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Response of residential water demand to dynamic pricing: Evidence from an online experiment

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Abstract

Urban water demand management is key to water supply sustainability in high-density, water-stressed areas throughout the world, and emerging technologies could transform it. In particular, smart metering could allow for conserving water by dynamically changing prices to reflect water scarcity and supply cost variability. Yet, little is known on end-users' reaction to short-term price changes, an essential determinant of the effectiveness and acceptability of dynamic water pricing. This paper reports on the design and results of an online experiment that measures end-users' water consumption decisions when confronted with time-varying prices, and investigates the interaction between pricing and water scarcity awareness. We design a series of treatments where players must indicate their shower length given different water prices, price variations, and scarcity scenarios. Beyond corroborating the theory that higher prices lower usage, the experiment finds evidence of a dynamic pricing effect: users respond more strongly to a given price if they have been exposed to a lower price before. This suggests short-term residential price increases could be effective at boosting water conservation.

Keywords: dynamic pricing; urban water; online experiment; water scarcity

1. Introduction

Are time-varying prices an effective water conservation measure? This question has been of little practical value until recently in a sector where price changes over time were the exception rather than the norm (Olmstead and Stavins, 2009). However, recent technological advances such as "smart" meters make it possible to manage water demand by moving from time-invariant to time-varying volumetric prices, known as dynamic pricing (Pérez-Urdiales and García-Valiñas, 2016; Lopez-Nicolas et al., 2018; Rougé et al., 2018; Vesal et al., 2018). Smart meters gather household's water consumption data on sub-daily basis (e.g., a few minutes to an hour), thanks to the installation of high resolution sensors and their integration in utility's data systems, making possible the transmission of detailed feedbacks to users (Cominola et al., 2015).[1] Examples of cities that have deployed smart meters on a large scale include San Francisco and London.[2]

Dynamic prices aim to enhance water use efficiency because they reflect real-time variations of water supply costs and incentivize water conservation among customers. Several time-varying factors influence water supply costs, including demand peaks, demand trends, water scarcity, and opportunity costs related to alternative human and ecosystem-related water uses (Brelsford and Abbott, 2017). In principle, dynamic pricing could help better consider these factors and help manage residential water demand (Rougé et al., 2018). In particular, increasing water prices during scarcity scenarios could send end users a signal on water value, leading to a decrease in demand and more efficient water allocation across time and

[1] Smart meters will also facilitate the integration of electricity and water demand side management (Maas et al., 2020).

[2] Further information can be retrieved from the websites of The San Francisco Public Utilities Commission (https://sfwater.org/index.aspx?page=386) and Thames Water (https://www.thameswater.co.uk/help/water-meters/getting-a-water-meter).

among uses (Pulido-Velazquez et al., 2008; Pulido-Velazquez et al., 2013; Macian-Sorribes et al., 2015). Recent work has demonstrated it is possible to design such tariffs for residential users in drought-prone Valencia, Spain, while balancing economic efficiency with other tariff objectives such as cost recovery and equity (Lopez-Nicolas et al., 2018). Frequent price variations over time are commonplace in many industries, from travel to online and traditional retail. In recent years, electricity utilities also experimented with dynamic pricing policies, linking the unit price charged to end users with variations in the marginal costs of electricity supply (Faruqui and Sergici, 2010; Ito et al., 2018; Joskow and Wolfram, 2012; Wolak, 2010). Yet, political resistance to time-varying prices and unavailability of cheap enabling technologies (Dutta and Mitra, 2017) have proved to be important hurdles to the implementation and diffusion of dynamic pricing in the electricity sector. These barriers may prove even higher in the water sector where time-varying prices could be considered as an infringement on the essential right to water.

What is more, impacts of dynamic pricing on water use are uncertain due to contrasting evidence from the economic literature. Established wisdom suggests that price elasticity of demand should be lower in the short run than in the long one (Hicks, 1939). The common rationale for this is that it takes time for consumers to become fully aware of a price increase and adapt their choices. This is true for goods as varied as gasoline (Espey, 1998; Sterner, 2007; Brons et al., 2008; Havranek et al., 2012) and electricity (Holtedahl and Joutz, 2004; Halicioglu, 2007) or cigarettes (Becker et al., 1994). For residential water use, short-term price elasticity may be even lower because end users may find it difficult to fully adjust to the new price if price variations are sudden or expected to be frequent.

That being said, different mechanisms can lead end users to respond to dynamic pricing. First, end users may over-react to sudden changes in water price. Adaptation-level theory holds that agents judge a stimulus relative to the level to which they have become adapted (Helson 1964). Consumers immediately compare a new price to the past reference price (Mizutani et al., 2018), i.e., to a predictive price expectation that is shaped by past purchasing experiences and the current context (Briesch et al. 1997; Kalyanaram and Winer 1995; O'Donoghue and Sprenger 2018). Second, water consumers may become more sensitive if prices were to change more frequently. Agents incrementally react to repeated stimulation, because a sensitization process drives the behavioral outcome of a sequence of stimuli (Groves and Thompson, 1973).

Empirical evidence for price elasticity of residential water demand upholds the intuitive idea that demand is more elastic in the long run (e.g., Espey, 1997; Marzano et al., 2018; Nauges and Thomas, 2003). In some studies, the price-driven reduction of consumption has been estimated in the short run by exploiting the introduction of increasing block rates (Wichman, 2014) or an additional price block (Nataraj and Hanemann, 2011). However, they were one-off price shocks, perceived by customers as persistent. Accordingly, the estimated price responses can hardly be conceivable as dynamic pricing effects. Besides, a recent study (Schleich and Hillenbrand, 2019) has provided evidence that the short-term effect of a price increase was stronger than that of a price decrease, and showed that computing a unique short-run elasticity for both types of price changes amounted to underestimating the short-term impacts of tariff hikes. This contrasting evidence suggests the possible impacts of dynamic pricing on demand are not a foregone conclusion and require further investigation. These dynamic water price changes can also continue on the long term, making it debatable whether they are exclusively short-term in nature. Further complicating the picture, price information magnifies water demand response when it is available (Gaudin, 2006), so that the possibility to inform end users of their consumption-related costs in real time could impact effectiveness of smart-meter-enabled dynamic pricing.

This work investigates the role of dynamic pricing in residential water demand management. The paper tests (1) whether the price effect is larger (or smaller) when end users face dynamic pricing, and (2) how water scarcity awareness moderates price effects. It answers both questions through an experimental setting. We recruit 424 players and ask them to use a small endowment to buy some running water and take a hypothetical shower. A group of players faces an increase in the unit price of water, whereas a control group is allowed to buy water at a steady price. Our experimental setting allows us to discriminate between the effect of static pricing (lower showertime associated to a higher price) and the effect of dynamic pricing (showertime reduction associated to a price increase). In addition, for each of the two groups, a subgroup is exposed to a hypothetical water scarcity scenario, which makes it possible to determine if water scarcity awareness magnifies or lessens the dynamic price effect (Garrone et al., 2019).

We contribute to the literature on the use of economic measures to foster resource conservation. In this field experimental studies have been drawing increasing attention. Most of them focus on electricity consumption and examine a wide range of time-varying price schemes, such as time of use, critical peak pricing, peak-time rebate, real-time price, and variable peak pricing (Faruqui and Sergici, 2011; Faruqui et al., 2014; Herter and Wayland, 2010; Ida et al., 2013; Qiu et al., 2018). There are field experiments that exploit pilots carried out in different geographical settings, but mostly in the United States (Aubin et al., 1995; Faruqui and Sergici, 2010; Pellerano et al., 2017; Wolak, 2007). In the realm of water economics, some field as well as natural experiments have been conducted to assess the effect of water tariffs and other policy instruments (Brent and Ward, 2019; Castledine et al., 2014; Ferraro et al., 2011; Wichman, 2014). To the best of our knowledge, this is the first experiment to attempt to study the effect of dynamic pricing on residential water consumption. Though relying on hypothetical water use, it exposes end users to price variations that are perceived as closely as possible to dynamic price changes. We do this by asking players to envisage a scenario in which a dynamic pricing policy would be adopted and try to answer truthfully, by exposing them to information they are likely to be exposed to along with the adoption of dynamic pricing policies, and by charging them for water usage. We find end users who face a price increase reduce water consumption to a greater extent than the consumption difference predicted by a static demand curve. Moreover, our findings suggest that water scarcity awareness neither amplifies nor depresses the dynamic pricing effect.

The rest of this paper is organized as follows. Section 2 presents the experiment’s rationale, including a treatment of potential experimental pitfalls. Section 3 presents the experimental data. Section 4 analyses the results and describes evidence supporting the existence of a dynamic pricing effect. Section 5 adds robustness checks to the results to address potential concerns with the experimental setting. Section 6 discusses the findings and Section 7 offers conclusions and recommendations.

