were to pay fully. Pricing strategies that have been successfully used to curb resource demand in richer countries (Jessoe and Rapson, 2014; Ito et al., 2018) might prove difficult to implement in low- and middle-income countries.

The study suggests a complementarity of pecuniary and non-pecuniary strategies. The non-pecuniary interventions show an immediate effect on water consumption and is easier to implement than price changes. In contrast, the pecuniary strategies show substantial reductions even in the long term, but are less effective in the short term. Non-pecuniary strategies are therefore particularly useful when price changes are difficult to implement and when environmental disasters are imminent or unforeseen.

¹⁴ Customers might be less price sensitive in the short term because they fail to notice the price changes (Ito, 2014). Customers seem to become more price-sensitive when prices are made salient (Finkelstein, 2009; Chetty et al., 2009; Jessoe and Rapson, 2014).

8. Conclusion

This study shows that imperfect procedural knowledge is a severe obstacle to efficient behavior, but can be overcome by providing low-cost information. The provision of a short list of mass-targeted strategies decreases water consumption by 5.2 percent, which is equivalent to a substantial short-term price increase of 21.1 percent and among the most effective non-pecuniary interventions in the literature. Imperfect procedural knowledge may inhibit efficient behavior in a wide range of other settings in which individuals require procedural knowledge to achieve desirable outcomes, as for example for health outcomes (e.g., diets and exercise routines), educational outcomes (e.g., teaching and learning techniques) or labor markets outcomes (e.g., effective job search strategies).

The study is conducted in a middle-income country. Although this experiment is not conducted among ultra-poor households, information acquisition is potentially more costly in poorer countries and cognitive capacity could be impeded by being poor itself (Shah et al., 2012). An important question is to which extent the findings of this study might translate to other settings. Imperfect procedural knowledge in the environmental domain has also been discussed as a potential obstacle in high-income countries. Gardner and Stern (2008) argue that US households lack accurate, accessible and actionable information on how to curb resource demand with respect to climate change. In a study from Switzerland, Tiefenbeck et al. (2018) argue that feedback from real-time smart-metering might be ineffective, if the adequate behavior to reduce consumption is insufficiently specified. Attari et al. (2010) and Attari (2014) provide survey evidence showing that US residents have systematic misperceptions towards the effectiveness of water, energy, transportation, and recycling activities. The lessons learned from my experiment, thus, might generalize to populations outside of my setting.

The findings of my study have direct policy implications. Environmental problems arguably account for three out of the top five global risks (World Economic Forum, 2019). Imperfect procedural knowledge helps to explain why interventions merely focusing on raising awareness or providing feedback seem to be insufficient to change behavior (McKenzie-Mohr, 2011; Buchanan et al., 2015). The provision of mass-targeted procedural knowledge might bear a lot of untapped potential. The implementation only costs 5 cent and reduces consumption by about 4,160 liters per customer within eight months, which is among the most cost-effective interventions in the literature.¹⁵ This is a key feature for policy-makers, who are often time and budget constrained.

¹⁵ The social-norm intervention of Ferraro and Price (2013), for example, reduced water demand by around 3,785 liters at a cost of only 0.575 USD (postal mailings). Such social-norm interventions are already among the most cost effective interventions in the literature (Benartzi et al., 2017).

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Appendix

Table A1. Robustness Check Main Results – Different Exclusion Rules

	(1)	(2)	(3)	(4)
	IHS Water Usage - Cut-off at 3000 N\$	IHS Water Usage - Cut-off at 2500 N\$	IHS Water Usage - Cut-off at 2000 N\$	IHS Water Usage - Cut-off at 1500 N\$
<i>Specified (August-March)</i>	-0.048*** (0.018)	-0.053*** (0.018)	-0.050*** (0.018)	-0.045** (0.018)
<i>Semi-specifiable (August-March)</i>	-0.020 (0.018)	-0.025 (0.018)	-0.030* (0.018)	-0.029 (0.018)
<i>Specifiable (August-March)</i>	0.010 (0.018)	0.012 (0.018)	0.008 (0.018)	0.010 (0.018)
<i>Specified (April-July)</i>	-0.012 (0.021)	-0.018 (0.021)	-0.010 (0.021)	-0.011 (0.021)
<i>Semi-specifiable (April-July)</i>	-0.004 (0.022)	-0.010 (0.021)	-0.016 (0.021)	-0.015 (0.021)
<i>Specifiable (April-July)</i>	0.025 (0.021)	0.023 (0.021)	0.021 (0.021)	0.018 (0.020)
Exclusion rule (largest invoice in N\$)	3000	2500	2000	1500
Observations	233,147	230,748	227,067	219,710
R-squared	0.074	0.075	0.077	0.082
Customers	14,837	14,684	14,451	13,984
Customer fixed effects	YES	YES	YES	YES
Month-year fixed effects	YES	YES	YES	YES

Notes: The table shows the ITT estimates from a difference-in-difference regression including month-year fixed effects and customer fixed effects on water consumption in comparison to the untreated group. Regressions 1-4 provide estimates under different exclusion rules. The outcome water consumption in kl is transformed using the inverse hyperbolic sine (IHS), which can be interpreted as the log transformation. Standard errors (in parentheses) are clustered at the customer level. * p<0.1; ** p<0.05; *** p<0.01.

