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Water consumer preferences for price caps: the roles of perceived investment efficiency, service quality, uncertainty, and motivation

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Water consumer preferences for price caps: the roles of perceived investment efficiency, service quality, uncertainty, and motivation

Many water utilities offer price caps to reassure consumers about future prices. Researchers have focused largely on the implication of price caps on total cost of ownership or conservation rather than consumers' preference for such guarantees. In this paper, we examine consumers' preferences for price caps. We first consider how consumers form expectations about their water prices, and secondly how they evaluate those expected prices against guarantees.

Our empirical investigation, using new survey data, confirms that as variability of historic prices increases, consumers use less historic information to form their expectations, and replace it with more subjective information, such as their perceptions of the water supplier's investment efficiency and the quality of their water. Further, water consumers who are more motivated to protect themselves, as demonstrated by averting behaviours even when they consider service quality to be good, more strongly prefer a guarantee when past prices have been highly variable.

Keywords: water utility pricing; regulation; price caps; expectations; motivation; survey data; uncertainty

JEL Codes: D81, D84

1. Introduction

There has been a recent increase in the demand from society for providers of public goods and services to be transparent about the way they invest in public goods (Araujo & Tejedo-Romero, 2016; Caamaño-Alegre, et al., 2013). Regulation is frequently introduced as a means of meeting demands for increased transparency (Vinnari & Näsi, 2008). Two main approaches in regulation are price caps and rate of return guarantees (Aubert & Reynaud, 2005). In the water industry, there has been significant research into the effect of different forms of regulation on price, consumer surplus, water consumption, and customer willingness to pay (Aubert & Reynaud, 2005; Brocas, et al., 2006). Price caps – guarantees that the prices will not exceed a certain amount, or percentage, within a specified timeframe (Aubert & Reynaud, 2005) – are often adopted directly by the water utility, even when the industry is not regulated.

Although these caps are introduced in part to satisfy consumers, little is known about how consumers value price caps. If consumers do not value price caps, then utilities and regulators may be investing undue resources in setting, monitoring, and/or sharing information about them. In this paper, we consider these important questions: in what instances do consumers value price caps, and are there certain types of consumers who value price caps more than others? The answers to these questions will provide an indication of the situations in which price caps may advance the goal of satisfying consumers.

To answer these questions about when and who value price caps, we first need to understand what prices consumers would expect in a no-cap situation (how they form expectations about future prices), and secondly, how they evaluate these expected prices against a guarantee.

There is a significant body of literature on how people form expectations. The expectations formation process is typically broken down into two components:

(1) The quantity and nature of information people use. Economists assume that individuals use a subset of the available information and apply simplifying calculation heuristics, on the premise that information processing is costly (Manski, 2004; Conlisk, 1996). Hubert & Mirza (2019) found that the most recent data appears to be the most relevant to the expectation.

(2) Their calculation methods. In terms of understanding how people process, or calculate, the selected information, there has been some recent progress that is relevant to the current study: the most recent “shock” is exaggerated (Landier, et al., 2018). Further, we know that not everyone calculates in the same way; people’s expectations about prices or other values sometimes deviate from the average (Bruin el at., 2011) - but the explanations for why and how this happen do not apply to a case such as ours. For example, Pfajfar and Santoro (2010) argue that such deviations are related to people’s degree of pervasiveness, rationality and learning/stickiness (Pfajfar and Santoro, 2010). However, both pervasiveness and learning/stickiness are only relevant when people form expectations multiple times, as in decisions to make repeat purchases or forming expectations about inflation. Most of the literature on expectations formation, in fact, relates to repeat decisions. Ours is a situation in which one-off expectations are set – a scenario that is not well covered in the literature. In addition, notably absent from explanations of deviations is risk appetite, which has been shown to have a significant bearing on decisions. Finally, there is little literature to shed light on whether some water consumers also form diverging expectations about future prices, and if so, what characteristics those consumers would exhibit.

Known characteristics from the research into water consumers may provide information that helps identify heterogeneity in their expectations. Water consumers are known to behave and think differently – undertake different averting behaviours, express a different willingness to pay – based on their perceptions about the quality of their water service, trust in water supplier, frequency or duration of historic water restrictions, and demographic characteristics (Orgill, et al., 2013; Robak, 2013; Chatterjee, et al., 2017; Wang, et al., 2018). But it is not known how these characteristics apply to preferences for price caps. An additional consideration that is prevalent in decision making is risk appetite. While our data do not contain consumers' risk profiles, we do know their perceptions of the quality of their service, as well as their averting behaviours to protect against poor quality service. We therefore use this interaction of a consumer's perceived service quality and associated averting behaviour as a proxy for risk appetite. It may be more accurately called "motivation to protect".

In this paper, to understand water consumers' preferences for price caps, we model their expected future prices using the standard price expectations model, i.e. where the cost of processing information is the only key mechanism to setting expectations, but extend it to also include the uncertainty of future prices, and consumers' motivation levels. Our approach creates a three-stage expectation-preference formation making framework: In the first stage, consumers decide how much information to use. In the second stage, projections are produced based on selected data, and in the third stage final preferences are created by adjusting projections based on uncertainty and motivation. The key insight of our model is that the direction and magnitude of the adjustment depend on the interaction between uncertainty and motivation.

To illustrate, consider a consumer who only has information about current past prices, and their own experience with the service. To form an expected price, the consumer would first decide how many of the past prices to use. She would use fewer historic prices if she found the cost of processing information was high. She then projects the historic price series forward. Then, to evaluate the guarantee relative to this price, she evaluates her beliefs about the water supplier's investment efficiency: if she believes them to invest efficiently, the guarantee loses value. However, if historic prices were highly variable and the consumer is strongly "motivated to protect", she will value the guarantee more strongly; whereas a consumer who is strongly unmotivated to protect, in the same situation, would devalue the guarantee, which implies that she is less likely to value a guarantee, relative to the averagely motivated consumer.

Our situation, where expectations are formed in a static expectations formation process (EFP) is in contrast to almost all previous studies where expectations are formed in each period in a multiple-period, time-series environment. In such dynamic models, it is typically assumed that consumers choose one of several available expectation predictors based on their costs and benefits, where the benefit is a measure of how accurate the predictor has been in the past. Expectations are re-evaluated in each period, leading to an adaptive belief system (e.g., Brock and Hommes, 1997). While such adaptive expectation formations may be preferred in financial (i.e. stock prices) and macroeconomic (e.g. inflation) applications where the nature of the economic system is of primary concern, this structure is not the norm in microeconomic applications such as consumers' preferences and willingness to pay for public investments, where static decisions are common.

The studies that are most similar to ours in the economics literature share our premise that agents have heterogeneous costs for processing information. This leads to a segmented market where agents are distinguished through the amount of information they use in their EFP. Baak (1999) assumes that there are two types of agents: one perfectly rational and one that is boundedly rational in the sense that she ignores market dynamics and treats price as if it is exogenous. Brock and Hommes (1997) also assume that there are two EFPs: one fully rational and one naïve, where the naïve assumes that the latest observed value persists into the future. Gaunersdorfer (2000) extends this model in the context of asset prices by introducing risk aversion where agents update their beliefs in each period conditioned on the variance of the asset returns. Chavas (1999) considers three types of EFPs: a naïve, a quasi-rational where expectations are based on observed realisations of past values, and a perfectly rational based on the anticipation of a complete supply-demand system. Branch (2004) also uses three EFPs, but he assumes there are two quasi-rational EFPs (one based on a VAR model and one on an adaptive model) and one that is naïve. Branch (2004) argues that expectations based on a VAR-model mimic a fully rational EFP.

