A Data-Driven Model to Evaluate the Medium-Term Effect of Contingent Pricing Policies on Residential Water Demand

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Abstract

The relative scarcity of water resources have encouraged cities to create mechanisms to control water demand and avoid water stress. In the decision-making process, water companies need to assess the price influence on water demand predictions to design better policies. The aim of this study is to assess the medium-term effectiveness of the implementation of a contingent tariff and its consequences for water demand elasticity to price. A novel model that requires only secondary data is proposed, that can be useful for guiding the drought planning process. The methodology consists in a framework that provides monthly predictions of water demand at the household level, considering price, seasonality, and previous water use. The results indicated that the contingent tariff promoted a reduction of 11-15% in water demand, but at a higher cost for low income households. Also, reduction in water demand was found to be inelastic to price increase. Using google search hits as a proxy for public interest, we found that water cost has a higher influence on users decision to save water than drought awareness.

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Key Points:

- A contingent tariff is effective in promoting water demand reduction
- Increasing block rate tariff combined with contingent pricing is unfair to lower income classes
- An increase in water cost is more compelling to consumers than information on drought conditions

Abstract

The relative scarcity of water resources have encouraged cities to create mechanisms to control water demand and avoid water stress. In the decision-making process, water companies need to assess the price influence on water demand predictions to design better policies. The aim of this study is to assess the medium-term effectiveness of the implementation of a contingent tariff and its consequences for water demand elasticity to price. A novel model that requires only secondary data is proposed, that can be useful for guiding the drought planning process. The methodology consists in a framework that provides monthly predictions of water demand at the household level, considering price, seasonality, and previous water use. The results indicated that the contingent tariff promoted a reduction of 11-15% in water demand, but at a higher cost for low income households. Also, reduction in water demand was found to be inelastic to price increase. Using google search hits as a proxy for public interest, we found that water cost has a higher influence on users decision to save water than drought awareness.

Plain Language Summary

The inadequate distribution of water have encouraged cities to promote water demand reduction in order to be able to supply enough water. In the decision-making process, water companies need to know in what extent the water tariff is determinant to consumption. The aim of this study is to assess the effectiveness of the implementation of a penalty cost for excess water consumption during at least a year. The model requires only data that is already available for the companies and can be useful for guiding the drought planning process. The methodology consists in a framework that provides monthly predictions of water demand at the household level, considering price, seasonality, and previous water use. The results indicated that the contingent tariff promoted a reduction of 11-15% in water demand, but at a higher cost for low income households. Also, reduction in water demand was found to be inelastic to price increase. Using the frequency of google searches to measure public interest, we found that economic incentive is more likely to encourage the consumers to save water than knowing about the drought condition.

1 Introduction

The growing water demand associated with urbanization processes has increased water stress and the risk of shortage in several regions of the world (McDonald et al., 2014). For some of them, the elevated temporal and spatial variability in water availability offer an additional challenge to water supply management.

In this context, water companies and policymakers have been implementing demand control measures, since increasing water supply capacity is not always possible or effective. A widely used approach is the adoption of increasing block rates (IBR), which is expected to encourage rational water consumption. This kind of policy is typical of regions affected by droughts and developing countries (Romano et al., 2014; Zhang et al., 2017) and has complex impacts on consumer behavior (Rinaudo et al., 2012).

Another strategy to reduce water use under drought conditions is the implementation of contingent tariffs to households with an elevated consumption. In Brazil, Fortaleza and São Paulo's governments have used this approach to deal with water crisis (Priscoli and Hiroki, 2015). In Fortaleza, water pricing follows an IBR structure, and the contingent tariff was adopted three years after the beginning of a severe drought that reduced reservoir storage in about 63% (Pontes Filho et al., 2020).

Previous studies have reported that water scarcity impacts price elasticity, but the consequences are adverse. Consumers response to price change is related to different exogenous factors, such as climate (Monteiro and Roseta-Palma, 2011), income (Ma et al., 2014) and environmental attitude (Garrone et al., 2019). Debate continues about the effectiveness of price control policies for demand control, especially on IBR schemes (Mansur and Olmstead, 2012; Zhang et al., 2017; Matikinca et al., 2020).

The research to date has provided cross section analysis to evaluate price influence on water consumption – together with other socioeconomic and/or climatic variables - but is not able to address it over long time horizons. Most studies on water price use survey data, which can be expensive and time consuming. Water companies have a huge amount of smart meter data available that could be useful to extract information on use patterns and consumer behavior (Cominola et al., 2019). So far, however, no method has been proposed to use this data to predict medium-term water demand under price-related policies.

This study proposes a data-driven model to assess the medium-term effect of price-based water conservation policies at the household level. In addition, we calculate the elasticity of water demand reduction to price and we assess how much water price and public interest in the drought can affect consumption habits. The methodology can be used by water companies to assess price-related strategies of water conservation and does not require additional variables that could be difficult to obtain in a refined scale. Although this study considers a block tariff structure, the framework can be adapted to any other price strategy, if it is applied at the household level.

2 Materials and Methods

2.1 Study area

The city of Fortaleza, capital of Ceará, located in the Northeast region of Brazil, is the fifth most populated city of the country, with over 2.6 million inhabitants distributed across 314.9 km². The population is expected to grow to 3.1 million people in 2040 (Iplanfor, 2015). The city is part of the Metropolitan Region of Fortaleza, which comprises 19 municipalities of Ceará.

Fortaleza's water supply Jaguaribe-Metropolitano supply system (JMS), consisting of eight reservoirs which sum up to a storage capacity of 11,112 hm³. JMS transfers water from the Jaguaribe basin and supplies 36 municipalities. Urban and industrial demand of Fortaleza is 9.5 m³/s, corresponding to 80% of the volume released by the supply system.

2.2 Water tariff structure

During the period between 2012 and 2018, the northeast of Brazil suffered from a historic drought that significantly impacted its economy and water storage (Pontes Filho et al., 2020). The main reservoirs of Fortaleza's supply system were affected by the 2012-2018 drought, resulting in a significant reduction in water availability. To encourage domestic water conservation, which accounts for more than 80% of Fortaleza's water demand, the local water company implemented a contingent tariff.

The contingent tariff was implemented in December 2015 (Figure 1) and defined a minimum reduction of 20% of the water consumption based on the mean consumption between October 2014 and September 2015. If a household had a consumption above this threshold, an extra charge of 110% on the exceeded volume would be added to the bill. This percentage was updated to 120% in October 2016. Water price follows an increasing block tariff structure (Table 1), thus the contingent tariff also varies with the consumption block of the household. Users with a monthly consumption of up to 10 m^3 did not have to pay the contingent tariff.