Table A2. Robustness Check Main Results – Top Coded Water Consumption (99th Percentile)

	All	Low Users	High Users
	(1)	(2)	(3)
	Water usage in kl	Water usage in kl	Water usage in kl
<i>Specified (August-March)</i>	-0.525** (0.215)	-0.163 (0.137)	-0.746* (0.397)
<i>Semi-specifiable (August-March)</i>	-0.214 (0.216)	-0.008 (0.145)	-0.415 (0.403)
<i>Specifiable (August-March)</i>	-0.112 (0.215)	0.023 (0.144)	-0.214 (0.402)
<i>Specified (April-July)</i>	-0.213 (0.249)	-0.104 (0.194)	-0.160 (0.444)
<i>Semi-specifiable (April-July)</i>	-0.010 (0.256)	0.355 (0.222)	-0.364 (0.452)
<i>Specifiable (April-July)</i>	-0.056 (0.246)	0.147 (0.201)	-0.217 (0.440)
Observations	232,495	116,286	116,209
R-squared	0.029	0.057	0.035
Number of customer	14,796	7,391	7,405
Customer fixed effects	YES	YES	YES
Month fixed effects	YES	YES	YES

Notes: The table shows the ITT estimates from a difference-in-difference regression including month-year fixed effects and customer fixed effects on water consumption in comparison to the untreated group. The outcome variables is top coded at the 99% percentile (winsorized). All standard errors (in parentheses) are clustered on the customer level. * p<0.1; ** p<0.05

Table A3. Robustness Check Main Results - Using Pre-registered End Date

	(1) All	(2) Low Users	(3) High Users
<i>Specified (August-January)</i>	-0.052*** (0.019)	-0.007 (0.020)	-0.080*** (0.030)
<i>Semi-specifiable (August-January)</i>	-0.024 (0.018)	-0.008 (0.021)	-0.039 (0.029)
<i>Specifiable (August-January)</i>	-0.003 (0.019)	0.005 (0.020)	-0.006 (0.029)
<i>Specified (February-July)</i>	-0.028 (0.020)	-0.004 (0.022)	-0.032 (0.030)
<i>Semi-specifiable (February-July)</i>	-0.009 (0.020)	0.017 (0.022)	-0.034 (0.031)
<i>Specifiable (February-July)</i>	0.028 (0.020)	0.037* (0.022)	0.025 (0.030)
Observations	232,495	116,286	116,209
R-squared	0.074	0.106	0.077
Customers	14,796	7,391	7,405
Customer fixed effects	YES	YES	YES
Month fixed effects	YES	YES	YES

Notes: The table shows the ITT estimates from a difference-in-difference regression including month-year and customer fixed effects on water consumption in comparison to the untreated group. The outcome water consumption in kl is transformed using the inverse hyperbolic sine (IHS) which can be interpreted as the log transformation. Standard errors (in parentheses) are clustered on the customer level. * p<0.1; *** p<0.01

Table A4. Knowledge of Strategies

	All	Low Users	High Users	P-value Low=High
<i>Panel A: Knowledge of Conservation Strategies</i>				
Plans to reduce consumption in the future	0.703 (0.458)	0.720 (0.451)	0.686 (0.466)	0.547
↳ i) Proposes concrete way to reduce water consumption	0.735 (0.442)	0.684 (0.467)	0.787 (0.411)	0.108
↳ a) Store water in containers and lock tap	0.424 (0.496)	0.462 (0.502)	0.392 (0.492)	0.407
↳ b) Tell others in household to save water	0.223 (0.418)	0.200 (0.403)	0.243 (0.432)	0.541
↳ c) Use alternative water sources	0.144 (0.352)	0.169 (0.378)	0.122 (0.329)	0.425
↳ d) Tip included in specified treatment	0.079 (0.271)	0.062 (0.242)	0.095 (0.295)	0.471
↳ e) Other ideas	0.259 (0.440)	0.185 (0.391)	0.324 (0.471)	0.061
↳ ii) Doesn't know how to reduce water consumption	.265 (0.442)	.315 (0.467)	.212 (0.411)	0.108
↳ f) "Don't know"	0.327 (0.474)	0.333 (0.479)	0.316 (0.478)	0.898
↳ g) Vague answer (e.g., "use water wisely")	0.673 (0.474)	0.667 (0.479)	0.684 (0.478)	0.898

