

No. DP16-1

RCESR Discussion Paper Series

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March 2016

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The Mechanism of Inflation Expectation Formation among Consumers^{*}

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ABSTRACT

How do we determine our expectations of inflation? Because inflation expectations greatly influence the economy, researchers have long considered this question. Using a survey with randomized experiments among 15,000 consumers, we investigate the mechanism of inflation expectation formation. Learning theory predicts that once people obtain new information on future inflation, they change their expectations. In this regard, such expectations are the weighted average of prior belief and information. We confirm that the weight for prior belief is a decreasing function of the degree of uncertainty. Our results also show that monetary authority information affects consumers to a greater extent when expectations are updated. With such information, consumers change their inflation expectations by 37% from the average. This finding supports improvements to monetary policy publicity.

Keywords: inflation expectations, Bayesian updating, rational expectation, randomized survey experiments.

JEL Classifications: E31, C81, D80.

^{*} We thank Haruko Noguchi, Oreste Tristani, Aidan Meyler, Laurent Ferrara, and seminar participants at the European Central Bank and Banque de France. This work is supported by Japan Society for the Promotion of Sciences Grants-in-Aid for Research Activity (15H01945, 26380233).

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1. Introduction

Expectations vis-à-vis future inflation are very important for economic decision-making. People contemplate the future on many occasions, including when they consider how much to save, or whether to postpone the purchase of a house or not. Thus, economists have been discussing what inflation expectations are, how they influence the overall dynamics of the economy, and how they are formed. Occasionally, such expectations become central to policy debates because the effectiveness of some types of monetary policies crucially depends upon how these are formed (Blinder, 2000; McCallum, 1984; Sargent, 1982). In spite of their long history, inflation expectations have also been renowned for being difficult to measure (Mankiw et al., 2004; Schwarz, 1999).

Although measuring inflation expectations accurately is of particular importance when designing stabilization policies, it became even more significant since the Lehman shocks. In the late 2000s, central banks in the United States, Euro Area, United Kingdom, and Japan adopted a series of extreme expansionary monetary policies, such as zero or negative interest rate, private asset purchases, and forward guidance of bond purchases. These policies are called “unconventional” because their propagation mechanism does not go through standard processes such as increases in bank lending, but through the changes in consumers’ inflation expectation (Bernanke, 2007).

Because of its significance, the mechanism of inflation expectation formation has been investigated for decades both theoretically and empirically¹. In the heated debate on the formation process of inflation expectation, numerous studies have addressed the issue whether inflation expectations are consistent with the rational expectations hypothesis and, if they are not, what kind of constraints agents typically face. Full-information rational expectations (Muth, 1961), in which agents process all-new information immediately, have been rejected in many empirical contexts. Consequently, recent studies focus on some possible deviation from FIRE, in which people are heterogeneous when accessing or processing new information.²In the context of these studies, the expectation formation can be described by the Bayesian update formula, which illustrates how people change their expectation when they receive new information.

Among previous literature on limited-information rational expectation,³ Coibion and Gorodnichenko (2015) find that departure from full-information rational expectations looks similar at a macro-level among different economic agents, for example, between consumers and professional forecasters. In contrast, empirical literature found only weak evidence on the rational expectation hypothesis with limited information at an individual level (Pesaran and Weale, 2006). Recently a new strand of empirical work on inflation expectation at micro levels introduces the

¹ See Hoover and Warren (2013) for the history of the debates on rational expectation hypothesis.

² For the most recent work on this issue, see Coibion and Gorodnichenko (2015).

³ Literature in this regard often focuses on the importance of limitations in acquiring and processing the information that rational agents face (Carroll, 2003; Mackowiak and Wiederholt, 2009; Mankiw and Reis, 2002; Sims, 2003).

survey experiment, which is a useful tool to study the formation of these expectations (Armantier et al., 2014; Cavallo et al., 2014).

One of the key focuses when we apply the Bayesian updating formula is the possible influence of “uncertainty” and/or “informedness” of prior expectations on the learning process. According to this formula, consumers’ updated expectation conditional on new information can be illustrated as a weighted average of the expectation before the arrival of new information and the information itself. Although as a simple equation, it is far from simple to test empirically. The complexity comes from the fact that the weights assigned to both factors are generally different among consumers, depending on the extent of uncertainty and the degree of the usefulness of the new information each consumer uses, both of which are hard to measure.⁴ Suppose that considering the information term as the error term, we regress the posterior belief on the prior. Unfortunately, the regression coefficient of the prior is not a consistent estimator of the true weight because of two reasons: 1) the true weights are heterogeneous across individuals and 2) the weights are correlated with the error term, that is, the new information.