We use a newly collected data set from households in New Zealand. Our empirical investigation is based on household owners' stated choices between two pricing policies where these choices may have implications for what they pay for their future potable water service. The choice model is combined with a latent discrete model that assigns respondents in classes based on the number of past prices they have included in their calculations. Uncertainty is measured as the standard deviation of past prices and motivation is identified through a combination of whether respondents feel well protected from water microorganisms and whether they have installed water treatment equipment.

The results presented in this paper confirm that consumers express preference for a guarantee based on the interaction between uncertainty and motivation. The absolute adjustment is positively related with uncertainty and relative to an "averagely motivated" consumer, expected prices are significantly higher when consumers are highly motivated to protect and significantly lower when they are distinctly unmotivated to protect. These findings may explain why reported expectations are sometimes different from the central tendency of individuals' expectations distribution. We also confirm the widely held belief that agents are affected by the cost of processing information: the higher the cost, the less information they use.

The paper proceeds with a section where the empirical application and data characteristics are discussed. Section 3 provides some structure to the intuitions presented in this section and it conducts various econometric investigations. Section 4 concludes.

2. Data

Like much of the empirical literature on expectations formations, we use survey data to elicit expectations (see Pesaran and Weale (2006) for a comprehensive summary as at 2005, as well as Dominitz and Manski (2011), Engelberg et al. (2011), Gouret and Hollard (2011), and Hudomiet et al. (2011). To test consumers' preference for a maximum price guarantee, we ask residential customers to choose one of two available pricing options for their potable water service, where the choice they make will apply for the next ten years (2012-2021):

A. A price cap that guarantees the price will not exceed X $/year.

B. The status quo with no future price cap. The water utility is free to set whatever price it wants.

Respondents are given concrete reasons for why the cost of providing potable water may legitimately vary: (i) changing legislative requirements, (ii) variation in water treatment as a result of different river and groundwater contaminations, (iii) finding new water supplies to protect against increasingly dry summers, (iv) lumpy replacements of pipes. Moreover, respondents were presented with the total annual water rates in $/year during the current and past ten years, i.e. the rates from 2001 to 2011. There were twelve different versions of this question, varying in terms of standard deviation and slope for historic prices, and cap levels, as summarised in Table A1 in the Appendix. One full version of the question is also provided in the appendix.

Historical prices are not available at household level in New Zealand. For current prices, respondents were asked to report their most recent water bills, and for historic prices, scenarios were constructed that varied, relative to the reported bill, within the same range as real historic prices. In most scenarios, rates varied from 0 to +/-20% per year, which is within realistic annual rates variations, with one additional scenario extending to +/-50%. The Water New Zealand Benchmarking reports show that since 2008, water customers have experienced average annual rates increases of up to 26% and average annual rates reductions of up to 18% (Water New Zealand 2010, 2011, 2012). Households have a low awareness of what they pay for water, and an even lower awareness of what they paid in the past. Creagh (2010) found that in New Zealand, only 25% of fixed charged consumers reported that they could recall their last water bill. Furthermore, compared to annual household expenditures of $52,500 per year (Statistics New Zealand 2010), water bills averaging $300 per household per year means that water constitute less than 1% of households' budget. They would therefore not have reason to disbelieve these scenarios.

Respondents were also informed that the price cap option does not affect the quality of the service. Water quality is essentially regulated by law in New Zealand and the price can therefore increase above the capped level if it is driven by costly quality concerns; the New Zealand Health (Drinking Water) Amendment Act 2007 legislates compliance with the New

Zealand Drinking Water Standards, and the Local Government Act 2002 requires community consultation on price and levels of service quality. In a separate section of the survey not reported in this paper, a willingness to pay experiment showed that respondents were unwilling to pay their service provider more for any type of service quality improvement apart from protection from waterborne illness (self-reference to be provided for publication). This lack of willingness to pay suggests that current service levels may be greater than customers' requirements – and even if quality was not regulated, reduced quality does not seem to be a serious concern in this context.

As displayed above, the survey does not ask about price expectations directly, but for respondents' preferred actions for the next ten years. The results therefore represent respondents' combined expectations and preferences. Asking for the policy relevant choice, rather than the expected value directly is more realistic since citizens do not necessarily articulate their expectations. The disadvantage with this approach is that it requires expectations and preferences to be independent, or that preferences are explicitly controlled for. For example, if expectations are correlated with respondents' discount rates of future prices, conclusions could be distorted since a high discount rate may increase the preference for the status quo option. Also, respondents may have different beliefs about how efficiently water utilities follow the cost-recovery principle. If respondents believe a utility will raise its prices pre-maturely in anticipation of having its price capped, they may prefer the status quo option even if they expect future prices to be above the capped level. Both examples illustrate situations of omitted variables that would lead to biased results. In Section 3.3 we test whether risk preferences are correlated with discount rates and whether respondents' beliefs about how efficiently utilities operate their networks have any impact on estimated parameters.

Choices from 1213 residential potable water customers are analysed. From the original response set of 2066 we eliminated observations from respondents in areas where volumetric charging was in place. These respondents, who can control future water bills by adjusting the amount of water they consume, were found to be less sensitive to expected price and standard deviation of historic prices. We also excluded respondents who reported water bills exceeding $1200/year, water restriction frequencies exceeding 30 in a 30-year period, and maximum water restriction durations exceeding 52 weeks per year. None of the options completely dominated in any of the scenarios. Respondents generally treat the status quo option as a straight-line projection based on past prices since the status quo option was the most common when the straight-line projection was lower than the capped level, and the capped price option was the most common when the projection was above the cap.

Respondent and question statistics are summarised in Table 1 and, where relevant, national statistics are presented for comparison. Some of the characteristics were solicited in bands, including age, income and perceived taste of water. The subsequent estimations were evaluated using these variables in both pseudo-continuous and categorical formats. Prices (historical prices, price caps and projected prices) are expressed relative to the prices reported by the respondents in 2011. A price of 1.2 is therefore 20% above the price reported in 2011. The projected price is defined as the price in 2021 based on a straight-line projection using historical prices. The statistics show that projected prices range from 1.5 to 2.2, while price caps range from 1.0 to 2.5.