Although we consider these specific conditions in the prediction model, the methodology could be replicated under different price-associated water conservation measures.

Monthly consumption (m^3)	**2016 (BRL)**	**2017 (BRL)**
0 to 10	2.79	3.48
11 to 15	3.61	4.51
16 to 20	3.92	4.88
21 to 50	6.71	8.36

Table 1. Water tariff in Fortaleza for each consumption category for the years of 2016 and 2017.

2.3 Predictive model

The predictive model has three explanatory variables: previous water demand, monthly seasonality, and penalty price. The model was tested for multiple leading times, ranging from one to twelve months.

The penalty price was calculated as the cost of the volume of water consumed in the previous month that exceeded a threshold. This threshold sets how much water should be saved and is a percentage of the average monthly water consumption of the household for a baseline period. Here, the baseline period goes from October 2014 to September 2015 and the threshold is 20%.

At each step, the predictions for the previous month are used to determine the tariff block of each household. Then, we calculate the volume of consumed water that exceeded the threshold and how much it costed for the user. For example, when calculating water consumption at *n-months* ahead, the predictions for the month *n-1* are used to assess the water conservation measure (Figure 2). This strategy allowed us to avoid the simultaneity issue associated with water consumption modelling under block tariff policies.

Previous studies have used different price variables in econometric models of water demand, and there is not a generally accepted approach. Many authors find it more appropriate using the marginal price, i.e. the cost of increasing the water consumption at each time step (Rinaudo et al. 2012), while others prefer the average price (Zhang et al. 2017) or both (Ma et al. 2014; Deyà-Tortella et al. 2016). Although some researchers argue that the users might be more influenced by the average price (Deyà-Tortella et al. 2016), in case of a contingent tariff policy, they might pay especial attention to the additional charge expressed on the bill.

In addition to the lagged water consumption and the price component, a seasonal variable was included to account for seasonal behavior. This variable corresponded to the seasonal component extracted for each household with the STL method. This approach captures different patterns of seasonal behavior and adds more information to the model than the usual approach of using 11 dummy variables for the months.

The model was validated with a classical out-of-sample evaluation. The model was trained for the year of 2016 and tested for the year of 2017. We chose a machine learning regression model that has been widely used for electricity and wind prediction. Gradient boost regression also performs better than other linear and machine learning models in predicting residential water demand (Lee and Derrible 2020).

2.3.1 Seasonality extraction

The water demand time series was decomposed into trend, seasonal and remainder components using the Seasonal and Trend decomposition using Loess (STL) method (Cleveland and Cleveland 1990). This procedure was used to extract the seasonality of water consumption for each household. STL consists in sequential applications of the local regression model and provides an additive decomposition of the original signal (D) into three components:

$$D(t) = S(t) + T(t) + R(t)$$

where S, T and R are the seasonal, trend and remainder components, respectively. The algorithm work as follows:

The local regression smoothing estimates a function g(x) for the independent variable at any value of x rather than for the measurements x_i of the dependent variable. To calculate the regression curve g, an initial value for the parameter q is chosen; q values of x_i that are closest to x are selected and weighted on their distance from x. For $q \leq n$, where n is the number of observations in the data set, the weight for x_i is calculated as follows:

$$v_i(x) = W\left(\frac{|x_i - x|}{\lambda_q(x)}\right)$$

where *W(u)* is the tricube function, expressed as:

$$W(u) = \begin{cases} (1-u^3)^3 & if\ 0 \leq u < 1 \\ 0 & if\ u \geq 1 \end{cases}$$

For q > n, the weight for x_i is multiplied by *q/n*. Next, a polynomial of degree d is fit to the weighted data at (x_i, y_i). The fitted function corresponds to g(x). It is possible to add a robustness term for each pair (x_i, y_i) by multiplying it by the weight ν_i.

STL consists of two nested loops (Cleveland and Cleveland 1990). In the outer loop, robustness weights are calculated for each time point. This approach makes the STL method robust to outliers. The inner loop follows these steps: (i) Detrend the original signal; (ii) Estimate a smoothing function using Loess for each cycle-subseries, where *q* is the cycle periodicity (e.g. for a monthly time series, *q* is set to 12) and *n* is equal to 1; (iii) Apply a low pass filter to the smoothed cycle-subseries, which consists in sequential applications of a moving average; (iv) Detrend the smoothed cycle-subseries; (v) Remove the seasonality from the series; (vi) Smooth the deseasonalized series using Loess.

2.3.2 Gradient boosting

Gradient Boosting (GBM; Friedman 1999) is a learning method that converts weak learners, usually regression trees, into strong learners by combining them sequentially. The idea behind the method is that new weak learners can learn from the residuals of the output from the previous model; this ensemble technique is called bagging. For regression tasks, we want to find the function that best fits the data points in a set containing input variables x and a corresponding output variable y. To do this, the algorithm minimizes a loss function between y and the predicted values, in our case, the Mean Squared Error.

$$L(y, \hat{y}) = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

The gradient boosting method consists in a combination of weak learners that are added together. The individual models f_m are added one after the other to improve model performance.

$$\hat{y}_i = \sum_{m=1}^{M} f_m(x)$$

The weak learners, in this case, regression trees, are fitted on the residuals of the previous model. The general representation of GBM is expressed as follows:

$$F_m(x) = F_{m-1}(x) + \nu f_m(x),$$

meaning that the model f_m does not change the previously fitted model $F_{m-}1$. The term ν is a regularization parameter or the learning rate, which determines the number of iterations. Small values of the learning rate (ν < 0.1) reduce the chances of overfitting.

Gradient boosting applies a functional gradient descent method to minimize the loss function, where each new weak model is equivalent to the negative gradient of the MSE. The negative gradient is given as:

$$-g_m(x_i) = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)}$$

The algorithm stops when the loss reaches a threshold, or the maximum number of trees is built. We defined model parameters in a trial and error manner; the number of trees was set to 300 and the learning rate to 0.1. All analyses were performed using R programming language. The gradient boosting model was implemented with the package gbm (Greenwell et al. 2019).

2.3.3 Performance assessment

Model performance was evaluated for the entire prediction horizon, i.e., for twelve months of the testing period. Two measures were used: Root Mean Squared Error (RMSE) and R squared (R^2).

$$RMSE_j = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_{i,j} - y_{i,j})^2}{n}}$$

$$R_j^2 = \frac{\sum_{i=1}^{n}(y_{i,j} - \hat{y}_{i,j})^2}{\sum_{i=1}^{n}(y_{i,j} - \bar{y}_j)^2}$$

where $y_{i,j}$ is the observed water demand in household *i* at month *j*, $\hat{y}_{i,j}$ is the predicted water demand in household *i* at month *j*, $\bar{y}_{i,j}$ is the mean observed water demand at month *j*, and n is the number of households.

