Off-Peak Price Reductions for Water Demand Management

Yutaro Onuki (a233472a@r.hit-u.ac.jp)
Graduate School of Social Sciences, Hitotsubashi University
2-1 Naka, Kunitachi, Tokyo 186-8601, Japan.

Yurina Otaki (yurina.otaki@r.hit-u.ac.jp)
Graduate School of Social Sciences, Hitotsubashi University
2-1 Naka, Kunitachi, Tokyo 186-8601, Japan.

Abstract

Peak shifting is a key method to enhance the resilience of water supply infrastructure. Due to limitations related to the costs of smart meters, experimentally investigating the impact of a time-of-use tariff on inducing peak shifting in water usage has been challenging. Having introduced smart meters across 1,890 households, this study investigated behavioral responses to reduced water prices during off-peak hours (i.e., by increasing the relative cost of peak times). This was achieved by implementing a pricing scheme offering a 60% discount from 23:00 to 05:59 hours and a 20% discount from 10:00 to 16:59 hours. The results revealed significant changes in water usage behavior near the boundary between off-peak and peak times, suggesting a shift in water usage behavior towards the off-peak period. Moreover, a time-series analysis demonstrated the peak shifting induced by off-peak price reductions. Furthermore, this study examines cognitive processing and its impact on altering water usage behaviors on an hourly basis. These findings suggest that reducing prices during off-peak periods can effectively induce peak shifting across a broad range of times.

Keywords: Water demand management; time of using tariff; price reductions; peak shift.

Introduction

Recently, studies focusing on peak-shifting through the alteration of pricing have become increasingly prevalent in various demand management fields. Such as in the fields of public transit for train (Halvorsen et al., 2016), electricity (Brännlund & Vesterberg, 2021). Taking the field of water, implementing peak-shifting strategies offers benefits. For instance, the shift of water usage from peak to off-peak hours within a 24-hour cycle can minimize disruptions in the supply, thus enhancing the resilience of water supply infrastructure (UNEP-DHI Partnership et al., 2017).

The need for water demand management through pricing mechanisms is increasingly recognized (Olmstead, 2010). The time-of-use tariff (TOUT)—a rate structure based on the time of day—is particularly garnering attention for its influence on water consumption behavior. In assessing the impact of peak-shifting resulting from alterations in pricing structures, the investigation requires data on an hourly basis. The integration of mobile technology in smart meters and data loggers significantly facilitates access to comprehensive water consumption data (Hauber-Davidson & Idris, 2006). However, the lack of affordable smart meters capable of detailed temporal measurement of water usage has been a constraint, leading to limited research into the implications of tariff-induced peak-shifting in the domestic water domain.

The following section introduces several studies that aim to predict the impact of increasing water rates during peak times on water usage. Higher water rates during peak usage times within a day are expected to diminish water consumption during these periods (Rougé et al., 2018). Furthermore, decreased reservoir water levels, accompanied by increased water rates, are expected to lead to reduced water consumption (Lopez-Nicolas et al., 2018). Higher water prices influence decisions regarding shorter shower durations in online experiments (Marzano et al., 2020). Thus, TOUT policies, which enforce higher rates during peak usage times, may impact the water usage. However, price increases during peak times often face resistance from residents, making the implementation of such policies challenging (Olmstead & Stavins, 2009). A past study, which investigated public perceptions of a water tariff system where prices are higher during peak times and lower during off-peak periods, observed negative reactions. These included sentiments such as “It’s unacceptable for prices to rise when demand is high,” “Water bills seem likely to increase,” and “I want to use water freely” (Otaki & Kosuge, 2022). These studies demonstrate that residents strongly resist price increases. Thus, while an increase in water tariffs is perceived as detrimental, a reduction in water tariffs might be perceived as beneficial by the residents. Reducing prices during off-peak periods, thereby increasing the relative cost of peak times, could potentially encourage a shift towards off-peak usage. To the authors’ knowledge, no prior research has examined whether reducing prices during off-peak periods (i.e., increasing the relative cost of peak times) can influence water usage behaviors, particularly when measuring water usage hourly and altering actual pricing schemes accordingly. Hence, this study investigates whether reductions in off-peak prices can affect water usage behavior and induce a shift in peak consumption. Particularly, this study examines whether increasing the relative cost of peak times, without raising prices, influences the psychological aspects of individuals, thereby resulting in the occurrence of peak shifting. This research also examined how different financial incentives, specifically discounts of 20% and 60%, influence changes in water consumption behavior and the underlying cognitive processes on an hourly basis.