[Insert Table 1]

The survey was not designed to capture risk appetite; this characteristic only emerged as an important consideration when we analysed the data and explored, in the same dataset, why some consumers undertook averting behaviours while others did not (see Robak & Bjornlund (2018)). In that analysis, significant contributing factors for undertaking averting behaviours included taste, perceived protection from microorganisms, frequency of water restrictions, property ownership, and the number of service interruptions. As a proxy for risk appetite, we therefore explored interactions of perceived service quality characteristics (as a proxy for perceived risk), and the presence of any averting behaviour. However, since this is not a formal method for evaluating risk appetite, we have called it "motivation to act". This interaction reflects a risk averse consumer when they perceive low risks, yet undertake averting behaviours; and a risk seeking consumer when they perceive high risks, yet do not undertake averting behaviours. We found that risk appetite, or "motivation to act", was best reflected in respondents' choices to further protect themselves from waterborne illness, given their current perception of drinking water safety. The literature on consumers' perceived risk in water supply systems is vast, and focuses largely on perceived protection from microorganisms and chemicals (see e.g., de Franca Doria (2010); Nancarrow, et al (2010)). Based on this premise, respondents who feel their drinking water is safe, but purchase water treatment equipment nevertheless are defined as "highly motivated to protect", as a proxy for risk averse; respondents who feel that their drinking water is not safe, yet they do not purchase water treatment equipment, are defined as "strongly unmotivated to protect". Thus, RiAver and RiSeek indicate individuals with the most extreme motivation levels (risk preferences). Those with more neutral motivation levels are classified as "averagely motivated". An important drawback of our definition is that it only classes those consumers whose perceptions are at the positive and negative extremes; it does not capture consumers with more neutral perceptions about the quality of their water service. If those same consumers were placed in a situation in which they perceived high or low risk situations, their motivation levels may well show.

3. Analysis

As a starting point, we formulate our intuitions more precisely. The purpose of this part is to motivate the specification of our estimable model and it is not meant to propose theoretical propositions.

3.1 Formalising the intuitions

As a starting point, we formulate our intuitions more precisely. The purpose of this part is to motivate the specification of our estimable model and it is not meant to propose theoretical propositions.

Imagine a situation where consumer i forms a prediction at time t about a price p at time $t+n$. The expected price $\hat{p}_{t+n,i}$ is static in the sense that it is not updated in intermediate time periods. The consumer has access to the present price and k past prices $\boldsymbol{p}_k^- = \{p_t, p_{t-1}, \ldots, p_{t-k}\}$. The cost of processing one piece of information, c_i is assumed to be a function of the asymptotic, exogenous dispersion of the data generating process, ε, where $\frac{\partial c_i}{\partial \varepsilon} \geq 0$. Thus, the cost of processing information increases for higher levels of price dispersion. This follows from the assumption that the cognitive burden is positively correlated with the relative influence of noise.

When consumers have access to a certain budget C_i, their budget constraint can be formulated as $mc_i(\varepsilon) \leq C_i$, where m is the amount of past information being processed, i.e. $\boldsymbol{p}_m^- = \{p_t, p_{t-1}, \dots, p_{t-m}\}$ with $m \leq k$. Behaviourally inspired stopping-rules have been suggested, e.g. that agents use a fixed number of past values (Levin et al., 2004) or values from a fixed time period (Heemeijer et al., 2009). Hence, when consumers face heterogeneous processing costs and/or constraints on the amount of available calculation resources, they use different numbers of past p's. Once consumers have selected the amount of information to use we assume, like Branch (2004) and Evans and Honkapohja (2001), that consumers behave like econometricians and fit a function through the selected observations and extrapolate to form baseline expectations about the future.

It is assumed that consumers use the most recent information, adding older information in a stepwise manner. Next, in our experimental situation it is assumed that the pricing conditions have been fixed so each previous price is equally informative and consumers therefore attach the same weight to all past prices $\boldsymbol{p}_m^-$.

Once information has been selected, the remaining EFP can be decomposed into two stages where, in the first stage, consumers calculate the statistical properties of the expected value, i.e. a point value $\mu_{\hat{p}_{t+n}}$ and a measure of uncertainty $\sigma_{\hat{p}_{t+n}}$ to account for the probabilistic range of outcomes. Subject to the constraint $mc_i(\varepsilon) = C_i$ the point value can be formulated as:

$$\mu_{\hat{p}_{t+n,i}} = f(\boldsymbol{p}_m^-, m(c_i(\varepsilon), C_i)) \quad (1)$$

where $\frac{\partial m(c_i(\varepsilon),C_i)}{\partial c_i(\varepsilon)} < 0$ and $\frac{\partial m(c_i(\varepsilon),C_i)}{\partial C_i} > 0$. The expectation uncertainty $\sigma_{\hat{p}_{t+n},i}$ is positively related to the decision uncertainty $\sigma_{\boldsymbol{p}_m^-}$, where $\sigma_{\boldsymbol{p}_m^-}$ is the standard deviation of the m de-trended prices that is decreasing in m and increasing in ε.

A general expression for $\sigma_{\hat{p}_{t+n}}$ can be written as:

$$\sigma_{\hat{p}_{t+n,i}} = g_1\big(n, g_2(m(c_i(\varepsilon), C_i)^{-1} + \varepsilon)\big).$$

When all expectations refer to the same future time period, i.e. when n is fixed, this can be simplified to:

$$\sigma_{\hat{p}_{t+n,i}} = g(m(c_i(\varepsilon), C_i)^{-1} + \varepsilon), \tag{2}$$

which reflects that the expectation uncertainty is only a function of ε as $m \to \infty$. It has indeed been confirmed experimentally that agents report higher $\sigma_{\hat{p}_{t+n}}$ when $g(\cdot)$ increases (Sonsino and Regev, 2013).

When consumers form expectations based only on their cost characteristics, $\sigma_{\hat{p}_{t+n,i}}$, consumers calculate their expected values as in (1):

$$\hat{p}_{t+n,i} = f(\boldsymbol{p}_m^-, m(c_i(\varepsilon), C_i)). \tag{3}$$

When c_i and C_i are heterogeneous across consumers, the population consists of consumers with a mixture of m's. This is the classical expectations model that leads to the quasi-rational EFP when $m \geq 1$ and to the naïve EFP when $m = 0$. The special cases when $c_i = 0$ and $C_i > 0$, or when $c_i \ll \infty$ and $C_i = \infty$, represent the most rational consumer. A fully rational agent is also able to explain ε. Thus, this structure identifies the three EFPs that have been used in the previous literature.

When consumers calculate $\hat{p}_{t+n,i}$ according to (3), they may or may not be aware of the uncertainty of their estimate since it has no relevant meaning to them. Also, when consumers are fully rational they are perfectly certain about their prediction and when they are naïve, uncertainty is not quantitatively defined. However, when heterogeneous risk preferences – or motivation levels – are introduced and consumers are quasi-rational, uncertainty has direct relevance. This is operationalized in the second stage where the consumer interprets the available decision conditions by adjusting $\mu_{\hat{p}_{t+n}}$ based on $g(\cdot)$ and her private motivation levels. To formulate this, let θ_i represent consumer i's motivation level where $\theta_i \in [\theta_{min}, \theta_{max}]$ that is drawn from any distribution. $\theta_{max} > 0$ is the most motivated consumer and $\theta_{min} < 0$ is the least motivated consumer. Hence, the consumer's motivation level is a stochastic component built on the same logic as used by Nishimura (1998). In Nishimura's model, agents' willingness to pay follows a distribution function where they access the same imperfect information but their interpretations are unique.