2.4 Elasticity of water demand reduction to price

Different scenarios of price increase were considered, based on the tariff for the previous year (2015 for the training and 2016 for the validation period): no increase, 5, 10, 15 and 25%. To calculate the elasticity of water demand reduction to price, we used the predictions for the year of 2016 obtained with the model. The reduction is related to the average consumption during the baseline period (October 2014 to September 2015).

$$E = \frac{\Delta R/R}{\Delta P/P}$$

where R is the monthly average reduction in water demand and P is the average water block tariff.

Water demand elasticity was assessed for different socioeconomic classes, as users' response to water conservation policies tend be heterogeneous. These classes were based on the criteria used by the Brazilian Institute of Geography and Statistics (IBGE), which is based on per capita family income. IBGE uses the minimum wage to classify the families in five classes (Table 2). We also compared the predicted monthly reduction with the actual reduction aggregated water demand.

Class	Number of minimum wages	Number of households
A	20 or more	53
B	10 < N < 20	969
C	4 < N < 10	5,186
D	2 < N < 4	17,554
E	N < 2	13,927

Table 2. Socioeconomic classes and number of households in each of them.

2.5 Public interest and media coverage

We assessed public interest with the frequency of google searches of the terms “contingent tariff” and “drought” in Ceará, in a similar approach as Quesnel and Ajami (2017) and Kam et al. (2019). Media coverage was evaluated with the frequency of news related to the contingent tariff, which were collected from the websites of the three main local newspapers (Tribuna do Ceará, OPovo and Diário do Nordeste). These sources have a strong online presence and usually share the news on social media such as Instagram and Twitter. Data was collected with web scraping using Python and the BeautifulSoup 4 library.

To assess the marginal response and the relative influence of public interest in drought and the contingent tariff on water demand, a regression analysis was performed. Water demand was predicted as a function of water demand in the previous month, public interest and the contingent tariff cost for the previous month. Google search hits for the term “drought” were used as a proxy for public interest in water scarcity, from which the trend component was extracted using the STL method.

The GBM algorithm was used to perform the regression. For this analysis, we used data from 2012 (beginning of the drought) to 2017. The dataset was randomly split into 80% train and 20% test. After obtaining the predictive model, we extracted the marginal response of each variable using partial dependence plots and their relative influence. The relative influence is measured with the reduction of squared error associated with each variable, i.e. how much worse the model’s performance would be without that variable.

2.5.1 Partial dependence plot

The partial dependence plot (PDP) represents the marginal effect of indepedent variables on the response of a machine learning model (Friedman 1999). The partial dependence of the response on a variable x_l is represented by:

$$\hat{f}_{x_l}(x_l) = E_{x_s}\left[\hat{f}(x_l, x_s)\right] = \int \hat{f}(x_l, x_s) P(x_s)\, dx_s$$

Where x_l is the independent variable analyzed in the partial dependence plot, x_s is the subset of the other input variables of the regression model $\hat{f}$ and $P(x_s)$ is the marginal probability density of x_s. The function shows the effect of the variable x_l on the dependent vaiable by marginalizing over the other explanatory variables.

3 Data

Monthly water demand data for the period between 2009 and 2017 from 45,141 households were provided by the Water and Wastewater Company of Ceará (CAGECE). This analysis focused on households with consumption up to 50 m³/month. Households with monthly water consumption inferior than one m³ per month or the ones in which the total water consumption between 2009 and 2017 was less than five m³ were excluded from the dataset. The data cleaning process reduced the dataset to 37,685 observations.

Socioeconomic data from the 2010 Census were used to classify the households. Average per capita income is available at the census tract level, territorial units containing a maximum number of households that allow a survey to be carried out by a single person (IBGE). Fortaleza is divided into 3,043 census tracts, and 2,586 of them are attended by CAGECE's water supply.

4 Results and discussion

Model performance was evaluated for each month of the testing period (Figure 3). The model presented reliable predictions in terms of RMSE and R^2 for a short-term horizon (1 to 6 months ahead), and satisfactory results for a medium-term horizon (7 to 12 months ahead). The autoregressive component was the most important, i.e., removing it from the model would mean a significant increase in the loss function. This suggests that water demand is strongly dependent on past use.

A comparison between the predicted and observed mean percent reduction in residential water demand shows that the model provided accurate predictions (Figure 4). For this analysis, households were grouped according to their socioeconomic class, to assess variation in model performance and mean percent reduction in water demand. Classes D and E presented a rather regular behavior during the year, with an average reduction of 14.73% and 13.99%, respectively. Households in class B had the largest reduction in water demand: 17.58% over the year. Class A, with the smallest reduction (11.22% on average), presented a peak in January but almost no change in March.

The reduction in water demand was revealed inelastic to tariff variation (Figure 5). These results suggest that the contingent tariff itself would be enough to encourage a reduction in water consumption in all socioeconomic classes. However, the policy has adverse effects on each type of consumer. While the water tariff represents less than 1% of the average per capita income of classes A and B, it is about 23% of the income of class E, which represents 37% of the households (Table 3). The lower income classes had the lowest per capita consumptions during the baseline period, but still managed to reduce their demand after the implementation of the contingent tariff. Except for households in class B, none of the classes would reach the 20% reduction goal. Class B also had the highest average daily per capita consumption (Table 3) during the baseline period.

These findings agree with other studies that also found water demand is inelastic to price variation (Rinaudo et al. 2012; Deyà-Tortella et al. 2016). Also, Zhang et al. (2017) showed that increasing block policies are not effective to encourage a reduction in water consumption. Ma et al. (2014) indicated that the highest income group is not sensitive to price changes, while residents from the lower income group respond to marginal price and might even compare the tariff for different blocks to optimize their benefit. De Maria André and Carvalho (2014) found similar values of water demand elasticity to price in Fortaleza using survey collected data. The advantage here is that we used only secondary data and wer able to calculate elasticity for different socioeconomic classes.

Overall, the results indicate that the restriction policy might be unfair with the lower income classes, for which the tariff represents a significant percentage of their income and sill had to decrease their already low daily per capita demand. In a scenario where the customers must pay an additional charge for their excess consumption, price increase does not seem to affect consumer behavior.