In L. K. Samuelson, S. L. Frank, M. Toneva, A. Mackey, & E. Hazeltine (Eds.), *Proceedings of the 46th Annual Conference of the Cognitive Science Society.*

Methods

Due to the limited implementation of smart meters and water pricing flexibility, this study was conducted in Kosai City, Japan. In Kosai City, where smart meters were introduced in 1,890 households, policies to reduce prices during off-peak hours are feasible. For this research, data on hourly water-supply pond levels (m^3) from multiple water-supply ponds were used to analyze aggregated water usage across multiple households. In one water-supply pond where all households underwent the pricing intervention, the data from this pond were designated as the pricing group. In other ponds where households did not undergo the pricing intervention, the data from these ponds were categorized as the control group. Data from multiple observation ponds were summed up on an hourly basis for analysis according to their respective groups. The data provided span the period from 00:00 hours on April 1, 2021, to 23:59 hours on October 15, 2023.

In this study, the method of analysis involves comparing the change in water usage rates between the pre-intervention and intervention periods. The required number of data points for the analysis was calculated using G*Power (version 3.1.9.6; Faul et al., 2007). The results indicated that 113 data points per group were required to detect an effect size of d = 0.50 (*power* = 80%, α = .002, one-sided distribution, *t*-test). Due to Bonferroni adjustment for comparing data every hour within a 24-hour period, calculated as α = .05 divided by 24, resulting in α = .002. Furthermore, the analysis was conducted using a one-sided distribution, based on the anticipation of an increase in water usage during the discounted hours and a decrease during the periods when the rates remained unchanged. To align with the required number of data points, the intervention period lasted 121 days, generating 121 data points per hour. The period spanned from 00:00 hours on June 16, 2023 (Friday) to 23:59 hours on October 15, 2023 (Sunday), resulting in a total of 2,904 data points (121 data points per day multiplied by 24 hours) for each group. To align the days of the week for comparative data analysis and assess the daily seasonal effects using a time series model, the pre-intervention period was changed to start one day before the intervention period. Consequently, to facilitate comparisons with the intervention period, the pre-intervention period was set from 00:00 hours on June 17, 2022 (Friday) to 23:59 hours on October 16, 2022 (Sunday).

In the pricing group, a 60% discount was applied to the regular rates from 23:00 to 5:59 hours, and a 20% discount from 10:00 to 16:59 hours, while the rates remained unchanged from 06:00 to 9:59 and 17:00 to 22:59 hours. The discount applied during the daytime was set at 20%, while a 60% reduction was allocated for the late-night to early-morning period. This differential pricing strategy was based on the expectation that shifting peak usage from morning and night (06:00 to 9:59 and 17:00 to 22:59) to the late-night and early-morning hours (23:00 to 5:59) would be more challenging than shifting peak usage to daytime (10:00 to 16:59). Water usage was typically notified to each household via paper letters every two months; therefore, during the intervention period, only one notification regarding water usage and charges was dispatched to households in mid-August 2023.

In this study, a web-based survey was conducted with 1,890 households to assess whether they consciously altered their water usage behavior during the experimental period. They were presented with five response options: "attempted to change," "somewhat attempted to change," "neutral," "somewhat did not attempt to change," and "did not attempt to change."