The implication is that the consumer can adjust her point value: she adjusts $\mu_{\hat{p}_{t+n}}$ upward if she is highly motivated and downward if she is highly unmotivated. The size of the adjustment increases for more extreme motivation levels and higher uncertainty. Hence, relative to the benchmark situation above, consumers are now able to interpret information based on their private preferences. The adjustment term, which can be formulated as $f_2(\theta_i g(m(c_i(\varepsilon), C_i)^{-1} + \varepsilon))$, depends on motivation level θ_i, number of past prices m and the underlying data dispersion ε. This allows us to formulate the expression for $\hat{p}_{t+n,i}$ as:

$$\hat{p}_{t+n,i} = \underbrace{f_1\big(\boldsymbol{p}_m^-, m(c_i(\varepsilon), C_i)\big)}_{\substack{1st\ stage: \\ projection\ based \\ on\ selected\ info}} + \underbrace{f_2\big(\theta_i g(m(c_i(\varepsilon), C_i)^{-1} + \varepsilon)\big)}_{\substack{2nd\ stage: \\ adjustment\ based \\ on\ motivation\ level\ and \\ decision\ uncertainty}}, \qquad (4)$$

which can also be written as

$$\hat{p}_{t+n,i} = \mu_{\hat{p}_{t+n,i}} + f_2\big(\theta_i g(m(c_i(\varepsilon), C_i)^{-1} + \varepsilon)\big). \quad (5)$$

Here, $f_2(\cdot)$ is increasing in θ_i, decreasing in m and increasing in ε; as before, m is decreasing in c_i and increasing in C_i. It should be noted that θ_i and $g(\cdot)$ only enter the model as factors in an interaction, implying that neither motivation level nor price variability have an effect when the other is 0.

Given that price dispersion increases the cost of processing information and reduces the number of past prices used (m), the overall effect of price dispersion on the adjustment term is positive: higher dispersion leads to a higher adjustment term and a less precisely calculated expected value. This follows directly from the assumptions about the functions $f_2(\cdot)$ and $g(\cdot)$. Moreover, as ε increases, m decreases. Since $f_2(\cdot)$ is decreasing in m and increasing in ε, the overall effect on the adjustment term is positive.

3.2 Estimation

Based on the structure in Section 3.1, it is necessary to determine how many past prices, m, respondents include in their calculations. Since the number of past prices considered is unobserved we apply a 'best-fit' evaluation criterion based on adjusted BIC, where models are run iteratively and respondents are assumed to use between 2 and all 11 years of historic information. A measure of the projection, i.e. $\mu_{\hat{p}_{t+n}}$ in (5), is also needed. We proxy this with the straight-line projection based on selected prices and in this and subsequent sections of the paper we simply denote this as $\mu_{\hat{p}}$. Respondents' confidence in $\mu_{\hat{p}}$ is assumed to be based on a threshold price variation, $d^{\sigma_{p\bar{m}}}$, that takes the value 0 below the threshold and 1 above. In the baseline estimation we set

$$d^{\sigma_{p\bar{m}}} = \begin{cases} 1 \; if \; \sigma_{p\bar{m}} \geq 0.095 \\ 0 \; if \; \sigma_{p\bar{m}} < 0.095 \end{cases},$$

where $\sigma_{p\bar{m}}$ is the standard deviation around the least squared line through the past *m* prices. The interpretation of this threshold is that when $d^{\sigma_{p\bar{m}}} = 1$, the projection is perceived as relatively uncertain. Different thresholds are evaluated in the subsequent estimations.[1]

These variables are included in a choice model and a class assignment model and estimated as a latent class multinomial logit model. Within each class of respondent, a choice model reflects respondents' utility for a capped price option. The respondent will be more likely to choose the capped price as the projected price increases relative to the cap level. This is included in the model as $\mu_{\hat{p}} - p^{Cap}$. Moreover, we add the interactions between motivation levels and uncertainty, i.e. $RiSeek \times d^{\sigma_{p\bar{m}}}$ and $RiAver \times d^{\sigma_{p\bar{m}}}$, and expect the respondent to be less (more) inclined to choose the price cap when she is strongly unmotivated (motivated).

Demographic control variables reflect the literature's findings that people with higher incomes and men are likely to behave as risk seekers (e.g. Jianakolpous 1998; Holt and Laury 2002; Dominitz and Manski 2011), which is what we're trying to approximate with our "motivation level" variable. Respondents' rating for the taste of their water is also included as an application specific control. All control variables are included in the vector **Z**. Individuals' choice model can therefore be specified as:

$Prob[\text{individual } i \text{ choose Guarantee} | \text{class } c] =$

---

[1] We also evaluated models where standard deviation was used directly, i.e. as a continuous variable, but those models did not perform well.

$$G_{i|c} = \frac{\exp\left(\beta_{0c}+\beta_1\left(\mu_{\hat{p}i|c}-p_i^{Cap}\right)+\beta_2 d_c^{\sigma_{\hat{p}\bar{m}}}+\beta_3 RiSeek_i\times d_c^{\sigma_{\hat{p}\bar{m}}}+\beta_4 RiAver_i\times d_c^{\sigma_{\hat{p}\bar{m}}}+\mathbf{Z}_i\boldsymbol{\lambda}_c\right)}{1+\exp\left(\beta_{0c}+\beta_1\left(\mu_{\hat{p}i|c}-p_i^{Cap}\right)+\beta_2 d_c^{\sigma_{\hat{p}\bar{m}}}+\beta_3 RiSeek_i\times d_c^{\sigma_{\hat{p}\bar{m}}}+\beta_4 RiAver_i\times d_c^{\sigma_{\hat{p}\bar{m}}}+\mathbf{Z}_i\boldsymbol{\lambda}_c\right)}. \quad (6)$$

The amount and type of information used by respondents are unobserved by the analyst. This latent heterogeneity is assumed to be related to the cost of processing information where the cost is positively related to decision uncertainty. Thus, class membership is determined by the threshold variable $d_c^{\sigma_{\hat{p}\bar{1}1}}$. With H_{ic} denoting the prior probability for class *c* and individual *i*, the following multinomial logit represents the class assignment model:

$$Prob[\text{individual } i \text{ belong to class } c] = H_{ic} = \frac{\exp\left(\theta_{0c}+\theta_{1c}\, d_c^{\sigma_{\hat{p}\bar{1}1}}\right)}{1+\exp\left(\theta_{0c}+\theta_{1c}\, d_c^{\sigma_{\hat{p}\bar{1}1}}\right)}, \quad (7)$$

where $c = 1, \ldots, C$ and $\theta_C = 0$. For identification purposes, the *C*th parameter vector is normalized to zero. The result of eq. (7) will be the probabilities of respondents belonging to each class, where the class assignment is determined based on the magnitude of the probabilities. The combined likelihood that individual *i* belong to class *c* and chooses the capped price option can be formulated as $G_i = \sum_{c=1}^{C} H_{ic} G_{i|c}$. From this, the log likelihood to be maximised is:

$$lnL = \sum_{i=1}^{N} lnG_i = \sum_{i=1}^{N} \ln\left[\sum_{c=1}^{C} H_{ic} G_{i|c}\right]. \quad (8)$$

Maximization of eq. (8) is done with respect to the *C* structural parameter vectors ($\boldsymbol{\beta}$ and $\boldsymbol{\lambda}$) and the $C-1$ latent class parameter vectors ($\boldsymbol{\theta}$).