2. Experiment

The aim of the experiment is to measure the effect of dynamically changing the price on residential water consumption. To achieve this, our experiment allows us to decompose the overall response of water consumption to a change of price, or *price effect*, in two components. The *static* (or long-run) *price effect* is defined as the difference observed in water demand between end users who face different prices without having experienced price variations since long. When the price faced by end users is the outcome of a sudden price variation over time, the experiment is separating this static price effect from additional variations in water consumption. If they exist, we will call this second effect the *dynamic pricing component.*

Our treatment is dynamic pricing, as we expose treated players to an increase in the unit price of water. They go from a baseline question about their water consumption choice, where price is set to p_{low}, to an endline question on water consumption choice, where price is set to p_{high}. In order to control for any potential factor that may induce players to change their behaviors going from the baseline to the endline question, we maintain a control group with players who are not exposed to any price variations over time. Players in the control group face a unit price of water set to p_{high} both in the baseline and in the endline setting. The control group provides a counterfactual, a scenario where we ask players about their water consumption without contextual changes.

We confront players with a single specific water use, showering, for reasons explained in detail in Section 2.2, so that water consumption is represented by shower time. $ST(p_.)$ is the shower time chosen by players for water price $p_.$.

The *price effect* (PE) is the so-called "difference in differences" obtained by subtracting the average shower time change in the control group to that in the treatment (dynamic pricing) group:

$$PE(p_{low}, p_{high}) = \left[ST(p_{low})_{\ baseline} - ST(p_{high})_{\ endline}\right]_{\ Treatment}$$
$$-\left[ST(p_{high})_{\ baseline} - ST(p_{high})_{\ endline}\right]_{\ Control} \qquad (1)$$

The average treatment effect computed by differencing the answers of the two treatment groups for the baseline question provides us with the *static price effect* (SPE):

$$SPE(p_{low}, p_{high}) = [ST(p_{low}) \quad _{baseline}] \vee \quad _{Treatment} - [ST(p_{high}) \quad _{baseline}] \vee \quad _{Control} \quad (2)$$

The overall *price effect* (PE) is therefore the sum of the static pricing effect (SPE) and an additional *dynamic pricing component* (DPC:

$$PE(p_{low}, p_{high}) = SPE(p_{low}, p_{high}) + DPC(p_{high}) \;, \qquad (3)$$

where the dynamic pricing component is:

$$DPC(p_{high}) = [ST(p_{high}) \quad _{endline}] \quad _{Control} - [ST(p_{high}) \quad _{endline}] \quad _{Treatment} \quad (4)$$

2.1. Online survey platform and sample

We implemented the experiment through Microworkers (www.microworkers.com), for its popularity and ease of use (Crone and Williams, 2017). We conducted preliminary tests to determine what would be a large enough pool of English language respondents with cultural homogeneity on the Microworkers website. According to these tests, which mirrored those from previous assessments (e.g., Hirh et al., 2011), respondents were chosen in the pool of Microworkers participants from the USA and Canada. We tailored the phrasing of questions to fit that audience.

The task on Microworkers redirected respondents to a multi-part questionnaire that comprises survey and experimental parts (see Section 2.2 for details). We used SurveyMonkey to design the questionnaire because of the availability of advanced logic tools and survey customization options. These tools enabled us to set up the experiment with two four-digit PIN numbers that players had to enter as proof that they had gone through all the steps of the game. The first PIN number is dependent on the answer to the experimental question: the reported value determines the player's final payoff. The second PIN number is only available upon completion of the totality of the survey's question. A total of 424 survey points were obtained of which 415 had no missing values and were usable in the empirical analyses.

2.2. Experimental design

We focus on a single specific water use, showering, for three reasons. First, there is evidence that showering is one of the most water consuming actions in a household, accounting for a residential water consumption share that ranges from 19% to 25% (see Mayer et al., 1999; Beal & Stewart, 2011; Energy Saving Trust, 2013). Second, unlike many other water uses, showering is performed by the vast majority of the potential players, and showering time is under their full control. They experience the action of showering directly and are accordingly well aware of the satisfaction this brings them, if any. Third, unlike flushing the toilet (which competes with the shower for being the largest water consuming action in a household), the use of water to shower is not discrete, but can be continuously adjusted by the player. This gives us the possibility to measure the effect of pricing more effectively.

The game had four parts: 1) a pre-experiment survey, 2) a baseline shower time choice, 3) an endline shower time choice, where the player's final monetary payoff is determined, and 4) a post-experiment survey. As mentioned before, the design was both within-subject (we have both pre-price-change and post-price-change choices) and between-subject (players receive different price treatments). Each player was randomly assigned to Treatment or Control, and within them to two sub-treatments. These group assignments determined which initial unit water price the player would receive and under which water scarcity scenario she would be exposed when making an endline shower time choice. Table I shows the distribution of respondents across the four treatments. Each treatment features at least 100 respondents.

[Insert Table I about here]

We exposed players in the treatment groups to a price per minute of shower time of 5 cents when asked to make their baseline choice, whereas the price went up to 10 cents per minute of shower when players had to choose their endline shower time. The control groups, instead, were exposed to a price per minute of shower time of 10 cents when choosing both their baseline and endline shower times. These monetary amounts are not meant to strictly reproduce actual water tariffs in North American urban areas, but rather, to introduce an easily intelligible monetary incentive. This was a reason for sticking to a unique price of water that is tangible to respondents. Note that implied water prices are not very far from the range of water service tariffs in the United States. These range between USD 3 and 25 per kGal for water and wastewater services, depending on the municipality (US Department of Energy). Assuming an average flow rate of 2 gallons (7.6L) per minute, the price of water per minute of shower ranges between 0.6 and 5 cents per minute. If we also add to that the actual energy costs of heating the water (0.2 kWh for 2gal for the shower, priced at 13 cents per kWh on average: 2.6 cents per minute of shower), that makes our 5 cent estimate very reasonable.

The water scarcity sub-treatment is presented both by using the wording: "*Now assume that there currently is a severe drought in your area, similar to the recent drought in California (see pictures)*" and by showing two pictures that recall a drought scenario (see the Appendix A2).

Coming to the monetary incentive, respondents are informed that, at the end of the experiment, they will be rewarded for saving money from an initial \$1.5 endowment, *and* for getting satisfaction from their shower (see Appendix A2). Therefore they can understand that they will be paid "well" if they manage to balance expense reduction (shorter showers) and personal comfort (longer showers). However they do not know the analytical expression of the payoff function.

Actually, the underlying payoff function penalizes ridiculously low shower times, and rewards median shower times that give the best trade-off between cost and comfort (the longer the shower, the larger the expenditure, but the greater the satisfaction). A minimum of $2 is allocated for completing the survey, and the variable part depends on the response to the experimental question; shower times from 6 to 8 minutes yields the maximal payoff of $2.40. The shape on the payoff function, displayed in Figure 1, deliberately does not depend on the treatment, as we have been operating under the null hypothesis that treatment would not change behavior.

[Insert Figure 1 about here]

When asked to choose their showertime, respondents are unlikely to focus exclusively on earning maximization, and to neglect their true preference, owing to general reasons and to specific features of our experiment. First, recent literature has shown that people tend not to lie when confronted with the choice between answering truthfully and maximizing payoffs, even in anonymous experiments like ours (see Abeler et al., 2019). Second, we argue that in our setting the balance is further tipped in favor of reporting the true preference. Players can only *guess* the answer that maximizes the reward, since they only have some hints on the analytical payoff function without knowing it, that is, the outcome of any possible maximization is uncertain. Additionally, while the prospect of rich payoffs could overshadow lying costs, here only a limited amount of money is at stake.

The low average payoff may also create an issue as it could be argued that players may not take the experiment seriously enough. Besides mitigating the concern related to the payoff maximizing behavior just discussed, there is a key reason that led us to set low payoffs:

payoffs should mirror costs and benefits at stake when making decisions that our experiment seeks to reproduce. Water prices are low and the benefits of taking a shower should be on the same scale: this puts constraints on the range of possible payoffs to which players should be exposed. The maximal payoff compares with the expense born by US users. Besides, despite payoffs that are 10 times smaller, experiments run on an online platform (Amazon Mechanical Turk) are shown to replicate the results of experiments with the same design run in a physical laboratory (Horton et al., 2011).

2.3. Addressing experiment design challenges

The literature has long cautioned about superficially comparing results obtained by relying on contextual judgments. These are common in a within-subject design where the difference between a subject's behavior in two different settings is of interest. It has also warned about responses based on decisions made in isolation, as it is the case in a between-subject design – where the average difference between two sets of subjects in two different settings is of interest. Scholars argue that decision framing may significantly impact choices in both situations (Tversky and Kahneman, 1986; Andreoni, 1995).