Missing Value Imputation

A few missing values were detected due to adjustments in water meter readings: 93 data points (6 in the pricing group and 87 in the control group). To address these missing values, we employed the Prophet model (Taylor & Letham, 2017) for data imputation in both the pricing and control groups. This model encompasses an additive composition of distinct components, represented as:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon\_t \qquad (1)$$

where $y(t)$ is the variable to be forecasted; $g(t)$ denotes the trend component; $s(t)$ represents the seasonality component (Daily, Weekly, Yearly); and $h(t)$ is the holiday effect. The parameters for each component were utilized as predefined within the model, without custom setting. The default value for the "Change point prior scale" parameter, which represents the flexibility of the trend component, is 0.05. The default value for the "Seasonality prior scale" parameter, indicating the flexibility of the seasonal component, is 10. Additionally, the default value for the "Holidays prior scale" parameter, representing the flexibility of the holiday component, is 10.

Results

Change in Water Usage Rates between Pre-Intervention and Intervention Period

The normality of the data for each 24-hour period was assessed using the Shapiro-Wilk test in both the pricing and control groups, with Bonferroni adjustments applied. In 20 out of 24 hours for both the pricing and control groups, the data were not normally distributed ($p < .05$). The medians of the rate of change by hour are illustrated in Figure 1. This median was calculated by first determining the rates of change between corresponding data points during the pre-intervention and intervention periods in each group, and then computing the median for every 24-hour period. The pricing and control groups were compared using the rates of change (Wilcoxon rank sum test with Bonferroni adjustments applied). The results are presented in Table 1. Statistically significant differences were observed at around 00:00, 01:00, 02:00, 03:00, 04:00, 05:00, 06:00, 07:00, 11:00, 12:00, 13:00, 15:00, 16:00, 17:00, 18:00, 19:00, 20:00, 21:00, 22:00, and 23:00 hours ($p < .05$). At around 05:00, 15:00, and 23:00 hours, the intervention group showed a positive change rate compared with the control group, while other hours of significant differences showed a negative change rate.

The web-based survey was conducted to assess whether they consciously altered their water usage behavior. 448 of the 1,890 surveyed households provided responses. As a result, 215 participants (approximately 48%, answering “attempted to change” or “somewhat attempted to change”) consciously attempted to alter their water usage behavior to some extent, while 176 participants (approximately 39%, answering “somewhat did not attempt to change” or “did not attempt to change”) did not make any conscious effort to change their water usage behavior.

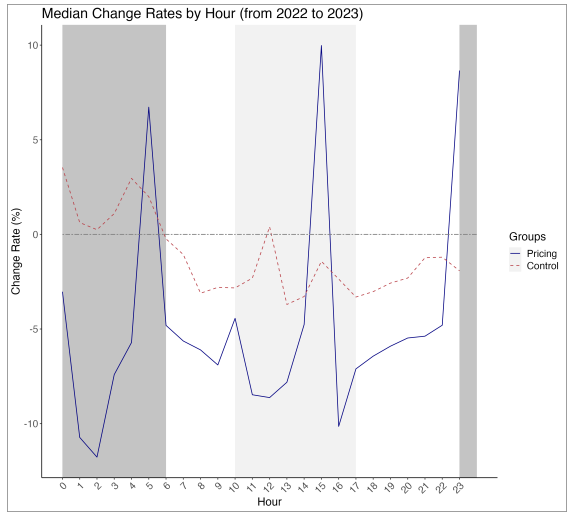


Figure 1 The figure shows the water volume ratios for the pre-intervention and intervention periods for both the pricing and control groups. The blue solid line represents the pricing group, while the red dotted line represents the control group. The dark grey, light gray, and white backgrounds indicate periods with a 60% discount, 20% discount, and without any discount, respectively. The Y-axis represents the change rate in water volume between the pre-intervention and intervention periods, while the X-axis denotes 24 hours.

Table 1: Results of the Wilcox test comparing the rates of water volume change between the pricing and control groups.