Survey experiments provide useful information for addressing this difficulty in an empirical analysis. However, the previous studies that employed such an experiment either assumes an identical weight among consumers (Cavallo et al., 2014) or adopts a very simple model (Armantier et al., 2014). In this paper, using large scale survey with randomized experiment, we found strong evidence of individual rationality. Several new ideas contributed to the results. First, we include serially correlated reporting errors in prior and posterior expectations, which turn out to be very important in the estimation. Second, we construct several different uncertainty measure to address the heterogeneity of the weights among consumers. By allowing for such heterogeneity, the model fits the data three times greater than that without heterogeneity in terms of the adjusted *R*-squared.

In summary, the main results obtained are as follows. First, consumers update inflation expectations in a responsive manner when they face new information, that is, consumers who receive information on future inflation change their expectation much more than others who do not receive such information. Consistent with Bayesian updating, our estimation results show that there is a systematic relationship between the provision of information and the updating of consumer expectations.

Second, consumers respond to provided information also through uncertainty channel. By applying Bayes formula on conditional probability, our structural model predicts that consumers change their expectations to a greater extent when (1) they are uncertain about the future before getting the new information and (2) the new information is useful. Consequently, the estimation

⁴ Previous literature, such as Pesaran and Weale (2006), pointed out that difficulty in the analysis of consumer expectations arises possibly because the information consumers employ in forming their expectations, including their individual experiences and subsequent outcomes of future inflation development, may be diverse but not observable for researchers.

results of our model indicate that the Bayesian model of expectation formation is consistent with survey responses among consumers who receive information published by the Bank of Japan (BOJ) compared to other categories of information. Although people tend to be influenced by new information that is not necessarily relevant, we can still infer that they can distinguish the context and importance of information received to a certain extent.

The rest of the paper is organized as follows: section 2 describes the experimental design; section 3 provides an overview of the results of the survey experiment and introduces the theoretical framework on the updates of expectations; section 4 analyzes individuals' updating behavior vis-à-vis their inflation expectations upon being provided with information and discusses the consistency of survey results with the model in section 3; and section 5 provides a brief summary and prospects for future research.

2. Experimental design

In this section, we describe the experimental framework that serves as the basis for our empirical analysis. This framework builds on existing literature, in particular, on the study of Armantier et al. (2014). The data were captured through an original survey conducted over the internet from January 23 to February 2, 2015. The target population consists of individuals aged 20–69, registered as survey respondents with one of Japan's major private survey companies.⁵ In total, 21,374 individuals were selected from the respondents, based on the Population Census 2010 in terms of gender, age, marital status, and regional composition. From these individuals, 14,426 participated in the survey (the response rate was 67.5%). Each participant was randomly assigned to one of six information groups. The members of each group were randomly subdivided into two groups: 75% of the members were designated as a “treatment group,” and 25% as a “control group.” Each treatment group provided 1,750 to 1,800 responses, depending on the response rate; each control group, meanwhile, provided around 600 responses.

Our innovations in terms of the experimental framework are summarized as follows. First, we created six groups of individuals and provided them with different types of public information vis-à-vis future inflation, and second, these six groups are roughly categorized into two types. The first type is provided with inflation outlook information published by professional institutions (i.e., government, the Bank of Japan (BOJ), or professional forecasters⁶), and the second type is provided with company news releases with regard to planned price increases in specific grocery items. These

⁵ The data source is the “Survey of Consumers' Inflation Expectations and Learning.” This survey was conducted by INTAGE, a Japanese market research firm, as a contract survey sponsored by Hitotsubashi University.

⁶ The outlook vis-à-vis the future inflation rate, generated by around 40 professional forecasters in the private sector, is surveyed and published each month by the Japan Center for Economic Research.

items include noodles, frozen meals, and ice cream, which are familiar and frequently purchased by consumers, regardless of their attributes including age and income.⁷

The basic structure of the experiment is as follows (Figure 1).

1. Eliciting inflation expectations from each subject (first question on inflation expectations)

In this stage, all respondents are first asked to provide their predictions of the future inflation rate over the upcoming 12 months for the overall economy. Respondents can choose to provide either a point forecast (as a percentage figure) or a range forecast (upper/lower limits as percentage figures). In this survey, we define “price levels” as those of the goods and services usually purchased by the respondents and which contain consumption taxes.⁸

Respondents are then immediately requested to provide probabilistic forecasts as well. As such, the survey partitions the real number of future inflation into 8 intervals⁹ and asks them to report their subjective probabilities that the future inflation rate will take a value in each interval.