In particular, a within-subject design is susceptible to carry-over, demand and sensitization effects (Charness et al., 2012). Carry-over effects involve the possibility that the exposure to the first setting may affect the behavior in the subsequent setting (Greenwald, 1976), or in other words, that answering an experiment's baseline question affects the answer to the endline question. The demand effect consists in the bias induced in the players' responses by the natural inclination to satisfy what they perceive to be the experimenter's expectations, be it consciously or not (Rosenthal, 1976; White, 1977). Despite the potential presence of demand effects both in between- and within-subject designs, they are likely to be stronger in the latter, where moving the player from one setting to another makes her starkly aware of the change to the experimental environment. Sensitization effects come from over-sensitivity to repeated stimuli stemming from a change in parameters as a result of a non-associative learning process in which repeated administration of an inducement leads to a progressive amplification of a response (Shettleworth, 2010).

The proposed experimental design is both within-subject (with both pre-price-change and post-price-change choices) and between-subject (players receive different price treatments). Without understating the caveats above, experiments such as the one proposed in this paper have relevance that stems from their external validity. Indeed, the context where an individual faces an abrupt price increase is naturally reproduced by a within-subject design. Besides, some of the psychological factors that are often held responsible for the disagreement between results obtained using within- and between-subject designs are the same that can explain the emergence of what we call the dynamic component (DC) in the response to price change. As a result, they should not be treated as spurious elements but as cognitive mechanisms which could make dynamic pricing instruments distinct from fixed-price policies in that they elicit a different demand response – as indicated by evidence from cases where water utilities increased the volumetric fare (e.g., Inman and Jeffrey, 2006). This holds true for carry-over and sensitization effects, but leaves out the demand effect, which has to do with the peculiarity of the experimental setting and not with the pricing treatment itself.

Therefore, the experiment comprises robustness checks to tackle the issue of demand effect and boost its internal validity. First, we ask players about the perceived intent of the experiment and check whether the latter is able to significantly predict the assignment of players to the Treatment group. Second, we check whether players who are more able to detect the intent of the study as well as more willing to change their choices given the experimenter's intent react to a different extent when they are in the Treatment group. Additionally, we address the concern that the DC of price effect may have been overestimated because of unobservable differences between the Treatment and the Control groups (for details on the robustness checks, please see Section 5).

3. Data: survey and experiment

We use a set of pre-experimental questions identical across all treatments to provide a series of controls to experimental data. This part consists of two subsections. The first subsection checks on sample representativeness and controls for sample heterogeneity by asking players basic questions about their gender, age and level of education, along with basic information about their household (number of adults/children) and accommodation (property type, tenure and number of bathrooms). The second subsection includes questions about the players' water consumption habits and their perception of consumption and prices. Players have to estimate their households' daily water consumption as well as the monthly water bill, compare their household's water consumption with that of similar households in the area, and guess what activity consumes the most water on a monthly basis. Players are then invited to provide information on the frequency of their showers and baths on a weekly basis and on their shower time. To control for the fact that respondents might bias their answer based on what they perceive to be the experiment's intent (e.g., by selecting a lower shower time if they believe experimentalists want to reward conservation), we checked the perceived intent in post-experiment questions.

Table II reports the distribution of the players by gender, age and education. The sample is evenly distributed between male and female with a slight predominance of the latter gender group (213 vs. 202). The most populated age range of respondents is between 21-30 (47.4%); the sample also includes players below 20 (12.0%) and more than 50 (7.4%). Two hundred and twenty-nine players out of 418 (54.8%) have a degree which is higher than or equivalent to the university degree, whereas only approximately 43.5% of the players have reported to have a certificate which is below or equivalent to the high school degree. It is worth mentioning that since we control for the demographic characteristics of the players in our regression models, stratification based on gender, age and/or education does not cause any problems of consistency.

[Insert Table II about here]

Table III shows the descriptive statistics relative to the players' shower and bath habits. On average, the sampled players take 5.67 showers per week, with a reported maximum number of 11. Before the experiments, we also request players to provide an estimate of the time they spend in the shower. They were free to enter any integer value between 0 and 60 minutes. We call this variable *Satisfaction* to differentiate it from the *Shower time* indicated in the experimental section of the survey. Its mean value across the sample is 11.2 minutes while its median value is 10 minutes.

[Insert Table III about here]

As far as the experiment is concerned, reported shower time (*ST*) can range from 1 to 15 minutes. When only baseline questions are considered, the variable has a mean value of 8.12 minutes and a standard deviation of 3.34 minutes; the mean value goes down to 6.33 minutes (with a standard deviation of 2.91 minutes) in response to endline questions. We can also look at the variations in the showertime when going from the baseline to the endline question for Treatment and Control groups. Figure 2 shows the boxplots of the showertime also discriminating subgroups confronted with the water scarcity scenario from those that faced a regular one.

[Insert Figure 2 about here]

The preliminary evidence is that both treatment (dynamic change in the water price) and water scarcity condition lead to a decrease in the showertime. Moreover, the two mechanisms seem not to reinforce each other. Though we randomly assigned players to groups, this evidence should be handled with caution as we are not controlling for confounding factors (gender, age, education, water-using habits,…) that may introduce heterogeneity across groups. We will do that by estimating the regression models (see Section 4).

The first post-experiment survey section is about players' environmental concerns. Thus, players have to rate their personal environmental attitudes and report their most recent exposure to informational campaigns on water conservation issues (e.g. messages from conventional or social media). The second section aims to elicit players' perceived intent of the experiment, as well as their willingness to change behaviours based on that perceived intent. As explained above, this information is useful to perform robustness checks, and in particular to control for demand effects.

4. Results

Table IV presents the results obtained using both baseline and endline choices. We use a difference-in difference (DID) approach and estimate the following model:

$$ST_{it} = \beta_0 + \beta_1 Treatment_i + \beta_2 Endline_t + \beta_3 (Treatment_i * Endline_t)$$
$$+\beta_4 Scarcity_i + \beta_5 (Treatment_i * Scarcity_i) + \delta X_i + \varepsilon_{it} \qquad (5)$$

The dependent variable (ST_{it}) is the reported shower time in minutes by player i when answering to question$t = (baseline; endline)$. The explanatory variables are:

- *Treatment:* the treatment dummy taking the value 1 for players assigned to the treatment groups and 0 for players assigned to the control groups;
- *Endline:* a dummy taking the value 1 for endline choices and 0 for baseline ones, standing alone and interacted with *Treatment* (*Treatment**Endline*);
- *Scarcity:* a dummy referring to the scarcity scenario, standing alone and interacted with *Treatment* (*Treatment**Scarcity*).

Recall that scarcity is only introduced in endline questions. The model also includes a vector of controls at the player level X_i along with a error termε_{it}.

Columns (1-3) report the panel tobit estimates. We use tobit as our dependent variable is censored from above at 15 minutes (i.e., we may observe showertime equal to 15 minutes for some players whose preference was to shower for longer than 15 minutes). For the sake of comparison, we also report linear panel estimates in column (4).

We can refer to Equations (1-4) for the interpretation of the coefficientsβ_k with$k = 0, \ldots, 5$. $\beta_0$is the constant of the model and represents the estimated value of $\left[ST\left(p_{high}\right) \quad _{baseline}\right] \vee \quad _{Control}$; β_1 is the difference inST between players in the treatment group and those in the control group at the baseline question$(Endline = 0)$, i.e. $[ST(p_{low}) \quad _{baseline}] \vee \quad _{Treatment} - \left[ST\left(p_{high}\right) \quad _{baseline}\right] \vee \quad _{Control}$. This is, according to Equation (2), the effect of a static price change SPE when we are in a scenario characterized by regular water availability $(Scarcity = 0)$. Coefficient β_2 captures the drift induced by being confronted with the same choice one more time. β_3 is the overall price effect, PE, defined by Equation (1) as a difference-in-differences response to price change. β_4 accounts for the effect of being exposed to a water scarcity scenario for control group players. Finally, coefficient β_5 is the incremental effect of water scarcity for treatment group players.

The estimates that refer to specifications which include only the treatment dummies are reported in column (1) in Table IV. A first set of controls, i.e. the respondents' shower habits (number of showers per week (*Showers*)) and the satisfaction from showering (*Satisfaction*), are considered in column (2). Additional player-specific controls, i.e., gender (*Female*), age (*Age*), age-squared (*Age*^2), and education level (*Education*) are added in column (3).