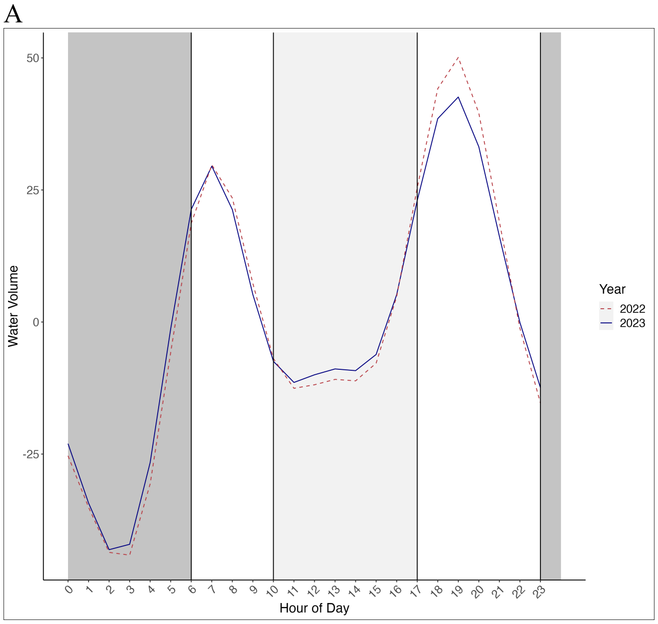
Hour	*Median* (Pricing)	*IQR* (Pricing)	*Mean Rank* (Pricing)	*Median* (Control)	*IQR* (Control)	*Mean Rank* (Control)	δ	*p*
0	−3.03	−20.487 to 12.726	107.35	3.53	1.383 to 6.575	137.65	−0.25	< .05
1	−10.73	−20.517 to 6.515	98.82	0.63	−1.976 to 5.381	146.18	−0.39	< .001
2	−11.77	−22.491 to −3.571	87.91	0.25	−3.905 to 5.87	157.09	−0.57	< .001
3	−7.41	−15.242 to 3.846	102.02	1.10	−2.807 to 5.022	142.98	−0.34	< .001
4	−5.71	−11.429 to 0	92.94	2.96	−0.387 to 6.91	152.06	−0.48	< .001
5	6.72	0 to 12.948	138.68	1.99	−3.471 to 7.001	106.32	0.27	< .01
6	−4.81	−9.975 to 1.031	102.53	−0.24	−4.012 to 6.773	142.47	−0.33	< .001
7	−5.63	−12.5 to 0	102.83	−1.06	−5.95 to 6.45	142.17	−0.32	< .001
8	−6.10	−12.146 to 0.735	109.14	−3.11	−7.029 to 7.062	135.86	−0.22	0.08
9	−6.90	−12.207 to 1.603	109.64	−2.80	−8.228 to 4.466	135.36	−0.21	0.11
10	−4.44	−11.374 to 4.536	117.19	−2.83	−9.186 to 4.752	127.81	−0.09	0.999
11	−8.47	−14.99 to −2.078	101.08	−2.31	−8.537 to 2.888	143.92	−0.35	< .001
12	−8.62	−13.806 to 0	92.98	0.40	−3.797 to 5.291	152.02	−0.48	< .001
13	−7.81	−19.839 to 1.878	107.79	−3.70	−7.481 to 1.216	137.21	−0.24	< .05
14	−4.76	−15.826 to 1.87	114.98	−3.28	−8.326 to 2.222	130.02	−0.12	0.999
15	9.98	−1.119 to 22.92	151.92	−1.42	−8.573 to 3.292	93.08	0.48	< .001
16	−10.14	−18.759 to −2.827	96.70	−2.36	−7.798 to 3.069	148.30	−0.42	< .001
17	−7.11	−10.734 to −3.261	100.70	−3.31	−6.889 to −0.57	144.30	−0.36	< .001
18	−6.43	−9.51 to −3.645	95.29	−3.02	−5.283 to −0.73	149.71	−0.45	< .001
19	−5.91	−8.145 to −3.025	94.31	−2.57	−4.225 to −0.979	150.69	−0.46	< .001
20	−5.47	−7.748 to −0.964	103.15	−2.31	−4.564 to −0.419	141.85	−0.32	< .001
21	−5.38	−11.332 to −1.176	93.81	−1.23	−2.838 to 0.823	151.19	−0.47	< .001
22	−4.80	−12.457 to 1.581	105.92	−1.20	−4.021 to 0.531	139.08	−0.27	< .01
23	8.66	−6.35 to 19.149	143.52	−1.92	−3.68 to 0.557	101.48	0.34	< .001

Note: IQR (Interquartile Range) represents the range between the first quartile (25th percentile) and the third quartile (75th percentile) of the data. $p < .001$***, $p < .01$**, $p < .05$*, and $p > .05$ n.s.