This result can be explained by the fact that the customers might be at the kink point of the block rate schedule or their willingness to pay for water rises under drought conditions, since it represents only a small percentage of their income. The first is the most reasonable explanation for classes D and E, while the second is consistent with higher income classes. Another aspect to be considered is the reservation capacity of households (water tanks or cisterns, private borehole drilling), which is higher for wealthy customers (Grande et al. 2016), who might be able to maintain their standards and still reduce the water volume from public supply.

Class	**A**	**B**	**C**	**D**	**E**
Elasticity of water demand reduction to price	0.515	0.212	0.426	0.314	0.295
Number of households	53	969	5,186	17,554	13,927
Percentage of the average per capita income related to the water tariff (%)	0.46	0.89	2.00	3.77	22.97
Average daily per capita consumption (L/hab/day) for the baseline period	102.25	123.36	105.19	96.78	94.96
Average daily per capita consumption (L/hab/day) after the restriction measures	90.06	104.99	92.37	84.60	83.69

Table 3. Reduction in water demand elasticity to price increase and characteristics of the socioeconomic classes.

It is important to bear in mind that the consumers are not necessarily aware of the pricing policy structure. Although the contingent tariff is clearly expressed on the water bill, increasing block tariff scheme is not detailed for households.

A clear increasing trend in public interest is observed after 2012 (when the drought started), while the number of news related to the restriction measure peaked in 2016 (Figure 6). While this could imply that the public was well informed about pricing policy, the finding cannot be extrapolated to all customers, since not all households have access to internet.

A regression analysis between water demand, public interest, the contingent tariff and past water demand was performed for each socioeconomic class (Table 4). The relative importance values imply that an increase in the cost associated with the contingent tariff has a higher influence on consumer behavior than information on drought. Also, it seems that residents with higher income have a more significant response to both the contingent tariff and information on drought compared to residents in classes with lower income.

Class	A	B	C	D	E
Past water demand	85.87	95.78	98.31	98.67	98.55
Contingent tariff cost	10.17	3.90	1.59	1.29	1.42
Public interest	3.96	0.32	0.10	0.03	0.02
R^2	0.69	0.69	0.75	0.74	0.73
RMSE	4.37	4.08	3.26	3.01	3.05

Table 4. Relative importance of the explanatory variables of the regression model between water demand, past water demand, public interest and contigent tariff.

PDPs were plotted for each regression model (Figure 7). The results indicate that water cost has an inverse relationship with water demand for all households, while an increase in the interest in the drought has little effect on consumer habits. It is worth mentioning that class A is the only one to present a direct relationship between public interest in the drought and water demand. However, we should be careful when interpreting these results since class A has a low number of households.

5 Conclusions

The main objective of this research was to address the influence of a contingent tariff on a predictive model of water demand in Fortaleza, Brazil. The model contained an autoregressive component and variables assessing seasonality and the cost associated with the contingent tariff. This study has found that the contingent tariff was effective and resulted in a 11-17% reduction in residential water demand. Also, reduction in consumption was inelastic to price increase in all socioeconomic classes.

The evidence from this study suggests that a price policy that associates IBT with a contingent tariff could be unfair to lower income households, for which the tariff represents a large percentage of household income. Hence, although the strategy warrants a high revenue for the water company (that can be allocated to water security projects), its equity is questionable. Managers should be careful when implementing pricing policies to ensure the affordability of water services to all consumers.

The findings of this study imply that price-related water demand control policies are effective, while drought awareness is less likely to encourage consumers to save water. The increase in public interest in the drought does not necessarily indicate that consumers are well informed about the risks associated with it. It is crucial that the users are aware of the water resources management strategies and the implications of their habits rather than having a limite perception of drought. This can only be accomplished if social dynamics aspects are considered when designing drought plans and policies.

The framework proposed here is flexible and can be useful for water companies planning to implement price-related measures to encourage water demand reduction. The predictions at the household level can be useful to design policies for different classes of consumers. The predictive model can be used to verify at what extent the changes in the price policy could influence water demand.

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Figure 1. Total domestic water demand (m^3) in Fortaleza from 2009 to 2017. The baseline period was used by the local water company to calculate the reduction goal for each household.

Figure 2. The predictive model has an autoregressive component (previous month water demand) and the penalty price as explanatory variables, in addition to the seasonality of the corresponding month. Starting from January, the water demand in December would be used to calculate the cost of the contingent tariff. For the next month, the penalty cost is calculated using the predicted water demand for January.

Figure 3. Model performance.

Figure 4. Real and predicted monthly reduction in aggregated water demand for the year of 2017 for each socioeconomic class.

Figure 5. Elasticity of water demand reduction to price for each socioeconomic class.

Figure 6. Public interest and media coverage on the contingent tariff policy.

Figure 7. Partial dependence plots for public interest and the contingent tariff cost. A regression model was built for each socioeconomic class.

Figure 1.