Notes: This table shows means and standard errors in parentheses. Row *i*) shows the fraction of interviewees proposing a way to save water conditional on planning to reduce water and *ii*) displays the remaining fraction of interviewees who are unable to propose a way to save water. Rows *a*) - *e*) show the fractions of answer types conditional on planning to reduce water and *f*) and *g*) display fractions of answer types among those who are unable to propose a way. Multiple answers are possible for purpose of water usage and answers *a*) - *e*). The last Regression shows the p-value of non-parametric tests testing for a difference between low and high users. Binary variables are tested using a two-sided Chi-square test. Other variables are tested using a two-sided Wilcoxon rank-sum test.

Table A5. Externalities on Payments by Low and High Users

	Low Users				High Users			
	(1) Total Consumption in N\$	(2) Total Payments in N\$	(3) Fraction of bill paid	(4) Debt in N\$	(5) Total Consumption in N\$	(6) Total Payments in N\$	(7) Fraction of bill paid	(8) Debt in N\$
<i>Specified</i>	-19.150 (16.622)	-16.075 (17.501)	0.023 (0.031)	-13.916 (21.651)	-95.699*** (32.953)	-3.741 (38.106)	0.082** (0.036)	-78.106* (40.441)
<i>Semi-specifiable</i>	2.209 (17.332)	6.376 (18.107)	0.017 (0.031)	-7.539 (20.373)	-42.739 (33.957)	12.126 (38.682)	0.031 (0.035)	-54.337 (40.135)
<i>Specifiable</i>	11.344 (17.508)	-5.955 (17.321)	0.004 (0.030)	7.152 (20.636)	1.071 (33.970)	57.970 (38.608)	0.010 (0.035)	-31.607 (41.463)
Observations	7,384	7,384	7,342	7,296	7,375	7,375	7,341	7,300
R-squared	0.127	0.163	0.049	0.603	0.248	0.270	0.057	0.608

Notes: Regressions show the ITT estimates of an OLS regression in comparison to the untreated group on aggregate measures until March 2018 for low and high users. Regression (4) and (8) show the debt in April 2018. I control for the pre-treatment values of variables and strata used for randomization as recommended by Bruhn and McKenzie (2009). The variables are top coded at the 99th percentile (winsorized). The average price of water is 13.15 N\$ per kiloliter. Robust standard errors are shown in parentheses. *** p<0.01; ** p<0.05; * p<0.1

Notes on table A6

Table A6 shows the treatment effects on payment behavior. Regression (1) shows the marginal effects at means on the extensive margin (probability of making a payment) of a probit regression. Regression (2) shows the effects on the intensive margin (the effect on the natural logarithm of the payment amount conditional on being larger than zero). Regression (3) estimates the combined effects of Regressions 1 and 2, using a two-part model (Belotti et al., 2015). Fitted values from the log transformation of the two-part model are obtained using Duan's (1983) smearing retransformation and standard errors are obtained by bootstrapping. I control for the pre-treatment values of variables and strata used for randomization in the regression, as recommended by Bruhn and McKenzie (2009). All standard errors are clustered at the customer level. Regressions (4-6) show the estimates for low users and Regressions (7-9) show the estimates for high users.

Regression (1) shows that the *semi-specifiable* treatment even increases the likelihood of making a payment by 0.9 percentage points ($p=0.042$). The *specifiable* treatment increases the probability of making a payment by 0.8 percentage points ($p=0.062$). Customers in the *semi-specifiable* and *specifiable* treatment may make these additional payments to fight water scarcity in their "own way", while customers in the *specific* treatment might feel that they are already playing their part by using less water. Such types of behavior, in which individuals try to compensate their past shortcomings, for example by acting more prosocially, are known as moral cleansing (e.g., Jordan et al., 2011).

The intensive margin (conditional on paying) is insignificantly different from zero. None of these effects accumulates to an economically meaningful increase or decrease in payment behavior: The estimates for the combined effect (Regression 9) range from to -0.81 N\$ ($p=0.697$) to 1.99 N\$ ($p=0.324$) and are statistically insignificantly different from zero. The results do not change either when I extend the time horizon until July 2018 (Table A7).

There are some statistically significant effects when looking at the subsamples of low and high users.¹⁶ However, these effects are not found for groups that actually reduced their water consumption in course of the intervention, and therefore they seem unrelated to changes of the billed amount. Therefore, I do not find evidence of a negative effect on payment behavior through lower billable amounts. If anything, the intervention might have improved financial performance, if the marginal cost of providing water is larger than zero.

¹⁶ When looking at the subsamples, there is a significantly negative effect for low users on the intensive margin (4.4 to 4.6 percent), although the billable amount among this group is unchanged. The *specifiable* treatment shows a positive treatment effect among the high users of 8.57 N\$ ($p=0.034$).