Time-Series Model Analysis

Water demand varies with the season, day of the week, and time of day (Arbués et al., 2003), necessitating consideration of not only daily but also weekly and monthly variations in water usage. Consequently, we employed the previously mentioned Prophet model (Taylor & Letham, 2017) to create time-series models and analyze the data. In this analysis, after eliminating the effects of monthly and yearly seasonality and trends, we examined the differences in daily variations of water use behavior between the pre-intervention and intervention periods. For the pre-intervention period, a time-series model using the pricing group data from 00:00 hours on April 1, 2021, to 23:59 hours on June 15, 2023 (19,344 data points gathered in 806 days at 24-hour intervals), was created. For the intervention period, another time-series model was developed for the intervention period, using the pricing group data (from 00:00 hours on June 16, 2023, to 23:59 hours on October 15, 2023; 2,904 data points gathered in 121 days at 24-hour intervals). Figure 2 isolates and illustrates only the daily variations of water use behavior after eliminating the effects of monthly and yearly seasonality and trends from the analysis of each time-series model, thus showing the differences between the two periods.

A



B

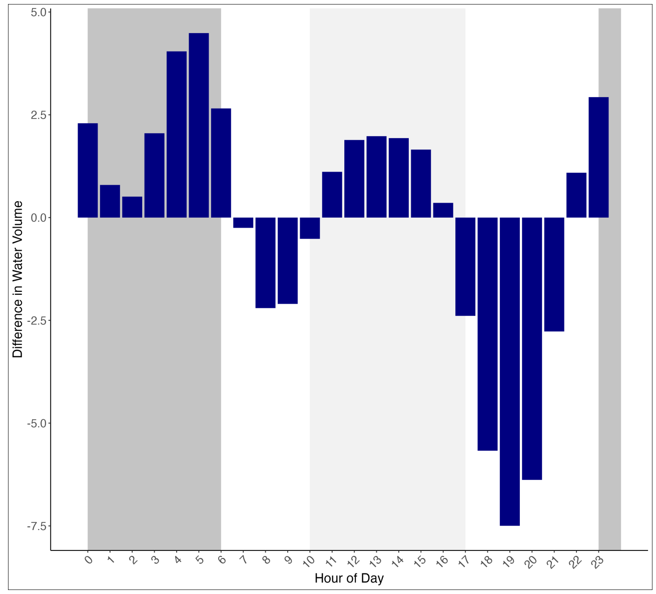


Figure 2. In Panel A, only the daily impact extracted from the time-series model analysis is presented, presenting data for both the pre-intervention and intervention periods. Panel B plots the difference between the pre-intervention and intervention periods. The X-axis in both figures represents time. The dark grey, light gray, and white backgrounds indicate periods with a 60% discount, 20% discount, and without any discount, respectively.

Discussion

This study investigated whether water usage behavior changes (e.g., peak shift) in response to the TOUT policies that reduce water prices during off-peak hours (i.e., increasing the relative cost of peak times). The research specifically focused on the effects of a 60% discount on the regular rates from 23:00 to 05:59 hours, a 20% discount from 10:00 to 16:59 hours, and regular rates from 06:00 to 9:59 and 17:00 to 22:59 hours. The experiment demonstrated that the water consumption change rate from the pre-intervention to the intervention period in the pricing group was significantly higher around 05:00, 15:00, and 23:00 hours—hours with reduced rates—compared with that in the control group. These significant changes were observed near the boundary between off-peak and peak times, suggesting a shift in water usage behavior towards the off-peak period. Conversely, during several peak hours (around 06:00, 07:00, 17:00, 18:00, 19:00, 20:00, 21:00, and 22:00 hours), the water consumption rate in the pricing group was significantly lower than that in the control group. These findings suggest that off-peak price reduction was effective in curtailing consumption during peak usage hours. The change rates observed in the control group indicated a decreasing trend in water usage, which could be attributed to factors such as the use of more water-efficient devices or changes in climate. Despite such a trend, the significant increase in water usage at around 05:00, 15:00, and 23:00 hours due to off-peak reduction indicates the substantial influence of the off-peak reduction. Peak shift, which can minimize disruptions in the water supply, results in enhanced resilience of the water supply infrastructure (UNEP-DHI Partnership et al., 2017). Thus, the results suggest that the TOUT policies that reduce water prices contribute to sustainable water use.