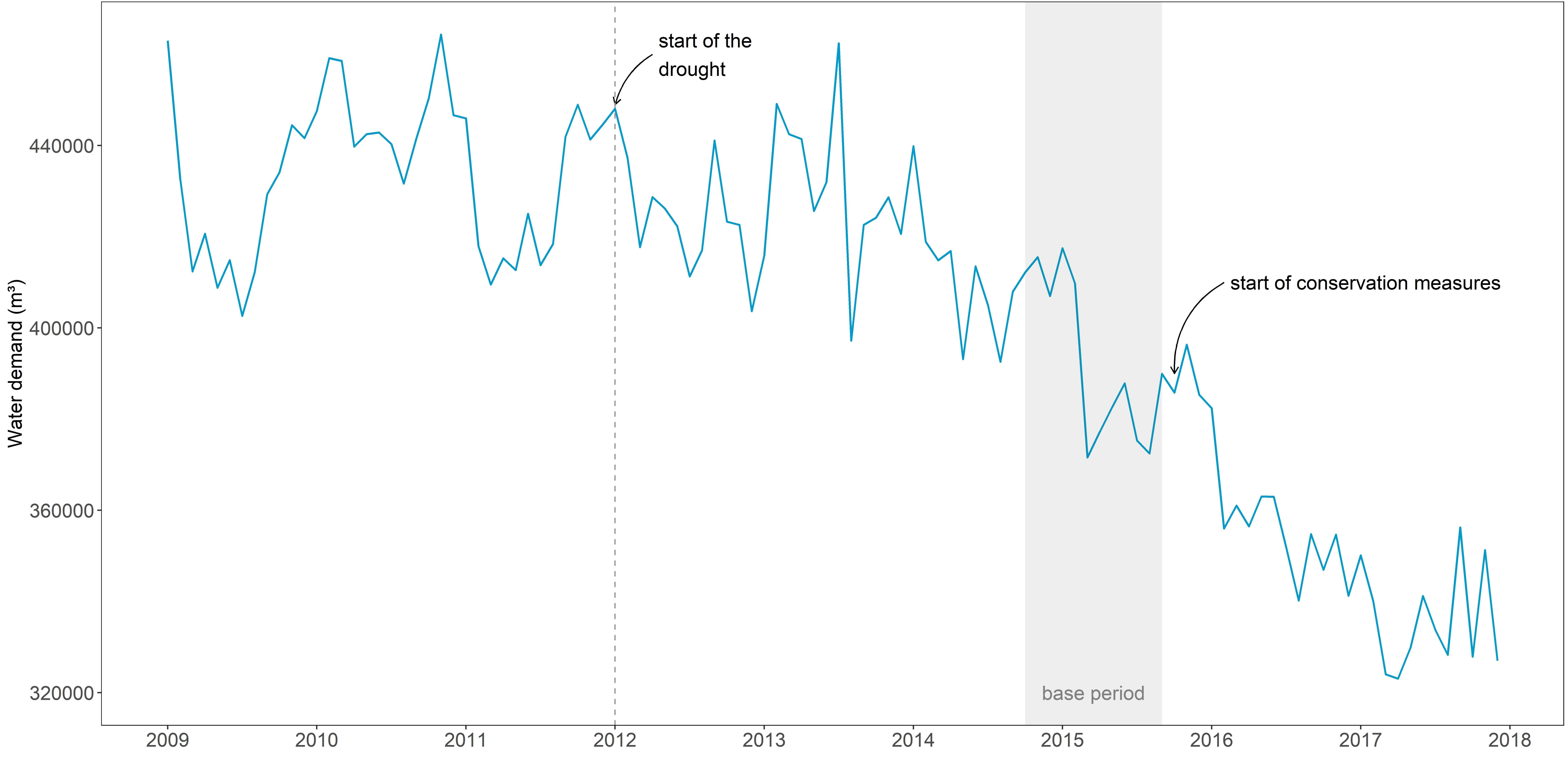

start of the drought
start of conservation measures
base period
Water demand (m³)
440000
400000
360000
320000
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018

Figure 2.

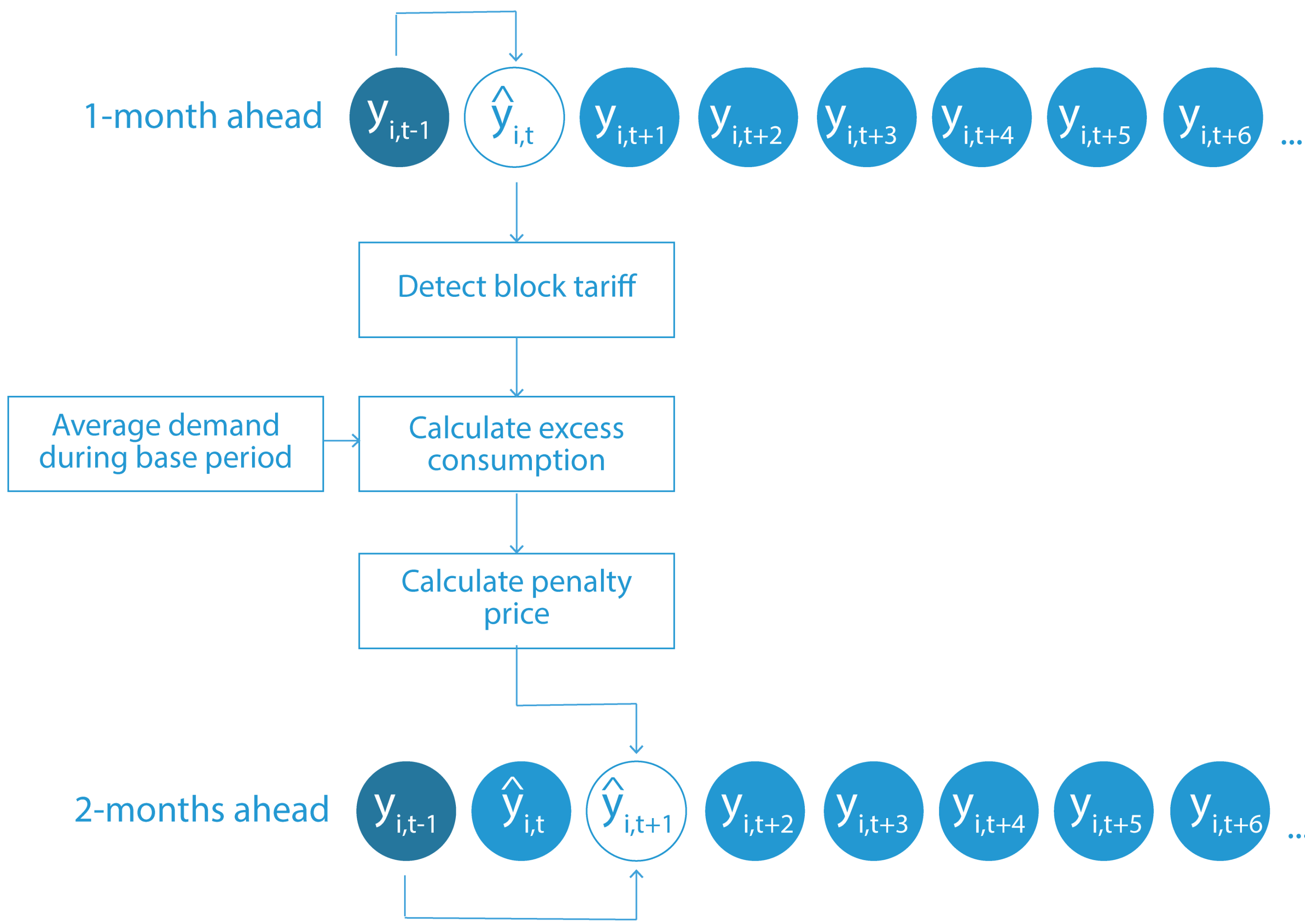
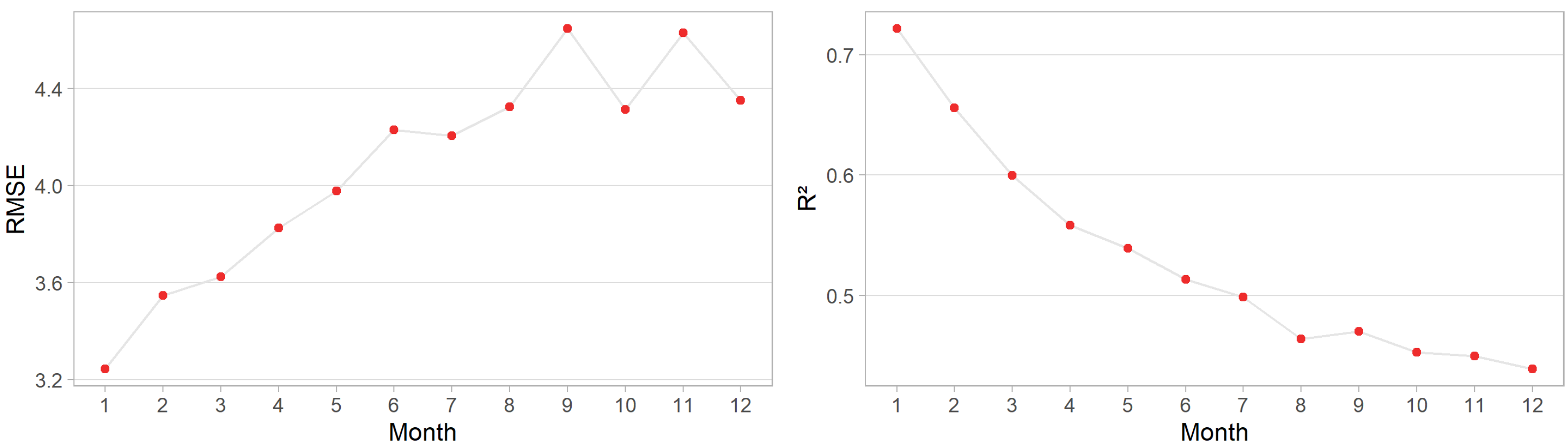