2. Eliciting prior perceptions on the information related to future inflation developments (subjective priors)

In the second stage, respondents are randomly asked one of six questions about either the inflation outlook of professional institutions or scheduled price changes of particular grocery items (see the Appendix 1 for details), either of which can measure their *ex ante* knowledge on information that is expected to be pertinent to future inflation. With regard to this question, respondents are asked to provide only point forecasts.

It is worth noting that before the survey periods, there were surges in the prices of raw materials (e.g., wheat, milk, etc.) and in energy prices, partly because of yen depreciation, and these generally increased commodity prices. As there have been many announcements regarding increases in goods prices that are frequently purchased or with which households are familiar, we expect these announcements to affect expectations of future inflation in the overall economy.¹⁰

3-1. Providing subjects in the treatment group with true measures of the aforementioned information, which would constitute a signal to the subject in the formation of expectations; in the case of the control group, the subject receives no signal (information treatment)

3-2. Eliciting inflation expectations from each subject again (second question on inflation expectations)

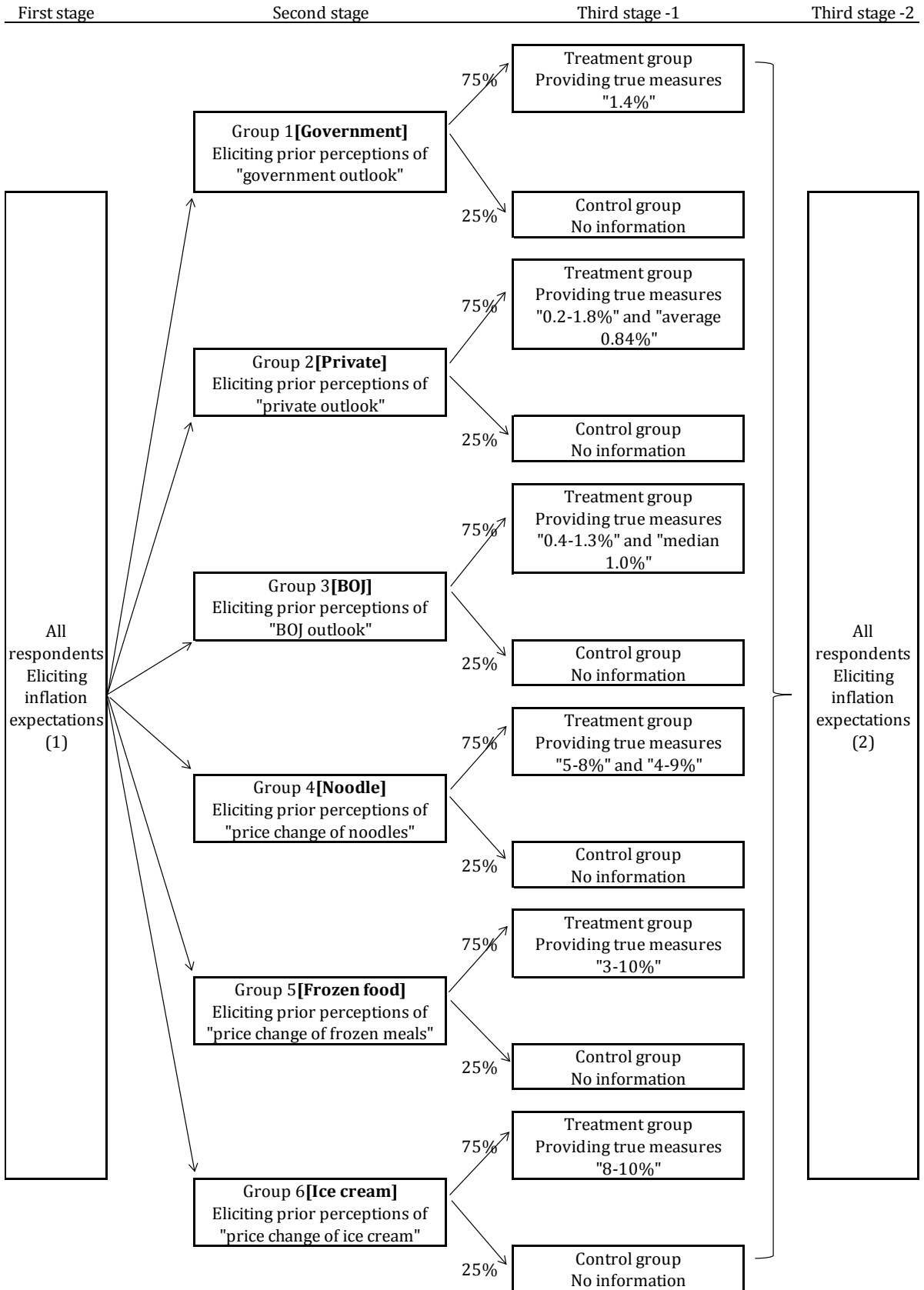
⁷ According to the Household Expenditure Survey (2014CY), the ratio of expenditures for noodles (i.e., Chinese noodles, cup noodles, and instant noodles) to that for all groceries was 0.98%, and its purchase frequency was 3,592 per 100 households. With regard to frozen meals and ice cream (i.e., ice cream and sherbet), these figures are 0.60% (1,524) and 0.82% (2,220), respectively.