Before final results are derived, the number of classes has to be determined. Initially, two types were assumed: one that uses current and historical prices to calculate predictions and one that does not use any of the available prices. We denote these two types as the 'calculating' and the 'non-calculating' classes. The non-calculating class controls for those respondents that have strong preferences in favour of either option for reasons other than what the future price will be. Such behaviour could originate from an ideological preference for market-based solutions, or that publicly controlled bodies should provide essential services. As reported earlier, the literature has often used a naïve class, consisting of respondents who ignore past information and assume that current conditions will persist. No support for such a class is found in this application. This could be due to the selected research design where respondents are presented with current and past information at no cost. In many real situations agents must engage in costly collection of past information. Since the price in 2011 is always below the cap level, the non-calculating class nests the naïve class since those respondents would always choose the status quo option. It is also possible that the non-calculating class nests respondents who use available prices and additional market information such as demand and supply conditions, dynamics etc., which is what a fully rational respondent would do. The calculating class is most similar to what has previously been characterised as 'backward looking', or 'quasi-rational'.

Next, we add another type of respondent to reflect the fact that 'calculating' respondents may use differing amounts of historic information. As a basic run, two types of calculating respondents are assumed: one that uses 'more' and one that uses 'less' of the available information.[2] These three-class models turn out to perform better than the two-class models in terms of adjusted BIC.

The number of years that the two calculating classes use to calculate expectations is estimated by running the three-class models using 11-*n* historical prices for the first calculating class, where *n* varies from 1 to 8, and 11-*p* historical prices for the second calculating class, where *p* varies from 2 to 9. The adjusted BIC results suggest that the two calculating classes use

[2] Models with four types of respondents were also evaluated but none of those converged.

11 and 5 years of historic prices. Thus, the straight-line projections for these two classes are denoted $\mu_{\hat{p}}|m = 11$ and $\mu_{\hat{p}}|m = 5$, respectively.

We use a *restricted* latent class multinomial logit model, as suggested by Hess and Rose (2007). This is because 1) $\mu_{\hat{p}i|c}$ and $d_c^{\sigma_{\hat{p}}\bar{m}}$ differ for the three classes; for the non-calculating class, they are not defined since those respondents do not use any price information, and 2) preference parameters regarding prices and motivation levels, i.e. the β parameters, should be identical for the two calculating classes.

3.3 Econometric results

Applying this restricted parameter approach when estimating (8) gives the results presented in Table A2. As revealed, respondents belong to the non-calculating class with a probability of 28%, and to the 11- and 5-year calculating classes with the probabilities of 33% and 39%. The calculating classes are significant at 5% and 8% relative to the non-calculating class. How do these proportions relate to previous findings? Chavas (1999) found that respondents using only backward information constituted 73% of respondents, 19% used all available information and market dynamics (the fully rational class) and 7% had naïve expectations. Our two calculating classes, i.e. those that are backward looking, make up 72% of the respondents. The non-calculating class that nests both the naïve and the fully rational respondents, comprising 28% probability, should be compared to the 26% found by Chavas. The shares of respondent types in Table A2 are therefore very similar to what Chavas found.

How about the intuitions presented in Sections 1 and 3.1? It was postulated that strongly unmotivated (motivated) consumers form higher (lower) expectations than "averagely motivated" consumers. This is confirmed since $RiAver_i \times d^{\sigma_{p}\bar{(\cdot)}}$ is positive and significant (at the 10% level) and $RiSeek_i \times d^{\sigma_{p_{\bar{(\cdot)}}}}$ is negative and significant (at the 5% level). Support is also found for that higher uncertainty pushes the expected value further away from the "averagely motivated" benchmark conditioned on respondents being either strongly motivated or strongly unmotivated. This is evident from the results presented in Table A3 where the threshold value used to determine $d^{\sigma_{p_{\bar{m}}}}$ vary in each Panel. Although the parameters are not always significant at any conventional level, it is clear that the parameter associated with $RiSeek_i \times d^{\sigma_{p_{\bar{m}}}}$ ($RiAver_i \times d^{\sigma_{p_{\bar{m}}}}$) decreases (increases) as the threshold value for $d^{\sigma_{p_{\bar{m}}}}$ increases. Table A3 also suggests that there is a non-linear relationship between motivation level and uncertainty: strongly unmotivated respondents are relatively uninfluenced by the threshold (i.e., they display risk seeking characteristics even for very low threshold levels), while strongly motivated respondents only become apparent at a higher threshold point.

Lastly, we also find support that variability in past prices is negatively related to the number of past prices used to calculate price expectations. This is revealed in the class assignment part of Table A2 where $\theta_1 < 0$ in both Class 1 and Class 2 and $\theta_1 | m = 11 < \theta_1 | m = 5$. Moreover, it should be pointed out that decision uncertainty alone does not generally influence respondents' predictions, as evidenced by the non-significant coefficients for $d^{\sigma_{p_{\bar{m}}}}$ in Tables A2 and A3.

Table A3 shows the results of our tests to identify the standard deviation threshold, where each 'Panel' identifies a threshold for standard deviation and the table shows whether standard deviation is significant on its own, or only when interacted with motivation levels. Hence, all empirical findings are consistent with the structure laid out in Section 3.1.

Our findings can be graphically summarised as shown in Figure 1; the level of calculation decreases as the variability of historic water prices and belief in water supplier investment efficiency increases. In addition, as people use less price information, they place greater importance on perceptions of service quality and pricing efficiency.

Relevance to water utility maximum price guarantee

These results suggest that there are at least three ways in which consumers form expectations and make decisions about guaranteed future prices. First, there is a 30% probability of a consumer making a decision without calculating an expected future price. This class of consumer is more likely to believe their water supplier invests very efficiently in the infrastructure, and more likely to be in a situation in which historic price variability was high, as indicated by the positive and significant class assignment variables "Veff" and "$d^{\sigma_{p\bar{m}}}$".

This "non-calculating" class of consumers could be choosing not to calculate because of the cognitive burden of calculating, given the high historic variability, and / or because they are basing their decision on their trust in the water supplier rather than a calculated value. In this class, respondents are more likely to accept a maximum price guarantee if they like the taste of their water, and / or believe their water supplier invests very efficiently in their water infrastructure. These characteristics are intuitively rational, as they indicate a form of trust in the water supplier. However, it is not clear why males or respondents with higher incomes would be more likely to accept a guarantee.

Consumers belong to one of the other two classes of consumers who calculate an expected future price, using five or 11 years of historic data, with a probability of 37% and 33%. As expected, for both classes, the respondent is more likely to select a guarantee when the expected price is higher than the maximum price guarantee. Here is where our proxy for risk appetite becomes significant, but only when historic price variability has been high; when the respondent is strongly motivated *and* historic price variability has been high, the respondent is more likely to select a guarantee. Conversely, if the respondent is strongly unmotivated and historic price variability has been high, she is less likely to select a guarantee.

3.4 Robustness

In Section 2 we warned for the bias that would occur if expectations are correlated with respondents' preferences and/or beliefs. Here we show that respondents' discount rate and risk preferences are uncorrelated and the results presented in Table A2 are unaffected when we add a proxy for respondents' perceptions of how efficiently utilities handle their networks.