[Insert Table IV about here]

The coefficient associated with *Treatment* (β_1), is statistically significant in all three specifications. It is positive, suggesting that players choose to buy more water for showering when they face the lower price p_{low} in the baseline question, i.e. when they are in the Treatment group and before being exposed to a price variation. This is the static price effect (SPE) (Equation (2)). Its magnitude, which represents the average shower time reduction with a higher price, ranges from 0.54 to 0.62 across the specifications, with the higher reduction corresponding to the most complete specification, i.e., last column on Table IV.

The overall effect of a change in the unit price of water (*PE*) is given by the coefficient β_3 of the interaction term *Treatment*Endline* (Equation (1)). Irrespective of the specification, *PE* is negative and statistically significant at the 1% level. This means that players in the Treatment group, i.e., those who have been exposed to the price increase over time, reduce their shower time when switching from the lower price p_{low} to the higher price p_{high}. The magnitude of the effect is similar across specifications with an average shower time reduction of 1.27 minutes. Since the average shower time in the baseline question in the treatment group is 8.39 minutes, the price variation from 5 to 10 cents reduces water consumption by about 15%. Importantly, the overall effect of changing the price (PE) is stronger than the one relative to the static price (SPE) both in magnitude and in significance. The difference has been tested to be significantly different from 0 at the 10% statistical level. This result suggests the existence of a dynamic pricing component (DPC) which accounts for the difference between the two effects. This would suggest that a dynamic price increase would have a stronger impact on water conservation than a static price difference.

In obtaining this result, we controlled for effects that could have led players to systematically give answers in the endline setting that are different from those given in the baseline one. In fact, the use of a Control group allows to capture the drift induced by making the same choice twice, through the coefficient β_2. This coefficient is negative and statistically significant, suggesting that players have reduced their shower time also when the price has remained unchanged.

Results also give indications on how price policy and water scarcity interact with each other. The combined evidence of a negative and statistically significant coefficient β_4 associated with *Scarcity* and a non-significant coefficient β_5 associated with the interaction term *Treatment*Scarcity* suggests that players would take shorter showers as a reaction to an announcement of water shortage whatever the price they face. The magnitude of this scarcity effect is large, leading them to reduce shower time by 1.69 minutes on average according to the most thorough specification (column (3) of Table IV). It is present regardless of whether the scarcity scenario is introduced alongside a price measure or not. Evidence of this is the lack of statistical significance for coefficient β_5 at any conventional level in all the specifications. Accordingly, water scarcity and price policy seem to be two independent mechanisms that can be used together for maximal demand response.

5. Robustness checks

As discussed in Section 2.3, demand effects might arise in our design. This means that players' answers might be impacted by their desire to comply with or defy the perceived intent of the experiment. We address demand effects in two ways.

First, demand effects are less likely if players are not able to recognize the intent of the study. The post-experiment survey asked players what they thought the intent of the study was. Results available in Table V show that there is no significant correlation between perceived intent and both the assignment of players to the Treatment group (column 1) and their reduction in showertime going from the baseline to the endline choice (column 2). It suggests that there is no one clear way in which demand effects might act.

[Insert Table V about here]

Second, if demand effects are present, they should differently affect players who are more able to detect the intent of the study and are more willing to change their choices given the experimenter's intent. We proxy for this ability using the Self-Monitoring Scale (Snyder 1974), and find no evidence that self-monitoring ability moderates the treatment effect.

We asked consumers to respond to each of the following four statements on a five-point Likert scale, from Strongly Agree to Strongly Disagree. The statements are:

- "It's important to me to fit in with the group I'm with."
- "My behavior often depends on how I feel others wish me to behave."
- "My behavior is usually an expression of my true inner feelings, attitudes, and beliefs."
- "I would NOT change my opinions (or the way I do things) in order to please someone else or win their favor."

SMS Factor provides a synthetic indicator of the willingness to change choices to comply with the experimenter's intent. In order to construct the indicator, we performed a principal component analysis using the variables relative to the four dimensions of self-monitoring reported above. The analysis identifies one dominant factor, which alone accounts for 42% of the total variance. It loads positively on the first two dimensions and negatively on the last two. For each player, we define the variable *SMS Factor* by the factor score coefficient resulting from principal component analysis. Accordingly, a higher value of *SMS Factor* indicates a higher willingness to comply with the perceived experimenter's intent.

[Insert Table VI about here]

As evidenced in Table VI, none of the interacting terms between our treatment dummies and *SMS Factor* is statistically significant. In addition, the coefficients of *Treatment*, *Treatment*Endline, Endline* and *Scarcity* ($\beta_1, \beta_2, \beta_3, \beta_4$) preserve sign and statistical significance.

Another concern with the results reported in Table IV is that the *dynamic pricing component* (DPC) may have been overestimated as a consequence of unobservable differences between the treatment and the control groups. Indeed, suppose that the players in the treatment group, exposed to p_{low} in the baseline setting and to p_{high} in the endline one, have had reasons to report shorter shower times than players in the control group (who are exposed to p_{high} both in the baseline and the endline setting). Then, the idiosyncratic differences between the two groups would have led to an underestimation of the static price effect (SPE) and, in turn, to the emergence of a difference between the overall *price effect* (PE) and the SPE, which we refer to as the *dynamic pricing component* (DPC) of the price effect.

In order to rule out this issue, we quasi-externally validate our results using an additional sample of players whom we recruited for a pilot wave of the experiment. Since we used the pilot wave to refine our experimental design, it differs in some features from the final design described in the paper. The two most important differences in the pilot wave are the lack of an endline setting and the possibility for players to choose their shower time in a range of 1-10 minutes rather than 1-15.

With these differences in mind, we can use the pilot wave to show that the estimated SPE using the final sample is not biased by unobservables. In fact, since both players in the pilot and final waves are exposed to the same p_{high} and p_{low}, depending on having being assigned to the treatment and control group, we can compute the two SPEs and confirm that they do not differ across samples. Table VII shows the results of this additional test.

[Insert Table VII about here]

As expected, coefficient β_1 associated with *Treatment* is positive and statistically significant, reflecting the increase in shower time when players are exposed to p_{low}. More interestingly, for the purpose of the test, is the coefficient of *Treatment**Pilot*. It is not statistically significant, suggesting that the estimated difference between the SPEs relative to the two samples is not statistically different from 0, thus confirming that our results are not driven by idiosyncratic players' behaviors. Not surprisingly, players in the pilot wave reported, on average, shorter shower times as a consequence of the narrower range they could use to give their answers (see the negative and statistically significant coefficient of the variable *Pilot*).

6. Discussion and policy implications

In our experimental setting, results show that residential water consumers respond to a price increase by lowering consumption. Besides that expected finding, experimental findings also suggest that a sudden price variation from a baseline price to an endline price causes a larger average demand response than what would be predicted by the difference between average consumptions for the same price difference in situations where there has been no price change. This is a significant result as it indicates the existence of an effect associated to the dynamic price change itself. By definition, in the experiment the price change is also immediately communicated to end users. For water planners, this means that dynamic water pricing, when accompanied with real-time communication on price variations, could be a viable option for short-term water conservation gains in critical situations caused by water scarcity or demand peaks. An immediate consequence is that smart, two-way devices are to be installed if consumers have to make an informed decision. A careful design of dynamic pricing programs is necessary to generate those benefits that may sustain the costs for rolling out the new advanced infrastructure (Wolak, 2010).

Nevertheless, a broad diffusion of smart meters is not sufficient for the dynamic pricing benefits to materialize. While a perfectly informed consumer should react to marginal price, most consumers will not devote much time or effort to study the tariff structure or changes in rates because of information costs (Arbues et al., 2003). In the electricity sector, evidence suggests consumers suffer from inattention issues when confronted with dynamic pricing. For instance, they have been shown to be insensitive to the magnitude of the price change (Gillan, 2018). Automation fosters the response of end users to changes in prices (Dutta and Mitra, 2017), but it does not solve the attention problems (Gillan, 2018). New research efforts are necessary to identify information and communication technologies (e.g. social media, machine learning) that enable end users to fully capture dynamic pricing benefits in a cost-effective way. Research should also factor in the water and electricity sectors' differing contexts: for instance, insensitivity to the magnitude of a price increase could be used for water conservation if future research confirmed the existence of a dynamic pricing effect. Indeed, the (non-dynamic) price elasticity of residential water demand is generally low in part because water bills are often relatively inexpensive (Espey et al., 1997; Dalhuisen et al., 2003; Marzano et al., 2018). Inattention from the public to the magnitude of a price increase could then enable a dynamic pricing effect to foster short-term water conservation regardless of its limited effects on households' finances.