The web-based survey aimed to determine if participants intentionally modified their water consumption behavior. Findings revealed that about 48% of the participants made a deliberate attempt to adjust their water usage behavior to a certain degree. In contrast, approximately 39% reported that they did not intentionally endeavor to alter their water usage behavior. This outcome suggests that the off-peak discounts were effective in prompting cognitive changes in about half of the participants. Future research should investigate whether these cognitive changes translated into actual modifications in water usage behavior and whether even individuals who reported not attempting to change their behavior were influenced in their water usage patterns.

Previous research has primarily focused on reducing water usage by increasing the prices at peak usage times. However, increasing prices during peak times often induces resistance from residents (e.g., Olmstead & Stavins, 2009; Otaki & Kosuge, 2022). Reducing prices during off-peak hours without increasing peak-time prices would be an effective new method to encourage peak shifting while avoiding resistance from residents. According to prospect theory, individuals value losses more than gains (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Therefore, when not considering the extent of resident resistance, a TOUT policy that raises prices during peak times is expected to have a greater impact on water usage behaviors than a TOUT policy that lowers prices during off-peak periods. Future research should consider comparing the effects of peak shifting by increasing prices during peak times with the effects of reducing prices during off-peak times, while also considering the extent of resident resistance. A previous study suggested that many consumers may postpone water usage for activities such as dishwashing and laundry until off-peak times (Kappel & Grechenig, 2009). Future research should clarify the lifestyle changes that lead to the shift in water usage. Additionally, future studies should be examined to understand which types of individuals are more likely to alter their water usage patterns.

Time-Series Model Analysis

In comparing the water consumption of pre-intervention and intervention periods in the pricing group, which was conducted without utilizing time-series models, the increase during off-peak periods and the decrease during peak hours was observed. However, water usage was observed to decrease significantly in many instances during off-peak periods. When using time-series models, the effects of seasonality (annual and weekly), trends, and holidays were removed to focus solely on daily seasonality (i.e., variations in water usage behavior throughout the day). The time-series analysis not only observed an increase across the wide range of off-peak periods but also unveiled a consistent reduction across the wide range of peak periods. The results suggest that the cognitive mechanism of individuals increasing their water usage during these off-peak discounted hours was not about increasing usage during specific shorter intervals but rather increasing it across the entire discounted period.

Typical daily water consumption patterns peak in the morning and evening (Cole & Stewart, 2013). This study confirmed that this pattern persisted in the pricing group, and the effect of TOUT policies that reduced water prices on reducing peak water consumption. Moreover, the peak shift was observed not only during the 20% discount period (i.e., daytime) but also during the 60% discount period (i.e., the late-night and early-morning hours). The differential pricing strategy was predicated on the assumption that shifting of water consumption from peak to off-peak hours would be less feasible during the late-night and early-morning hours compared to daytime hours. Contrary to these expectations, the results demonstrated that an increased discount rate during off-peak hours effectively induced a significant modification in water usage patterns, even during those periods regarded as resistant to change. Future research should examine the effective discount rates, expanding beyond the 20% and 60% reductions, to facilitate more efficient peak shifting by considering the specific off-peak hours during which peak shifting is challenging. Furthermore, future research should also focus on formulating discount rates within a framework that ensures financial viability. Thus, the rates should aim to facilitate peak shifting while simultaneously adhering to realistic budgetary constraints and upholding the economic sustainability of water supply systems.