1-month ahead
$y_{i,t-1}$
$\hat{y}_{i,t}$
$y_{i,t+1}$
$y_{i,t+2}$
$y_{i,t+3}$
$y_{i,t+4}$
$y_{i,t+5}$
$y_{i,t+6}$
...
Detect block tariff
Average demand during base period
Calculate excess consumption
Calculate penalty price
2-months ahead
$y_{i,t-1}$
$\hat{y}_{i,t}$
$\hat{y}_{i,t+1}$
$y_{i,t+2}$
$y_{i,t+3}$
$y_{i,t+4}$
$y_{i,t+5}$
$y_{i,t+6}$
...

Figure 3.



RMSE
4.4
4.0
3.6
3.2
1
2
3
4
5
6
7
8
9
10
11
12
Month
R²
0.7
0.6
0.5
1
2
3
4
5
6
7
8
9
10
11
12
Month

Figure 4.

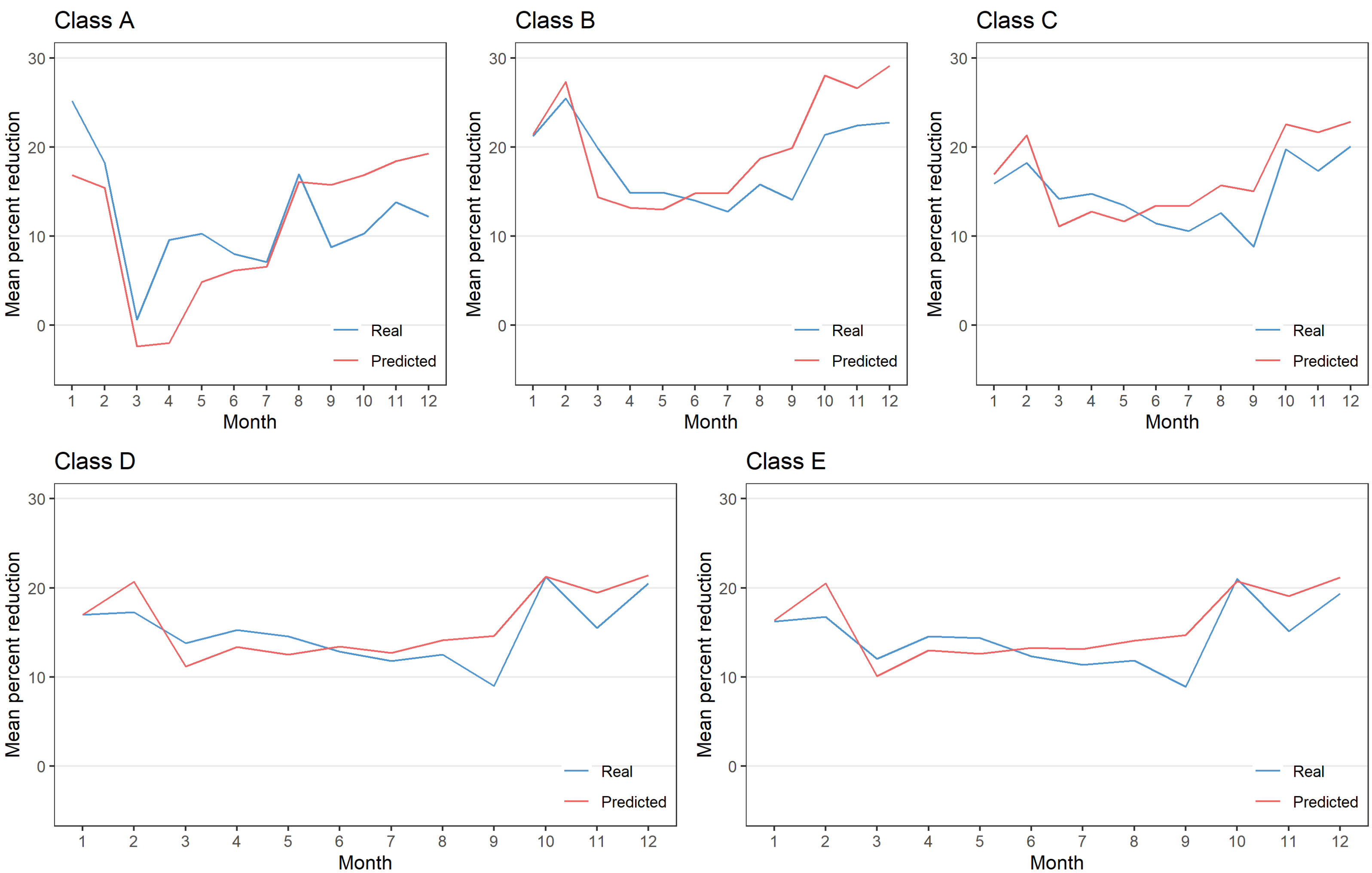

Class A
Class B
Class C
Class D
Class E
Mean percent reduction
Month
Real
Predicted
0
10
20
30
1 2 3 4 5 6 7 8 9 10 11 12

Figure 5.