The paper also showed the pricing effect is also present when players are notified that the price increase was caused by water scarcity (Garrone et al., 2020). Price policies appear not to interfere with awareness campaigns and other information policies aimed at producing water savings during water scarce periods. To the contrary, experimental results suggest that impacts of information measures on water consumption would add up to the dynamic pricing effect, meaning that a multi-pronged approach to water conservation during water scarce periods could be most effective. What is more, a coordinated set of policies would likely reach a larger audience than any of these demand management measures alone.

The water conservation potential of dynamic pricing should be confirmed (or questioned) by further studies, and research efforts should also focus on understanding which accompanying measures enable the policy implementation on a wider scale. Research is also necessary to better gauge how technological, institutional and cultural specificities interact with cognitive decision-making from end-users, and how they react to information (Vatn, 2010).

Literature from the electricity sector also teaches a few lessons on the political conditions for implementing dynamic pricing programs. Since dynamic pricing passes through cost variations to end users, the latter are likely to experience a greater bill volatility relative to the case of time-invariant prices (Wolak, 2010). Besides, dynamic pricing may have adverse distributional effects, because low-income residential users have higher price elasticities and could reduce water demand disproportionately, jeopardizing the lifeline uses and cutting back their lifestyle (Agthe and Billings, 1987). These facts suggest that opposition from consumer associations and resistance from lawmakers and regulators are likely, but also highlights possible solutions, and the water sector has started exploring both. Thus, appropriate pricing schemes must redistribute money in a way that aligns with residents' concerns (Kallbekken and Aasen, 2010), yet more prosaically, price increases are a way for utilities to recover revenue losses from scarcity-induced reductions in consumptions (Sahin et al., 2016). It has been demonstrated that in theory, scarcity pricing schemes can satisfy the requirements of revenue equity and revenue sufficiency while sending residential users a clear signal on the resource's status. This being said, further research is necessary to support water utilities and regulators in the design and implementation of possible remedies to the price risks and equity issues that are associated to dynamic pricing, such as the voluntary opt-in participation (Borenstein, 2013) or the prioritization of rebate schemes (Olmstead and Stavins, 2009, Wolak, 2010).

7. Conclusions

This study described the design and results of an online experiment that ascertains and measures the contribution of dynamic pricing to the demand-side management of residential water. The experiments' subjects were recruited in the United States and Canada via an online working platform and online surveys. We exposed simulated consumers to treatments that differ in terms of the unit price of water and of whether the water is being taken from the environment under stress (Tembata and Takeuchi, 2018). Players chose their shower length given price changes and environmental conditions. The experiment suggests that consumers would respond to increases of unit prices over time by lowering consumption. It also found evidence of a dynamic pricing effect, i.e., that water consumers respond to a greater extent to price variations that are sudden and close in time and for which they have received a communication. This suggests variation of water prices could be effective at reliably securing water conserving behavior. A decrease in water use in water scarcity scenarios was observed in the experiment even without dynamic pricing, leading the authors to conclude that if these findings are confirmed, a conservative utility interested in parsimoniously introducing time-varying water charges to test its effectiveness might first try time-of-day pricing as reductions of water use during drought may be achievable by other means.

We acknowledge that the evidence we provide needs confirmation in separate field studies, which we don't pretend to replace. Rather, we point out a need for carefully crafted field studies to pave the way for successful dynamic pricing strategy (environmentally effective, socially equitable and economically efficient).

Declaration of compliance with codes of ethics.

The work has been carried out in accordance with The Code of Ethics of the World Medical Association (Declaration of Helsinki) for experiments involving humans. The manuscript is in line with the Recommendations for the Conduct, Reporting, Editing and Publication of Scholarly Work in Medical Journals. It is representative of the human population (sex, age and ethnicity) as per those recommendations. Consent was obtained for experimentation with human subjects. The privacy rights of human subjects was always observed.

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FIGURES

Figure 1

Payoff as a function of showertime

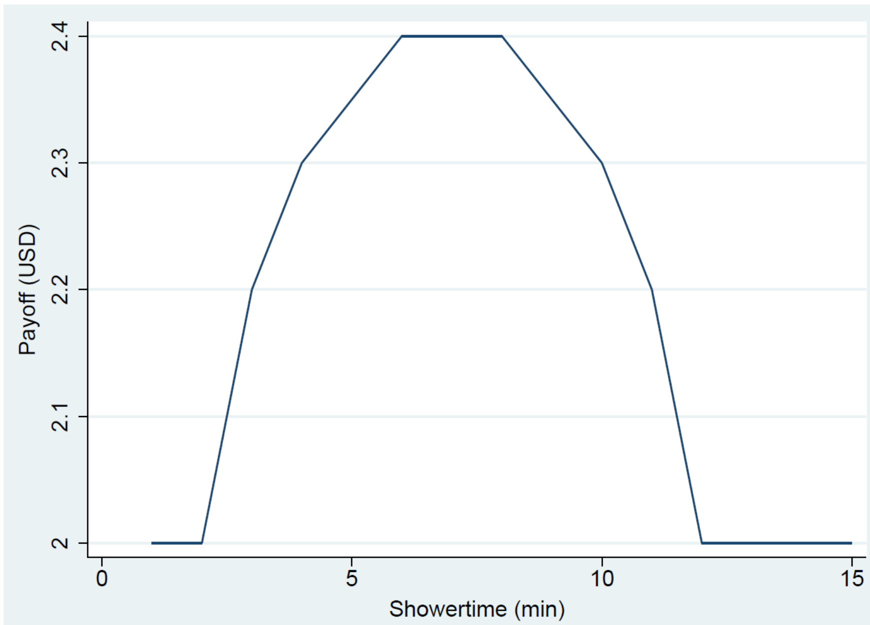
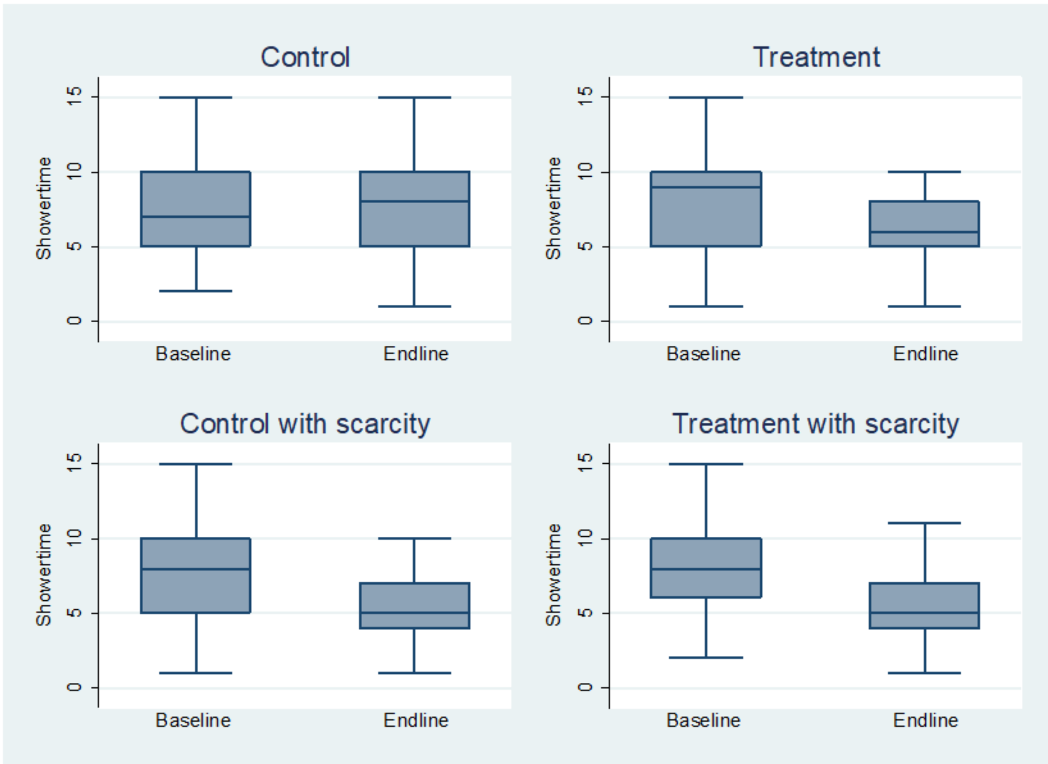


Figure 2

Boxplots of showertime for Treatment and Control groups



The figure displays the variations in showertime (in minutes) going from the baseline to the endline question for Treatment and Control groups (both with and without scarcity). Each boxplot shows median, minimum, maximum, first and third quartiles (excluding outliers). Players in the Control groups pay 10 cents per minute of shower under both the baseline and the endline question. Players in the Treatment groups pay 5 cents per minute of shower under the baseline question and 10 cents per minute of shower under the endline question.