Respondents' discount rate can be relevant in this context since high rates make high future prices less influential. Since the price in 2011 is always below the capped price level, respondents with high discount rates can be more likely to prefer the status quo. If the discount rate is correlated with risk preferences, results in Tables 2 and 3 suffer from omitted variables. It is necessary therefore, to rule out that such correlation exists.

Discount rates are not observed directly, but in a separate part of the survey we asked one question, consisting of two scenarios, that were designed to obtain average individual discount rates for segments of respondents. This question allows us to test whether the discount rates for the three motivation levels (strongly motivated, averagely motivated and strongly unmotivated) are statistically different.

The questions for the individual discount rates were randomly assigned and asked respondents whether they would choose to invest in each of two scenarios involving future benefits. An example scenario is shown below.

Your water rates are…

$380 per year from 2012 to 2017, and; *(implies an immediate 27% increase in price)*

$270 per year from 2018 to 2041. *(implies an eventual 10% reduction in price)*

Would you support this rates structure? (Yes/No).

Twelve scenarios were developed, based on rates increases and eventual rates decreases of varying levels and durations. The scenarios implied discount rates ranged from 0% to 109%, as shown in Table A4.

When respondents stated that they were willing to invest in exactly one of the two scenarios, it is possible to approximate their discount rates with the average of the two scenarios. However, if they indicate that they are unwilling to invest in either scenario we only know that their rates are above the higher of the two scenario rates and if they are willing to invest in both, we know that the true rates are below the lower of the two scenario rates. To determine the discount rates for respondents who indicate that they either want to invest in both or neither of the two scenarios, we impute their rates based on observations for respondents who indicate that they would invest in exactly one scenario. 447 respondents indicated that they are willing to invest in one scenario and 736 are willing to invest in neither or both scenarios.

To identify the variables to use as a basis for imputing discount rate, we tested the variables that the literature has found to be significant in predicting individual discount rates: size of reward, income, age, ethnicity, number of dependents, employment/retirement status, education, and market knowledge (Harrison, Lau & Williams 2002; Kirby & Marakovic 1996; Hausman 1979; Warner & Pleeter 2001; Coller & Williams 1999). We use income, male, age, and an indicator of whether the second scenario had a higher discount rate to control for a possible order effect. We found gender and income to be the only significant demographic predictors of discount rate, after removing the highest income category ($145,000+) from our analysis.[3] Results of this estimation are presented in Table A5 in the Appendix. While income on its own is not a significant predictor of individual discount rate, at higher incomes, men have a higher discount rate than women. The observed discount rates ranged from 0.5% to 84.5%, and the predicted discount rates, based on the model above, ranged from 12.5% to 46.4%.

To test whether the discount rate is correlated to motivation levels, we use the discount rate (consisting of actual and imputed values) as an explanatory variable in logit models where strongly unmotivated and strongly motivated were used as dependent variables.[4] Table A5 shows that discount rate was not even vaguely significant in either of the two models, indicating that individual discount rates and motivation levels are not correlated in this study.

A further concern is respondents' beliefs about utilities' price setting behaviour. As mentioned earlier, if respondents believe utilities will raise their prices pre-maturely in response to having their prices capped in the future, respondents might prefer not to have their prices capped. First, it should be noted that rates are restricted by law to correspond to costs and long-term plans.[5] For utilities to increase prices, they must therefore manipulate costs, and investments in particular that determines the largest part of the total cost. There is no direct measure available of respondents' beliefs about utilities' price setting behaviour in time periods

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[3] Respondents from the highest income category responded statistically inconsistently with their income category. We removed these respondents from the analysis, as well as two respondents who claimed to have experienced restrictions for more than 52 weeks in a year, leaving 1183 observations on which to test correlation between risk appetite and individual discount rate.

[4] We used 100 imputations of discount rate in both models.

[5] Local Government (Rating) Act 2002.

between 2011 and 2021, but since inefficient prices (in the sense that prices are above *necessary* costs) presupposes inefficient investments, we can use respondents' perceptions about 'investment efficiency' (*Veff*) that is a measure we have access to. As displayed in Table 2, the addition of this factor does not improve the model in terms of the CAIC, but it maintains the story of the basic model and also shows that respondents that believe their water supplier invests very efficiently in their water supply infrastructure are less likely to calculate a future price and more likely to choose the capped price option. These findings are consistent with our intuition.

[Insert Table 2]

4. Conclusions

This paper provides a model that can be used to understand consumers' price expectations, and preference for price guarantees, for water services. The model may also be useful for understanding expectations formation in other, one-shot decision applications such as investments in public infrastructure. We found that consumers who invested in water treatment equipment, even when the quality of their water was good, acted as "strongly motivated" consumers, and had significantly different preferences for guarantees, than consumers who did not treat their water.

4.1 The expectations formation process

Our paper extends existing empirical expectations-preference model by including agents' motivation levels. We argue that motivation levels and decision uncertainty interact and move the preferences away from the projected point values based on historical information. Our paper is the first to consider a three-stage expectations-preference process where the agent decides how much information to use in the first stage, a projection is formed in the second stage and an adjustment process is applied in the third stage. This structure may explain the observed behaviour that expected point values are different from central tendencies of agents' density distributions. We also confirm the established knowledge that as the cost of processing information increases, agents use less of the available information when they calculate their expectations. Our analyses rely on a unique dataset, based on static choice scenarios applicable in many microeconomic situations and for purchases of durable products. This model generates a much wider range of expectations values in a population of heterogeneous agents compared to mainstream models that primarily rely on processing cost.

It seems clear that much research remains to understand and to measure expected values. Based on this study, we suggest that the structure provided here is tested also when expectations are recorded directly. The proxy for risk preferences we use can also be developed as we only identify the most extreme motivation levels. It is also relevant to more closely investigate unobserved preferences and beliefs and whether they are correlated with expectations. Another relevant extension for empirical models is to measure the impact of social interactions. Expectations are rarely formed in isolation and at present there is no empirical work on either who agents interact with or how they are influenced by other agents.

In interpreting individuals' preferences, researchers should take care to account for heterogeneity both in relevant historical information and in individual characteristics. Reducing decision uncertainty by providing more information can be an effective alternative to specific product characteristics. With more detailed data, researchers may find there are more classes of individuals, and that those classes may be distinguished by both historical information and individual characteristics.

4.2 When maximum price guarantees are warranted

Water suppliers should recognise that there are different ways in which consumers calculate, or form, their expectations for future prices – and that this calculation process depends on historic variability and trust in, or at least perceived investment efficiency of, their water supplier.

Consumers value guaranteed maximum prices, so water utilities and regulators are acting in the interest of consumers by offering them – particularly when historic prices have been highly variable. However, the value of these guarantees can be undermined when consumers have less trust in the water supplier. The water supplier may need to build trust with the consumer before guarantees are perceived as legitimate. If perceived investment efficiency is low, guarantees are more likely to be valued when historic price trends suggest the future price will be significantly higher than the guarantee. Further, if consumers have not previously been motivated to act to protect themselves, they may not favour a price guarantee.

In general, consumers calculate a future price by extrapolating historic prices forward and then adjust their expectation upwards (downwards) if they are risk averse (seeking) and historic prices are highly variable.

Further research is required to more accurately reflect consumer risk appetite and trust in water supplier.