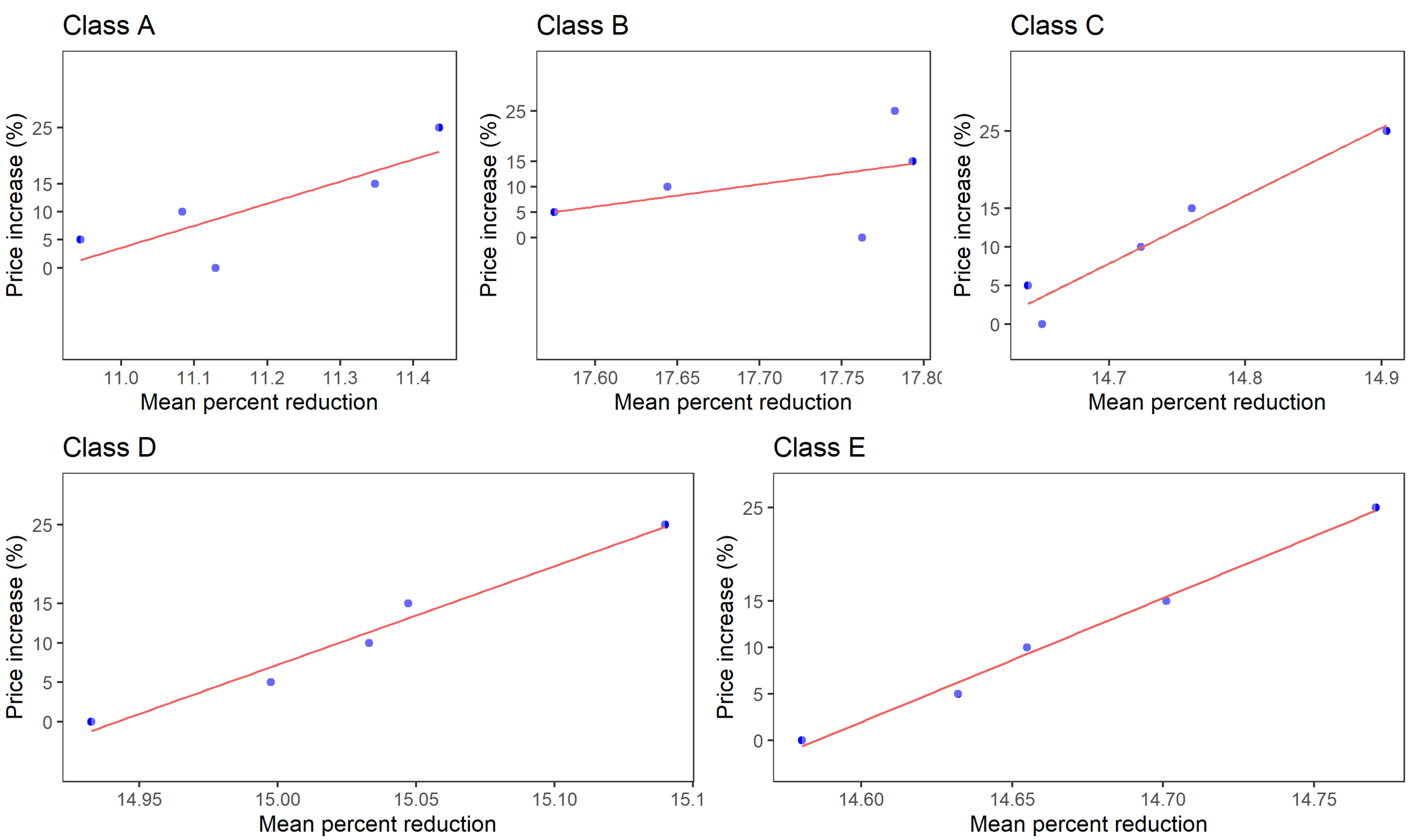

Class A
Price increase (%)
25
15
10
5
0
11.0
11.1
11.2
11.3
11.4
Mean percent reduction
Class B
Price increase (%)
25
15
10
5
0
17.60
17.65
17.70
17.75
17.80
Mean percent reduction
Class C
Price increase (%)
25
15
10
5
0
14.7
14.8
14.9
Mean percent reduction
Class D
Price increase (%)
25
15
10
5
0
14.95
15.00
15.05
15.10
15.1
Mean percent reduction
Class E
Price increase (%)
25
15
10
5
0
14.60
14.65
14.70
14.75
Mean percent reduction

Figure 6.