TABLES

Table I

Treatment and Control groups

Distribution of players across Treatment and Control groups

	Water availability scenarios		
	Scarcity	*Regular*	*TOTAL*
Treatment	108	105	213
Control	105	106	211
TOTAL	213	211	424

The table illustrates the distribution of players across four groups generated by the combination of the Treatments and Control groups with two water availability scenarios.

Table II

Players

Distribution of players across age, gender and education

Age	Gender		Education							Total
	Female	Male	Doctoral degree	Master/Professional School degree	University degree	Associate degree	High School degree	Apprenticeship or equivalent	No degree	
≤ 20	23	26	0	2	6	0	40	0	2	50
21-30	94	103	3	36	75	2	74	2	6	198
31-40	59	45	2	22	40	4	30	1	5	104
41-50	20	15	2	13	9	1	9	1	0	35
50	16	14	0	8	11	0	10	1	1	31
TOTAL	212	203	7	81	141	7	163	5	14	418

The table illustrates the distribution of players by gender and education along the columns and by age ranges along the rows.

Table III
Showers and baths

	Obs	Mean	Median	Sd	Max	Min
Pre-experiment survey						
Showers per week	415	5.669	6.5	2.496	11	0.5
Satisfaction	415	11.166	10	5.907	60	0
Baths per week	415	1.376	0	2.277	8	0
Experiment						
ST (baseline answers)	414	8.118	8	3.337	15	1
ST (endline answers)	413	6.332	6	2.910	15	1

The table illustrates the descriptive statistics relative to the number of showers per week, the shower time, satisfaction from showering and the baths per week.

Table IV

Main models estimates

Dependent variable: *ST*		*Tobit panel*		*Linear panel*
	(1)	(2)	(3)	(4)
Treatment (β_1)	0.574*	0.537*	0.620**	0.591**
	(0.321)	(0.296)	(0.298)	(0.284)
Endline (β_2)	-0.579**	-0.530**	-0.540**	-0.503**
	(0.247)	(0.245)	(0.246)	(0.235)
*Treatment*Endline* (β_3)	-1.238***	-1.271***	-1.276***	-1.252***
	(0.349)	(0.346)	(0.348)	(0.333)
Scarcity (β_4)	-1.593***	-1.691***	-1.689***	-1.676***
	(0.333)	(0.327)	(0.329)	(0.315)
*Treatment*Scarcity* (β_5)	0.656	0.719	0.739	0.759*
	(0.470)	(0.462)	(0.465)	(0.445)
Showers		-0.082	-0.096*	-0.087*
		(0.054)	(0.055)	(0.052)
Satisfaction		0.208***	0.214***	0.205***
		(0.023)	(0.024)	(0.022)
Female			0.017	0.006
			(0.278)	(0.266)
Age			0.065	0.064
			(0.074)	(0.070)
Age^2			-0.001	-0.001
			(0.001)	(0.001)
Education			0.147	0.142
			(0.103)	(0.098)
Constant	7.922***	6.080	4.206***	4.205***
	(0.227)	(0.441)	(1.308)	(1.249)
Observations	827	827	821	821
Players	414	414	411	411

The table reports the results of tobit and simple panel regressions using both baseline and endline choices. The dependent variable is the shower time indicated by the players. The explanatory variables in all the regressions are the treatment dummies that define our treatment groups. Depending on the specification, we control for the number of showers per week, the satisfaction from showering, gender, age and education. Standard errors are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

Table V

Perceived intent of the experiment

	Player in the treatment group (1)	*Showertime reduction* (2)
Intent:		
Measure whether people make consistent choices when it comes to waterconsumption	-0.641	0.048
	(0.761)	(1.531)
Promote water conservation	-0.416	-0.011
	(0.760)	(1.530)
Test whether people are able to quantify water costs	-0.305	0.117
	(0.774)	(1.560)
Understand how much people are concerned with water resources exploitation	-0.877	-0.264
	(0.768)	(1.543)
Understand the impact of water price on your decisions	-0.154	-0.311
	(0.757)	(1.521)
Understand what lifestyle people have	-0.431	0.792
	(0.870)	(1.764)
Constant	0.431	-1.667
	(0.749)	(1.504)
Players	413	413

The table reports the results of a probit regression in column 1 and OLS in column 2. In column 1, the dependent variable is a dummy variable set equal to 1 for players assigned to the Treatment group and 0 for players assigned to the Control group. In column 2, the dependent variable is the showertime reduction going from the baseline to the endline question. The independent variables are a set of dummies set equal to 1 for players who responded that the intent of the study was as listed in the leftmost column and 0 otherwise.

Table VI

Controlling for self-monitoring scale

Dependent variable: *ST*			
	(1)	(2)	(3)
Treatment (β_1)	0.530*	0.504*	0.584**
	(0.320)	(0.295)	(0.297)
Endline (β_2)	-0.588**	-0.536**	-0.544**
	(0.247)	(0.245)	(0.246)
*Treatment*Endline* (β_3)	-1.218***	-1.251***	-1.248***
	(0.348)	(0.346)	(0.348)
Scarcity (β_4)	-1.578***	-1.679***	-1.676***
	(0.332)	(0.327)	(0.328)
*Treatment*Scarcity* (β_5)	0.667	0.735	0.743
	(0.469)	(0.462)	(0.465)
*Treatment*SMS Factor*	-0.180	-0.353	-0.292
	(0.320)	(0.296)	(0.300)
*Treatment*Endline*SMS Factor*	0.099	0.108	0.128
	(0.348)	(0.345)	(0.353)
*Treatment*Scarcity*SMS Factor*	0.293	0.271	0.246
	(0.471)	(0.463)	(0.470)
*Endline*SMS Factor*	0.112	0.077	0.075
	(0.242)	(0.240)	(0.241)
*Scarcity*SMS Factor*	-0.293	-0.225	-0.235
	(0.329)	(0.324)	(0.325)
SMS Factor	0.034	0.218	0.254
	(0.224)	(0.207)	(0.210)
Players characteristics	No	No	Yes
Players' shower habits	No	Yes	Yes
Observations	826	826	820
Players	413	413	410

The table reports the results of panel tobit regressions using both baseline and endline choices. The dependent variable is the shower time indicated by the players. The explanatory variables in all the regressions are the treatment dummies that define our treatment groups, stand alone and interacted with a factor measuring the attitude of players in a self-monitoring scale. Depending on the specification, we control for the number of showers per week, the satisfaction from showering, gender, age and education. Standard errors are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% levels, respectively.

Table VII

Controlling for unobservables

Dependent variable: *ST*	(1)	(2)	(3)
Treatment	0.749**	0.691**	0.771***
	(0.328)	(0.296)	(0.298)
Pilot	-1.795***	-1.468***	-1.536***
	(0.387)	(0.349)	(0.350)
*Treatment*Pilot*	0.438	0.567	0.565
	(0.507)	(0.456)	(0.457)
Scarcity	-1.287***	-1.336***	-1.246***
	(0.440)	(0.394)	(0.395)
Players characteristics	No	No	Yes
Players' shower habits	No	Yes	Yes
Players	825	825	822

The table reports the results of panel tobit regressions using only baseline choices. The dependent variable is the shower time indicated by the players. The explanatory variables in all the regressions are the treatment dummy that define our treatment groups, stand alone and interacted with a dummy identifying the experiment wave in which players have been recruited and a dummy set equal to 1 if players have been exposed to a scarcity scenario and 0 otherwise. Depending on the specification, we control for the number of showers per week, the satisfaction from showering, gender, age and education. Standard errors are reported in parentheses. ** and *** denote statistical significance at 5% and 1% levels, respectively.