Acknowledgments

We express our gratitude to the Waterworks Division of Kosai City in Shizuoka Prefecture, Japan, for their provision of water consumption data. We thank Mr. A. Nonami and Mr. D. Yamauchi for valuable discussions. This work was supported by the Japan Society for the Promotion of Science KAKENHI grant 23H03603 (Y.Otaki, Y.Onuki), the Japan Society for the Japan Society for the Promotion of Science KAKENHI grant 22J00286 (Y.Onuki).

References

Arbués, F., García-Valiñas, M. Á., & Martínez-Espiñeira, R. (2003). Estimation of residential water demand: A state-of-the-art review. *The Journal of Socio-Economics*, *32*(1), 81–102. https://doi.org/10.1016/S1053-5357(03)00005-2

Brännlund, R., & Vesterberg, M. (2021). Peak and off-peak demand for electricity: Is there a potential for load shifting? *Energy Economics*, *102*, 105466. https://doi.org/10.1016/j.eneco.2021.105466

Cole, G., & Stewart, R. A. (2013). Smart meter enabled disaggregation of urban peak water demand: Precursor to effective urban water planning. *Urban Water Journal*, *10*(3), 174–194. https://doi.org/10.1080/1573062X.2012.716446

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/bf03193146

Hauber-Davidson, G., & Idris, E. (2006). Smart water metering. *WATER*, *33*(3), 38–41.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–291. https://doi.org/10.2307/1914185

Kappel, K., & Grechenig, T. (2009). “show-me”: water consumption at a glance to promote water conservation in the shower. *Proceedings of the 4th International Conference on Persuasive Technology*, 1–6. https://doi.org/10.1145/1541948.1541984

Lopez-Nicolas, A., Pulido-Velazquez, M., Rougé, C., Harou, J. J., & Escriva-Bou, A. (2018). Design and assessment of an efficient and equitable dynamic urban water tariff. Application to the city of Valencia, Spain. *Environmental Modelling & Software*, *101*, 137–145. https://doi.org/10.1016/j.envsoft.2017.12.018

Marzano, R., Rougé, C., Garrone, P., Harou, J. J., & Pulido-Velazquez, M. (2020). Response of residential water demand to dynamic pricing: Evidence from an online experiment. *Water Resources and Economics*, *32*, 100169. https://doi.org/10.1016/j.wre.2020.100169

Olmstead, S. M. (2010). The economics of managing scarce water resources. *Review of Environmental Economics and Policy*, *4*(2), 179–198. https://doi.org/10.1093/reep/req004

Olmstead, S. M., & Stavins, R. N. (2009). Comparing price and nonprice approaches to urban water conservation. *Water Resources Research*, *45*(4). https://doi.org/10.1029/2008wr007227

Otaki, Y & Kosuge, N. (2022). The Potential for Utilizing Water Usage Data from Smart Water Meters (in Japanese). *Journal of Japan Water Works Association*, *91*(6), 2–9. https://doi.org/10.34566/jwwa.91.6_2

Halvorsen, A., Koutsopoulos, H. N., Lau, S., Au, T., & Zhao, J. (2016). Reducing Subway Crowding: Analysis of an Off-Peak Discount Experiment in Hong Kong. *Transportation Research Record*, *2544*(1), 38–46. https://doi.org/10.3141/2544-05

Rougé, C., Harou, J. J., Pulido-Velazquez, M., Matrosov, E. S., Garrone, P., Marzano, R., Lopez-Nicolas, A., Castelletti, A., & Rizzoli, A. E. (2018). Assessment of smart-meter-enabled dynamic pricing at utility and river basin scale. *Journal of Water Resources Planning and Management*, *144*(5), 04018019. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000888

Taylor, S. J., & Letham, B. (2017). *Forecasting at scale* (e3190v2). PeerJ Preprints. https://doi.org/10.7287/peerj.preprints.3190v2

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297–323. https://doi.org/10.1007/BF00122574

UNEP-DHI Partnership, UNEP-DTU., & CTCN. (2017). *Shifting the timing of use from peak to off-peak periods*. The Climate Technology Centre and Network. https://www.ctc-n.org/resources/shifting-timing-use-peak-peak-periods