In a world in which increasing variability is expected, particularly in climate, another valuable contribution would be to test our expectations formation process on consumers' willingness to pay for improvements to water service attributes that protect against variability. The most relevant of these attributes would be protection against water restrictions – an attribute for which some water suppliers are likely to have highly variable performance.

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Appendix

Table A1 shows the standard deviations of past prices, projected rates and the guarantee levels when projections are based on a straight line fit through the 5 and 11 most recent prices using OLS. Figure A1 shows the full question.

[Insert Table A1]

[Insert Figure A1]

Table A2 provides the results of the initial three-class model.

[Insert Table A2]

Table A3 shows the analysis undertaken to identify the threshold at which the variability of a historic trend became most statistically significant.

[Insert Table A3]

Table A4 shows the discount rates implied in the scenarios presented to respondents

[Insert Table A4]

Table A5 presents the logit model to investigate the relationship between risk appetite and multiple imputed values of discount rates

[Insert Table A5]

Table A6 shows the results for the model used to calculate respondents' imputed discount rates.

[Insert Table A6]

Tables

Table 1. Descriptive statistics

Variable	Description	Mean	Std Dev	Min	Max	National average*
Male	1=Male	0.42	0.49	0	1	0.49
IncCate	Personal income category. 1: <$15,000; 2: 15-25,000; 3: 25-35,000; 4: 35-45,000; 5: 45-55,000; 6: 55-65,000; 7: 65-75,000; 8: 75-85,000; 9: 85-95,000; 10: 95-105,000; 11: 105-115,000; 12: 115-125,000; 13: 125-135,000; 14: 135,000+	4.3	2.9	0	14	3.3
Volume	1: Consumer charged volumetrically; 0: fixed charges	0.4	0.5	0	1	0.36**
TasteRate	Reported taste of water. 0: Terrible; 1: Bad; 2: Could be better; 3: Excellent	2.4	0.7	0	3	NA
Age	Age category. 1: <25 1; 2: 25-34; 3: 35-44; 4: 45-54; 5: 55-64; 6: 65	4.0	1.7	1	6	3
$RiSeek$	1=Respondent classified as risk seeking (respondent do not feel well protected from microorganisms but do not have water treatment equipment or behaviours)	0.03	0.17	0	1	NA
$RiAver$	1=Respondent classified as risk averse (respondent feel well protected from microorganisms but have water treatment equipment or behaviours)	0.04	0.19	0	1	NA
Veff	1=Respondent believes their water supplier invests “very efficiently” in the water supply system.	0.14	0.35	0	1	NA
Questions						
p^{Cap}	Value of guarantee relative to price in 2011	1.5	0.4	1.0	2.5	
p01	Water price in 2001	0.8	0.2	0.5	1.4	
p02	Water price in 2002	0.8	0.2	0.5	1.2	
p03	Water price in 2003	0.9	0.3	0.5	1.5	
p04	Water price in 2004	0.9	0.2	0.5	1.3	
p05	Water price in 2005	0.8	0.2	0.5	1.2	
p06	Water price in 2006	0.9	0.2	0.5	1.1	
p07	Water price in 2007	0.9	0.2	0.5	1.1	
p08	Water price in 2008	0.9	0.1	0.7	1.0	
p09	Water price in 2009	1.0	0.2	0.8	1.5	
p10	Water price in 2010	1.0	0.2	0.9	1.5	
p11	Water price in 2011	1.0	0.0	1.0	1.0	
$\sigma_{\boldsymbol{p}_{11}^{-}}$	Standard deviation of de-trended prices from 2001-2011	0.08	0.04	0	0.15	
$\sigma_{\boldsymbol{p}_{5}^{-}}$	Standard deviation of de-trended prices from 2007-2011	0.06	0.06	0	0.18	
$\mu_{\hat{p}}\|m = 11$	Straight line projected price in 2021 based on prices from 2001-2011	1.25	0.19	0.98	1.64	
$\mu_{\hat{p}}\|m = 5$	Straight line projected price in 2021 based on prices from 2007-2011	1.44	0.43	0.77	2.23	

* From StatsNZ Census 2006 (http://www.stats.govt.nz/browse_for_stats/ people_and_communities/geographic-areas/urban-rural-profile-update.aspx).

** Estimate based on StatsNZ urban and 'rural with high urban influence' for Whangarei, Auckland, and Tauranga.

*** http://www.stats.govt.nz/Census/2006CensusHomePage/QuickStats/

AboutAPlace/SnapShot.aspx?type=region&tab=Culturaldiversity&id=9999999

NA= not available / not applicable

Table 2. Results of three-class model

Variable	Class 1: 11 years Mean (SE)	Class 2: 5 years Mean (SE)	Class 3: Non-calculating Mean (SE)
Equation 6: Choice model			
Gap between expected price and price cap ($\mu_{\hat{p}} - p^{Cap}$)	14.64** (6.697)	14.64** (6.697)	
Historic price variation is high ($d^{\sigma_{p\bar{m}}} = 1$)	0.07 (1.443)	0.07 (1.443)	
Respondent risk seeking *and* historic price variation is high ($RiSeek_i \times d^{\sigma_{p\bar{m}}}$)	-12.8* (6.843)	-12.8* (6.843)	
Respondent risk averse *and* historic price variation is high ($RiAver_i \times d^{\sigma_{p\bar{m}}}$)	7.7* (4.579)	7.7* (4.579)	
Taste rating	1.7 (1.035)	-14.1** (6.213)	2.4** (0.974)
Believe water supplier invests very efficiently in water supply system	-1.8 (-0.849)	-17.6** (7.780)	3.9* (1.980)
Male	-16.2* (8.367)	15.3** (7.263)	8.5** (3.598)
Income	0.4 (0.261)	-3.7** (1.686)	1.0** (0.496)
Constant	9.2** (4.581)	64.2** (27.822)	-10.9** (5.070)
Equation 7: Class assignment model			
Historic price variation is high ($d^{\sigma_{p\bar{m}}} = 1$)	-0.7*** (0.234)	-0.4 (0.264)	
Believe water supplier invests very efficiently in water supply system	-0.8* (0.364)	-1.1*** (0.400)	
Constant	0.5** (0.228)	0.5** (0.261)	
Class probability	0.33	0.37	0.30
Log likelihood	-629.01		
Number of free parameters k	25		
Consistent Akaike information criterion (CAIC)	1295		
Adjusted Bayesian information criterion (Adjusted BIC)	1301		

Notes. * p<0.1, **p<0.05, ***p<0.01. $d^{\sigma_{p\bar{m}}}$ is a dummy variable taking the value 1 when $\sigma_{p_{\bar{m}}} \geq 0.095$.