Appendices

Appendix A1 - Players by geographic origin

Table A.1

Distribution of players by geographic origin

Canada					
Province	#	%	Province	#	%
Alberta	7	1.67	Ontario	11	2.63
British Columbia	7	1.67	Prince Edward Island	1	0.24
Manitoba	2	0.48	Quebec	3	0.72
Nova Scotia	1	0.24	*TOTAL*	32	7.66
The United States					
State	#	%	State	#	%
Alabama	7	1.67	Montana	1	0.24
Arizona	7	1.67	Nevada	7	1.67
Arkansas	2	0.48	New Hampshire	2	0.48
California	35	8.37	New Jersey	9	2.15
Colorado	6	1.44	New Mexico	2	0.48
District of Columbia	1	0.24	New York	22	5.26
Florida	29	6.24	North Carolina	14	3.35
Georgia	24	5.74	Ohio	17	4.07
Idaho	4	0.96	Oklahoma	6	1.44
Illinois	12	2.87	Oregon	5	1.20
Indiana	6	1.44	Pennsylvania	14	3.35
Kansas	4	0.96	South Carolina	6	1.44
Kentucky	9	2.15	Tennessee	11	2.63
Louisiana	6	1.44	Texas	44	10.53
Maine	1	0.24	Utah	3	0.72
Maryland	4	0.96	Vermont	1	0.24
Massachusetts	6	1.44	Virginia	9	2.15
Michigan	18	4.31	Washington	8	1.91
Minnesota	7	1.67	Wisconsin	8	1.91
Mississippi	3	0.72	Wyoming	1	0.24
Missouri	5	1.20	*TOTAL*	386	92.34

Appendix A2 - Online experiment questionnaire

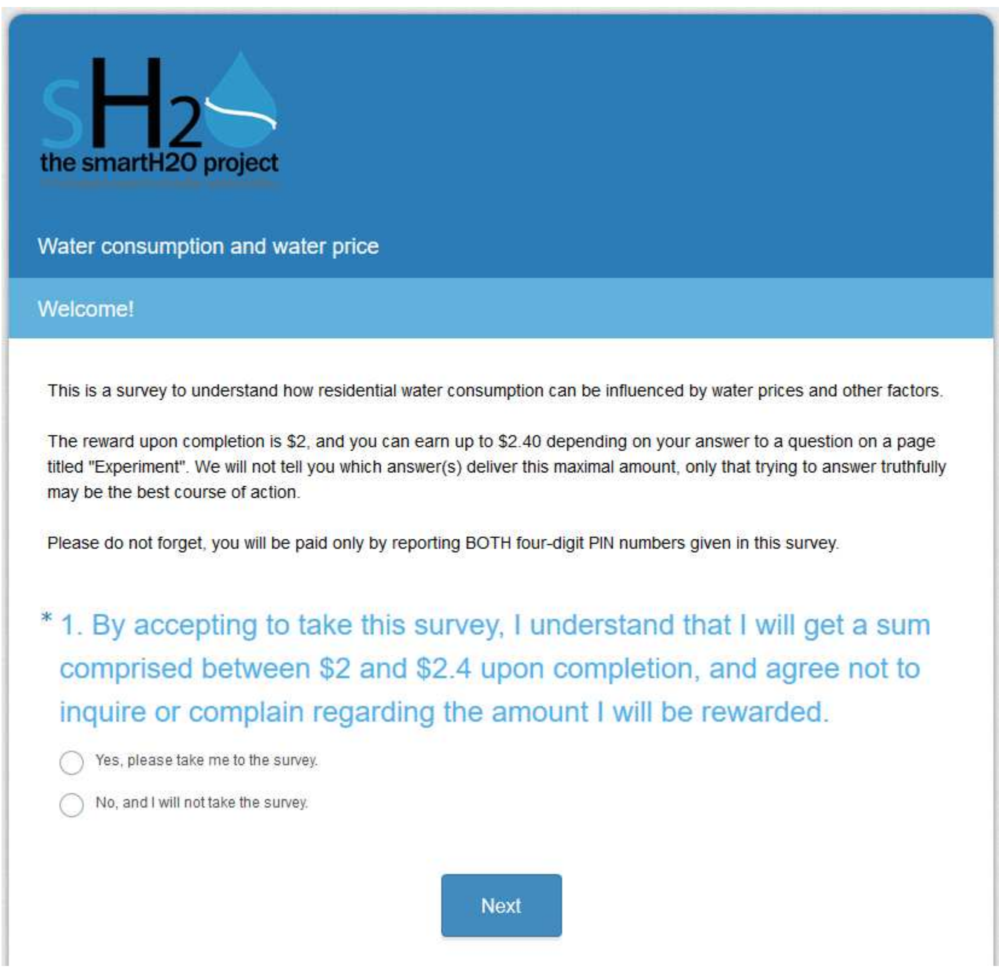
In what follows, each of the subsections represents one page of the survey, and each title corresponds to the page title in the survey.

Page 1: "Welcome!"

[The experiment involves different rewards for individuals that fulfilled their task equally well – but that replied differently to the experimental question. Usually in crowdsourcing sites, including Microworkers, rewards are rather targeted to workers who perform better than others. Therefore, a disclaimer was introduced on the survey's first page to avoid potential complaints from online workers (Figure A2.1). We have had to handle 0 complaint throughout the experiment.

Figure A2.1 gives this first page for versions A and C, corresponding to "static" pricing. In versions B and D, the phrase "depending on your answer to a question on a page" is replaced with "depending on your answer to the second question on a page"].

Figure A2.1. First page of the survey, including visual layout.



Page 2: “General questions”

We start this questionnaire with a series of questions about you.

Q2. In what country do you currently reside?

- United States
- Canada

Q3. In what state / province do you currently reside?

[Textbox where respondents enter response]

Q4. What is your gender?

- Female
- Male
- Other

Q5. How old are you?

[Textbox where respondents enter their age]

Q6. How many adults currently live in your household (including you)?

- 1
- 2
- 3
- 4
- 5 or more

Q7. How many children and teenagers, by age, currently live in your household? Please enter a number for each age group.

Aged 0-4	[number entered in textbox]
Aged 5-9	[number entered in textbox]
Aged 10-14	[number entered in textbox]
Aged 15-18	[number entered in textbox]

Q8. What is the highest level of education you have completed?

- No Degree
- Apprenticeship or equivalent
- High School Degree
- Professional School Degree
- University Degree
- Master Degree

- Doctoral Degree
- Other (please specify)
  [textbox]

Q9. Do you own or rent the property you currently live in?

- I own it
- I rent it
- Other (please specify)
  [textbox]

Q10. In which type of housing do you currently live?

a. Single-family home
b. Shared home
c. Apartment
d. Other

Q11. How many bathrooms are there in your home?

- 0
- 1
- 2
- 3
- More than 3

Page 3: "Your water consumption"

We continue with questions about your water consumption.

Q12. How much do you estimate your household's daily water consumption to be?

- Less than 200 litres per day
- 201-300 litres per day
- 301-400 litres per day
- 401-500 litres per day
- More than 500 litres per day
- I don't know

Q.13 Do you know your household's monthly bill?

- Yes, precisely
- Yes, more or less
- No

If you know it, you can enter amount here:

[textbox]

Q14. How much water do you think your household consumes compared to the average household in your area?

- Much more
- Somewhat more
- Same as average
- Somewhat less
- Much less

Q15. Which of the following activities do you think conumes the most water on a monthly basis?

- Bath
- Shower
- Washing machine
- WC
- Garden irrigation
- Dishwasher
- Tap

Q16. How many baths do you personally take every week?

- I do not take baths
- Less than 1
- 1-3
- 4-5
- 6-7
- More than 7

Q17. How many showers do you personally take every week?

- Less than 1
- 1-3
- 4-5
- 6-7
- 8-9
- 10 or more

Q18. On average, how long do you personally spend showering (with the water running)?

- 1 minute
- 2 minutes
- 3 minutes
- 4 minutes
- 5 minutes
- 6 minutes
- 7 minutes

- 8 minutes
- 9 minutes
- 10 minutes
- More (please specify)
  [textbox]

Q19. On a scale from 1 to 10, how would you rate your personal satisfaction depending on the time spent showering? 1 is minimal satisfaction while 10 is maximal satisfaction.

	1	2	3	4	5	6	7	8	9	10
3-minute shower										
6-minute shower										
9-minute shower										

Page 4: "Experiment"

<u>Version A:</u>

You are given $1.5 to spend on showering. Assume that having the shower running costs 10 cents per minute.

You want to keep money on your $1.5, but you also get satisfaction from showering, and this satisfaction increases with shower time. So you will have to find a compromise between saving money and personal satisfaction!

Q20. What shower length do you choose, given the price per minute given above, and your own satisfaction from showering? Please choose how long you would have the shower running, between 1 and 15 minutes.

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10
- 11
- 12
- 13
- 14
- 15

You still have $1.5, like in question 20. Assume that your water utility **keeps the water price at 10 cents per minute** despite the need to reduce consumption**.**

You are paid depending on how much money is left on your $1.5, but also depending on how much satisfaction you get from your shower (and your satisfaction still increases with shower time).

Q21. What is your new shower length, between 1 and 15 minutes?

- 1 minute
- 2 minutes
- 3 minutes
- 4 minutes
- 5 minutes
- 6 minutes
- 7 minutes
- 8 minutes
- 9 minutes
- 10 minutes
- 11 minutes
- 12 minutes
- 13 minutes
- 14 minutes
- 15 minutes

Version B:

You are given $1.5 to spend on showering. Assume that having the shower running costs 5 cents per minute.