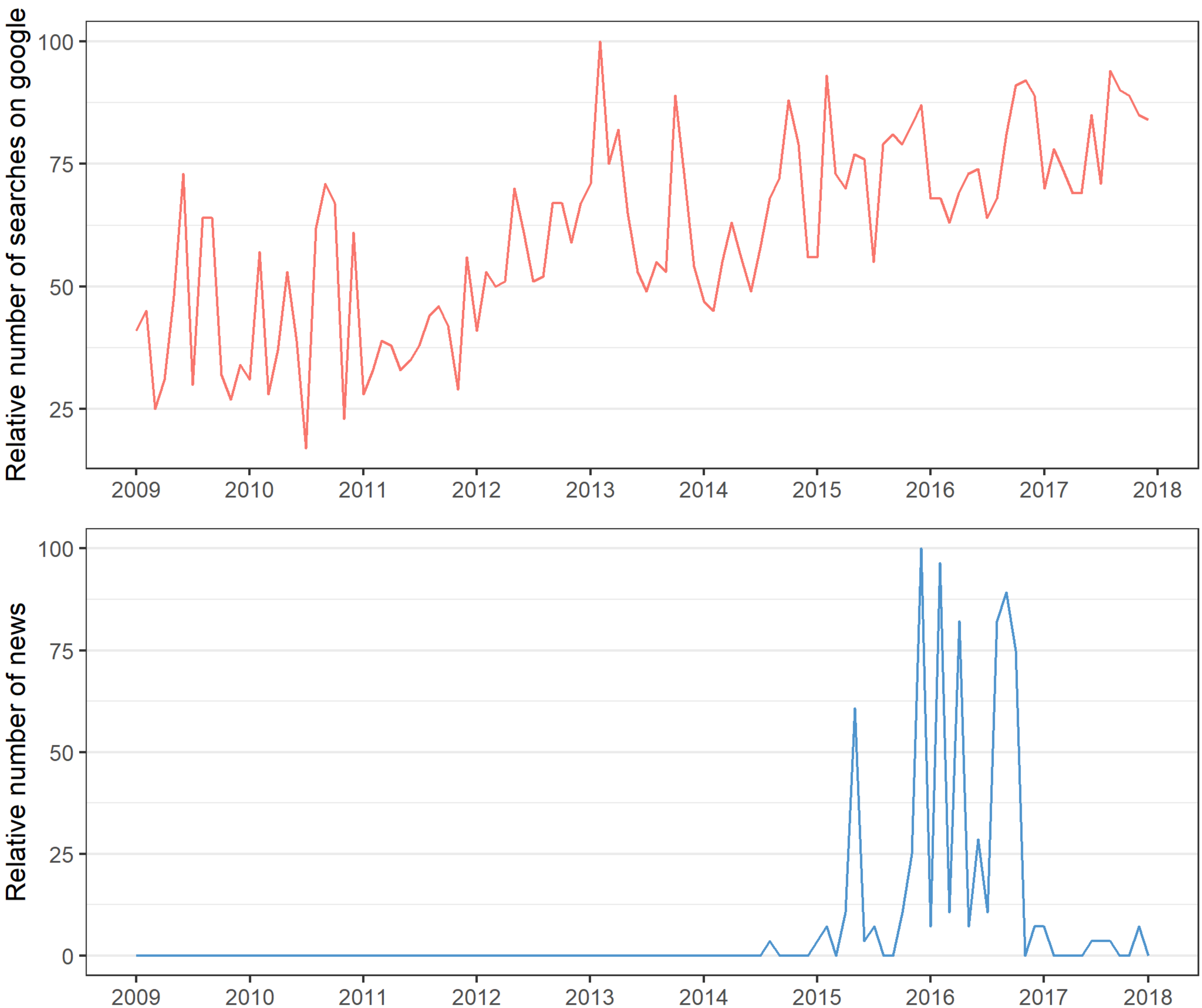
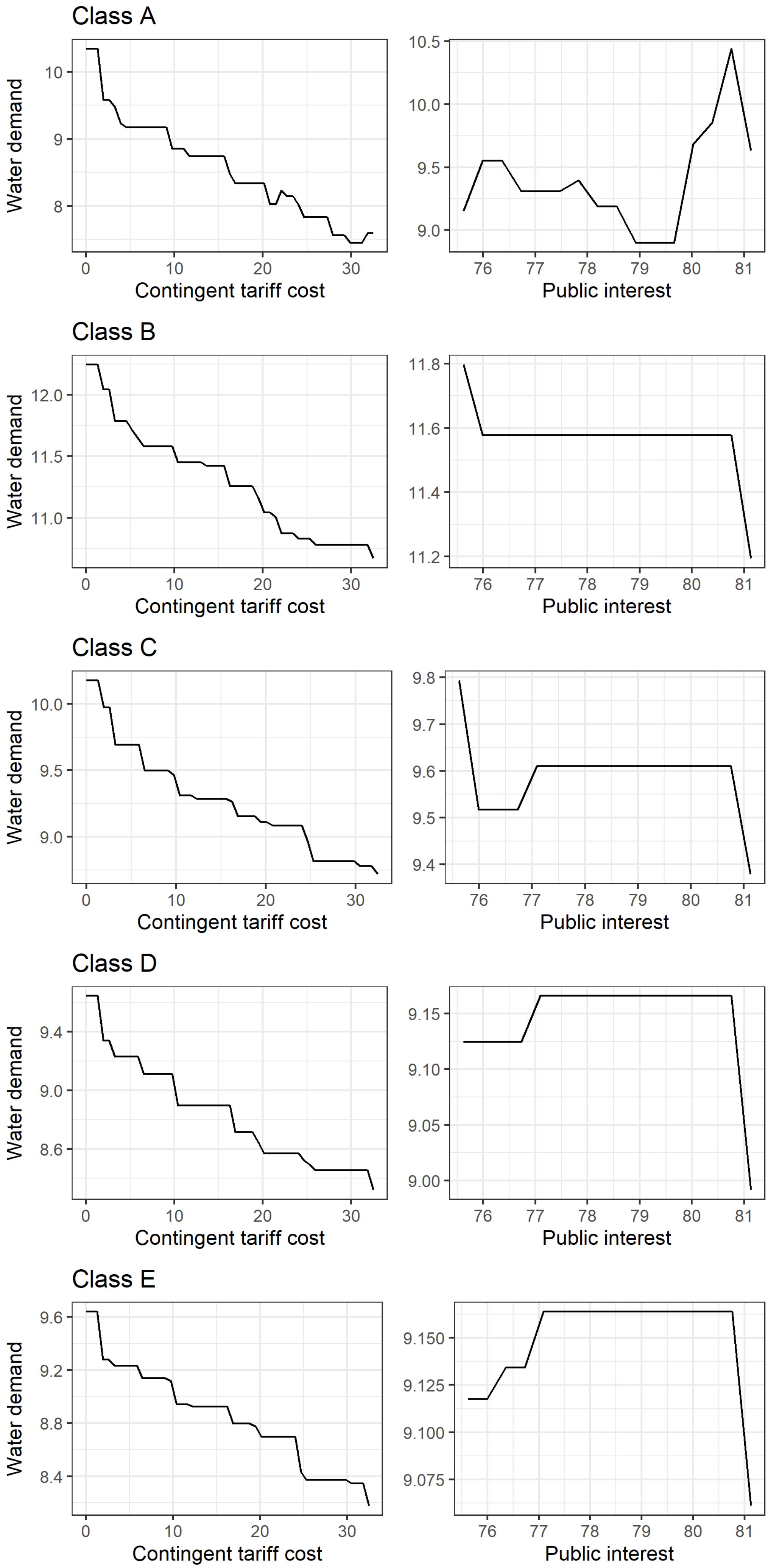

Relative number of searches on google
100
75
50
25
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
Relative number of news
100
75
50
25
0
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018

Figure 7.



Class A
Water demand
10
9
8
0
10
20
30
Contingent tariff cost
10.5
10.0
9.5
9.0
76
77
78
79
80
81
Public interest
Class B
Water demand
12.0
11.5
11.0
0
10
20
30
Contingent tariff cost
11.8
11.6
11.4
11.2
76
77
78
79
80
81
Public interest
Class C
Water demand
10.0
9.5
9.0
0
10
20
30
Contingent tariff cost
9.8
9.7
9.6
9.5
9.4
76
77
78
79
80
81
Public interest
Class D
Water demand
9.4
9.0
8.6
0
10
20
30
Contingent tariff cost
9.15
9.10
9.05
9.00
76
77
78
79
80
81
Public interest
Class E
Water demand
9.6
9.2
8.8
8.4
0
10
20
30
Contingent tariff cost
9.150
9.125
9.100
9.075
76
77
78
79
80
81
Public interest