Table A6. Externalities on Payments by Low and High Users Using Two-Part Model (until March 2018)

	All			Low Users			High Users		
	(1) Payment propensity (binary)	(2) Payment amount in N\$ (if >0)	(3) Combined Effect	(4) Payment propensity (binary)	(5) Payment amount in N\$ (if >0)	(6) Combined Effect	(7) Payment propensity (binary)	(8) Payment amount in N\$ (if >0)	(9) Combined Effect
<i>Specified</i>	0.002 (0.004)	-0.013 (0.017)	-0.807 (2.075)	-0.000 (0.006)	-0.032 (0.022)	-2.024 (1.530)	0.004 (0.007)	-0.009 (0.024)	0.487 (3.867)
<i>Semi-specifiable</i>	0.009** (0.004)	-0.028 (0.017)	0.217 (2.067)	0.006 (0.006)	-0.044** (0.021)	-1.391 (1.554)	0.012* (0.007)	-0.020 (0.024)	3.000 (4.021)
<i>Specifiable</i>	0.008* (0.004)	-0.011 (0.017)	1.992 (2.019)	0.007 (0.006)	-0.046** (0.022)	-1.160 (1.609)	0.009 (0.007)	0.022 (0.024)	8.566** (4.037)
Observations	117,674	38,783	117,674	60,156	17,732	60,156	57,518	21,051	57,518
R-squared	0.0994	0.327	-	0.0885	0.275	-	0.1031	0.266	-

Notes: This table reports ITT effects on payment behavior (Regressions 4-6) for the eight months post-intervention for the full sample, in comparison to the untreated control group. Regression (4) shows the effect of the treatments on the likelihood of making a payment (marginal effects at means). Regression (5) reports the ITT effect on the intensive margin. Regression (6) multiplies the effects of Regressions (4) and (5) to get an estimate of the combined effect using a two-part model (Belotti et al. 2015). Regressions (7-9) provide equivalent estimations for low users and Regressions (10-12) for high users. Fitted values from the log transformation of the two-part model are obtained using Duan's (1983) smearing retransformation, and standard errors are obtained by bootstrapping. Regressions control for strata used for randomization as recommended by Bruhn and McKenzie (2009). Control variables are top coded at the 99th percentile. Four customers attrite in August. All reported standard errors are clustered at the customer level to account for serial correlation. * p<0.1; ** p<0.05

Table A7. Externalities on Payments by Low and High Users Using Two-Part Model (until July 2018)

	Full Sample			Low Users			High Users		
	(1) Payment propensity (binary)	(2) Payment amount in N\$ (if >0)	(3) Combined Effect	(4) Payment propensity (binary)	(5) Payment amount in N\$ (if >0)	(6) Combined Effect	(7) Payment propensity (binary)	(8) Payment amount in N\$ (if >0)	(9) Combined Effect
<i>Specified</i>	0.005 (0.004)	-0.019 (0.017)	-0.314 (1.635)	0.004 (0.005)	-0.038* (0.022)	-1.466 (1.312)	0.005 (0.006)	-0.014 (0.024)	0.357 (3.189)
<i>Semi-specifiable</i>	0.010** (0.004)	-0.026 (0.017)	0.864 (1.633)	0.011* (0.005)	-0.042* (0.021)	-0.122 (1.302)	0.009 (0.006)	-0.021 (0.023)	1.287 (3.251)
<i>Specifiable</i>	0.007* (0.004)	-0.005 (0.017)	2.314 (1.654)	0.008 (0.005)	-0.042** (0.021)	-0.798 (1.275)	0.007 (0.006)	0.028 (0.024)	8.030** (3.300)
Observations	175,409	56,563	175,409	89,516	25,931	89,516	85,893	30,632	85,893
R-squared	0.0958	0.291	-	0.0861	0.241	-	0.0988	0.235	-

Notes: The table reports ITT effects on payment behavior (Regressions 1-3) for the full sample until July 2018. Regression 1 shows the effect of the treatments on the likelihood of making a payment (marginal effects at means). Regression 2 reports the ITT effect on the intensive margin. Regression 3 multiplies the effects of Regressions 1 and 2 to get an estimate of the combined effect using a two-part model (Belotti et al. 2015). Regressions 4-6 provide equivalent estimations for low users and Regressions 7-9 for high users. Fitted values from the log transformation of the two-part model are obtained using Duan's (1983) smearing retransformation and standard errors are obtained by bootstrapping. Regressions control for strata used for randomization, as recommended by Bruhn and McKenzie (2009). Control variables are top coded at the 99th percentile. All reported standard errors are clustered at the customer level to account for serial correlation.* p<0.1; ** p<0.05