You want to keep money on your $1.5, but you also get satisfaction from showering, and this satisfaction increases with shower time. So you will have to find a compromise between saving money and personal satisfaction!

Q20. What shower length do you choose, given the price per minute given above, and your own satisfaction from showering?

- 1 minute
- 2 minutes
- 3 minutes
- 4 minutes
- 5 minutes
- 6 minutes
- 7 minutes

- 8 minutes
- 9 minutes
- 10 minutes
- 11 minutes
- 12 minutes
- 13 minutes
- 14 minutes
- 15 minutes

You still have $1.5, like in question 20. Now assume that your water utility **doubles the water price to 10 cents per minute** in order to reduce consumption**.**

You are paid depending on how much money is left on your $1.5, but also depending on how much satisfaction you get from your shower (and your satisfaction still increases with shower time).

Q21. What is your new shower length, between 1 and 15 minutes?

- 1 minute
- 2 minutes
- 3 minutes
- 4 minutes
- 5 minutes
- 6 minutes
- 7 minutes
- 8 minutes
- 9 minutes
- 10 minutes
- 11 minutes
- 12 minutes
- 13 minutes
- 14 minutes
- 15 minutes

Version C:

You are given $1.5 to spend on showering. Assume that having the shower running costs 10 cents per minute.

You want to keep money on your $1.5, but you also get satisfaction from showering, and this satisfaction increases with shower time. So you will have to find a compromise between saving money and personal satisfaction!

Q20. What shower length do you choose, given the price per minute given above, and your own satisfaction from showering? Please choose how long you would have the shower running, between 1 and 15 minutes.

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10
- 11
- 12
- 13
- 14
- 15

You still have $1.5, like in question 20. Now assume that there currently is a **severe drought** in your area, similar to the recent drought in California (see pictures). Assume also that your water utility **keeps the water price at 10 cents per minute** despite the need to reduce consumption**.**

(Image credit: Robyn Beck, AFP/ Getty Images)


(Image credit: California Department of Water Resources)

You are paid depending on how much money is left on your $1.5, but also depending on how much satisfaction you get from your shower (and your satisfaction still increases with shower time).

Q21. What is your new shower length, between 1 and 15 minutes?

- 1 minute
- 2 minutes
- 3 minutes
- 4 minutes
- 5 minutes
- 6 minutes
- 7 minutes
- 8 minutes
- 9 minutes
- 10 minutes
- 11 minutes
- 12 minutes
- 13 minutes
- 14 minutes
- 15 minutes

<u>Version D:</u>

You are given $1.5 to spend on showering. Assume that having the shower running costs 5 cents per minute.

You want to keep money on your $1.5, but you also get satisfaction from showering, and this satisfaction increases with shower time. So you will have to find a compromise between saving money and personal satisfaction!

Q20. What shower length do you choose, given the price per minute given above, and your own satisfaction from showering?

- 1 minute
- 2 minutes
- 3 minutes
- 4 minutes
- 5 minutes
- 6 minutes
- 7 minutes
- 8 minutes
- 9 minutes
- 10 minutes

- 11 minutes
- 12 minutes
- 13 minutes
- 14 minutes
- 15 minutes

You still have $1.5, like in question 20. Now assume that there currently is a **severe drought** in your area, similar to the recent drought in California (see pictures). Assume also that your water utility **doubles the water price to 10 cents per minute** in order to reduce consumption**.**

(Image credit: Robyn Beck, AFP/ Getty Images)


(Image credit: California Department of Water Resources)

You are paid depending on how much money is left on your $1.5, but also depending on how much satisfaction you get from your shower (and your satisfaction still increases with shower time).

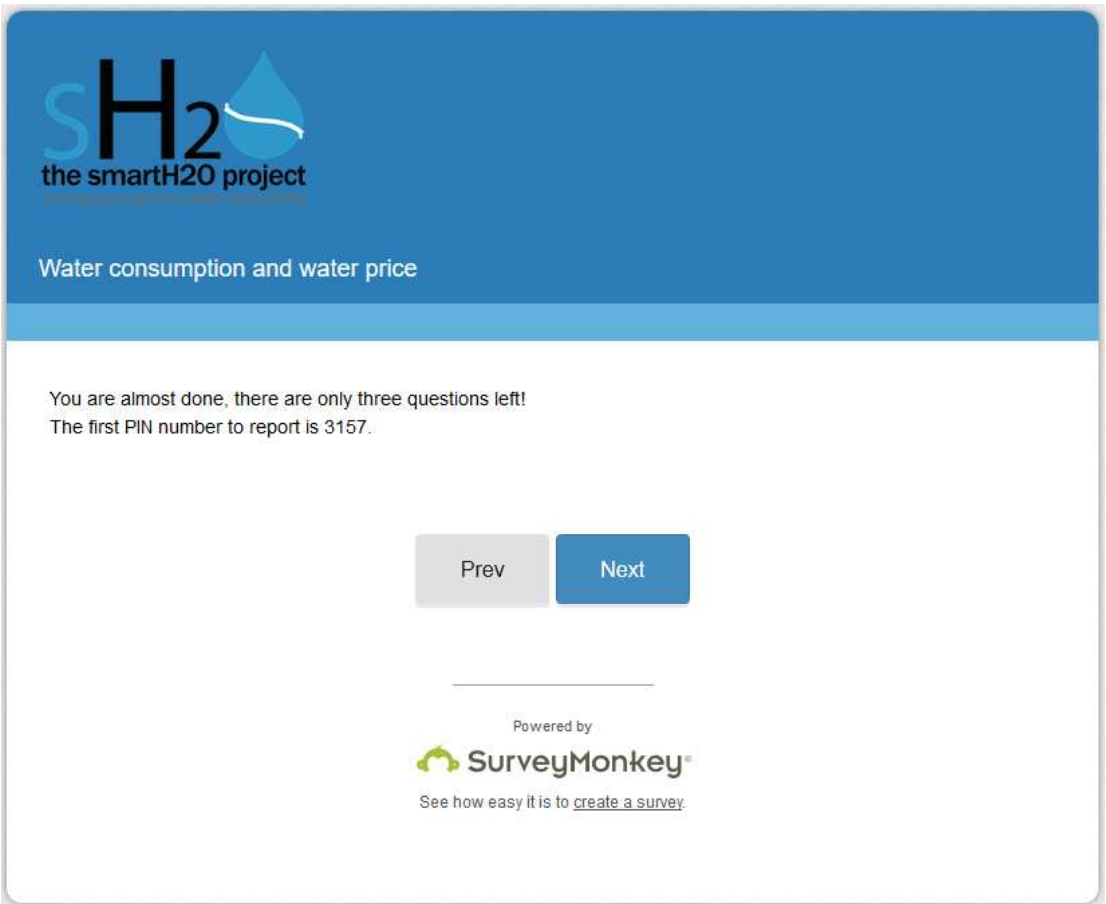
Q21. What is your new shower length, between 1 and 15 minutes?

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10
- 11
- 12
- 13
- 14
- 15

Pages 5 to 9

[Each response to the experimental question leads to a different page. Each page has a different PIN number. There is a correspondence between experimental response (showertime), PIN number, page redirected, and final payoff.]

Figure A2.2 First PIN number page. (The screenshot is from the "Test survey" mode, respondents do not have the possibility of hitting "Prev")



Page 10: "Last three questions"

[These are questions 21 to 23 for versions A and C only; for versions B and D these are questions 22 to 24. Yet questions, answers and surrounding text are strictly identical].

Q22. A recent study has shown that an 8-minute shower uses almost as much water and energy (for water heating) as the average bath. This means it produces almost the same associated greenhouse gas emissions.

What would your shower time from the previous question have been after knowing this information?

- 1 minute
- 2 minutes
- 3 minutes
- 4 minutes
- 5 minutes
- 6 minutes
- 7 minutes
- 8 minutes
- 9 minutes
- 10 minutes
- More (please specify)
    [textbox]

Q23. How would you rate your environmental attitude?

- I am extremely environmentally friendly
- I am very environmentally friendly
- I am fairly environmentally friendly
- I am slightly environmentally friendly
- I am not environmentally friendly at all

Q24. In the last three months, did you hear/read/see information campaigns on water conservation?
(for instance, TV or newspaper ads, billboards, etc)

- Very often
- Often
- Sometimes
- Rarely
- Never

Page 11

Figure A2.3. Final page of the survey, with the second PIN number. [The screenshot is from the "Test survey" mode, respondents do not have the possibility of hitting "Prev"]

the smartH2O project

Water consumption and water price

Thanks for completing this survey!
The second PIN number to report is 5344.

Prev Done

Powered by
SurveyMonkey
See how easy it is to create a survey.