Table A1. Description of historic rates scenarios relative to reported rates

	Description	Std Dev (11 years)	Std Dev (5 years)	Projected rate in year 2021 (11 years)	Projected rate in year 2021 (5 years)	Guarantee
1	Straight line, no variance	0.000	0.000	1.50	1.50	1.2
2	Rates vary randomly +/-50% from reported rates	0.079	0.042	1.38	2.23	2.0
3	Rates vary randomly +/-20% from reported rates	0.154	0.032	0.98*	1.31	1.5
4	Rates mostly constant until 2009, increased 2009-2011	0.040	0.024	1.16	1.47	1.1
5	Rates mostly constant until 2006, increased significantly from 2006-2011	0.076	0.04	1.28	1.83	1.7
6	Rates mostly constant (varying +/-3% per year) with two blips prior to 2005	0.106	0.000	1.04*	1.00	1.6
7	Rates mostly constant (varying +/-3% per year) with two blips since 2007	0.095	0.145	1.18	0.77	1.4
8	Rates mostly constant (varying +/-3% per year) with two blips since 2009	0.101	0.165	1.30	1.54	1.7
9	Rates constant with two step-wise increases in 2004 and 2011	0.028	0.036	1.07	1.16	1.3
10	Rates constant with two step-wise increases in 2002 and 2008	0.054	0.049	1.29	1.29	1.3
11	Rates constant with one significant rate increase in 2008	0.146	0.183	1.64	2.10	2.0
12	Rates constant with one significant rate increase in 2003	0.063	0.000	1.21	1.00	1.0

* Average of historic rates because regression produced a negative trend

Table A2. Results of three-class model

Variable	Class 1: m=11 years Mean (SE)	Class 2: m=5 years Mean (SE)	Class 3: Non-calculating Mean (SE)
Equation 6: Choice model			
Gap between expected price and price cap ($\mu_{\hat{p}} - p^{Cap}$)	9.530** (3.817)	9.530** (3.817)	
Historic price variation is high ($d^{\sigma_{p\bar{m}}} = 1$)	-1.082 (1.522)	-1.082 (1.522)	
Respondent risk seeking *and* historic price variation is high ($RiSeek_i \times d^{\sigma_{p\bar{m}}}$)	-8.303** (3.800)	-8.303** (3.800)	
Respondent risk averse *and* historic price variation is high ($RiAver_i \times d^{\sigma_{p\bar{m}}}$)	6.729* (3.722)	6.729* (3.722)	
Taste rating	1.083* (0.592)	-8.425** (3.775)	2.230** (1.126)
Male	-11.171** (4.744)	6.810 (4.150)	7.847** (3.644)
Income	0.268* (0.160)	-2.288** (1.023)	0.901* (0.466)
Constant	6.769** (3.214)	40.156** (16.900)	-9.952* (5.289)
Equation 7: Class assignment model			
Historic price variation is high ($d^{\sigma_{p\bar{m}}} = 1$)	-0.679*** (0.243)	-0.306 (0.284)	
Constant	0.467* (0.238)	0.489* (0.278)	
Class probabilities	0.33	0.39	0.28
Log likelihood	-631.21		
Number of free parameters k	20		
Consistent Akaike information criterion (CAIC)	1292		
Adjusted Bayesian information criterion (Adjusted BIC)	1297		

Notes. * p<0.1, **p<0.05, ***p<0.01.

$d^{\sigma_{p\bar{m}}}$ is a dummy variable taking the value 1 when $\sigma_{p_{\bar{m}}} \geq 0.095$.

Table A3. Standard deviation threshold tests

Variable	Class 1: 11 years Mean (SE)	Class 2: 5 years Mean (SE)
Panel A: Historic price variation considered high when $\sigma_{p_{\bar{(\cdot)}}} \geq 0.041$		
Historic price variation is high ($d^{\sigma_{p_{\bar{m}}}} = 1$)	-5.33**	-5.33**
	(2.136)	(2.136)
Respondent risk seeking *and* historic price variation is high ($RiSeek_i \times d^{\sigma_{p_{\bar{m}}}}$)	-3.87	-3.87
	(2.457)	(2.457)
Respondent risk averse *and* historic price variation is high ($RiAver_i \times d^{\sigma_{p_{\bar{m}}}}$)	-0.60	-0.60
	(1.569)	(1.569)
Panel B: Historic price variation considered high when $\sigma_{p_{\bar{(\cdot)}}} \geq 0.063$		
Historic price variation is high ($d^{\sigma_{p_{\bar{m}}}} = 1$)	-1.48	-1.48
	(1.029)	(1.029)
Respondent risk seeking *and* historic price variation is high ($RiSeek_i \times d^{\sigma_{p_{\bar{m}}}}$)	-2.13**	-2.13**
	(1.055)	(1.055)
Respondent risk averse *and* historic price variation is high ($RiAver_i \times d^{\sigma_{p_{\bar{m}}}}$)	0.04	0.04
	(0.919)	(0.919)
Panel C: Historic price variation considered high when $\sigma_{p_{\bar{m}}} \geq 0.094$		
Historic price variation is high ($d^{\sigma_{p_{\bar{m}}}} = 1$)	-0.15	-0.15
	(0.515)	(0.515)
Respondent risk seeking *and* historic price variation is high ($RiSeek_i \times d^{\sigma_{p_{\bar{m}}}}$)	-4.50*	-4.50*
	(2.332)	(2.332)
Respondent risk averse *and* historic price variation is high ($RiAver_i \times d^{\sigma_{p_{\bar{m}}}}$)	0.82	0.82
	(1.024)	(1.024)
Panel D: Historic price variation considered high when $\sigma_{p_{\bar{m}}} \geq 0.101$		
Historic price variation is high ($d^{\sigma_{p_{\bar{m}}}} = 1$)	-1.1	-1.1
	(1.523)	(1.523)
Respondent risk seeking *and* historic price variation is high ($RiSeek_i \times d^{\sigma_{p_{\bar{m}}}}$)	-8.3**	-8.3**
	(3.801)	(3.801)
Respondent risk averse *and* historic price variation is high ($RiAver_i \times d^{\sigma_{p_{\bar{m}}}}$)	6.7*	6.7*
	(3.72)	(3.72)

Notes: *p<0.1, **p<0.05, ***p<0.01.

Table A4. Implied discount rates in scenarios presented to respondents

Implied discount rate	Initial increase	Duration of rates increase (years)	Eventual decrease
0.0%	133%	10	3%
1.3%	13%	9	7%
3.0%	27%	6	10%
5.6%	33%	9	30%
9.4%	67%	5	37%
13%	30%	3	13%
17%	17%	8	43%
24%	10%	4	13%
30%	100%	2	70%
44%	23%	3	47%
60%	83%	1	50%
109%	37%	1	40%

Table A5. Logit model to investigate the relationship between risk appetite and multiple imputed values of discount rates

Variable	Risk seeking Mean (SE)	Risk averse Mean (SE)
Discount Rate	-0.0042 (0.0110)	-0.0034 (0.0099)
Age	-0.0347 (0.1025)	0.1558 (0.1024)
Income	-0.1173 (0.0790)	0.0158 (0.0634)
Male	-0.2392 (0.3740)	-0.0355 (0.3329)
Constant	-2.7233*** (0.5443)	-3.9163*** (0.5759)
Number of observations	1183	1183
Prob >F	0.5833	0.6979

Table A6. Results for model to calculate respondents' imputed discount rate

Variable (Predictor for individual discount rate)	Mean (SE)
Age	0.91
	(0.593)
Income	0.32
	(4.579)
Male	-10.24**
	(3.999)
$Male \times Income$	1.77**
	(0.843)
Second implied discount rate is higher	4.00**
	(1.94)
Constant	20.88***
	(3.30)
Number observations	447
Prob>F	0.0051

Figures