⁸ The consumption tax rate was 8% at the time of the survey, having increased from 5% in April 2014.

⁹ These intervals are: greater than 10%, 5-10%, 2-5%, 0-2%, ▲2-0%, ▲5-▲2%, ▲10-▲5%, and lower than 10%. Respondents are requested to make the probabilities sum up to 100%.

¹⁰ The prices of instant noodles, some frozen foods, and ice cream have all shown increases since mid-2013, according to both the consumer price index (CPI) and the wholesale price index. The year-on-year price increase rate remained positive; this occurred for the first time since 2009. The prices of raw materials (e.g., wheat, meat, or milk) and of products at the wholesale level move in a manner consistent with prices at the retail level.

Figure 1 Flow chart of the experiment



In the final stage, respondents are again asked to provide their views on the future inflation level. The question at this stage is the same as that posed in the first stage. Note that only respondents in the treatment groups are provided with the correct answer to the question posed in the previous stage and those in the control groups are not provided with true measures (see Appendix 1).

3. Overview of survey responses

3.1 Summary statistics

Table 1 presents descriptive statistics of the respondents' responses on inflation perceptions and inflation expectations, by information group. Additionally, Table A-1 in Appendix 2 provides the summary statistics of respondents' basic attributes. As we randomly assigned the subjects to six groups, the attributes are similar among groups. As a result, Table 1 also indicates that the inflation expectations before information treatment look quite similar among different information groups.

A key index of people's perception on inflation is "perception gap," which is defined as the subjective priors (elicited at the second stage) minus the true measure of treatment information. As is shown in Figure 1 (at the third, stage-1), we set the true measures as a range, rather than an exact figure (e.g., 8–10%), except for the government outlook group. Furthermore, we regard the perception gaps as zero if the subjective priors are within this range; otherwise, we employ the closest end of the band to subjective priors to derive perception gaps. The average perception-gap level is positive (1.9% points) and is greater in government, private, and BOJ groups than in noodle, frozen food, and ice cream groups.

Table 1 contains three different indexes related to inflation expectations. The first one represents the point estimates¹¹ before information treatment (first stage). The average is around the same level (6.6%) among different information groups and correlates positively with the inflation perceptions to a certain extent (0.274, significant at the 1% level). The average level of the posterior expectations (i.e., after the information treatment, at the third, stage-2) is lower (5.8%), although this level does vary greatly across groups.

As explained in the previous section, before treatment we elicit respondents' subjective probabilities of inflation levels for the upcoming year. We first estimate expected value of inflation expectations, then by using this value estimate subjective standard deviation of inflation expectations for each respondent.¹² The mean value is of 6.45 and the standard deviation is rather high at 4.16.

¹¹ If the responses are provided in range values, we employed the mid values of these ranges.

¹² The expected value of inflation expectations is estimated by taking the average of the expectations weighted by subjective probabilities. The subjective standard deviation is estimated by using this expected value as well as

Table 1 Summary statistics of inflation-related variables

	Total	Government	Private	BOJ	Noodle	Frozen food	Ice cream
Prior ¹							
mean	6.602	6.577	6.708	6.514	6.516	6.768	6.529
median	5.000	5.000	5.000	5.000	5.000	5.000	5.000
sd	5.383	5.481	5.403	5.117	5.407	5.572	5.301
Posterior ¹							
mean	5.744	3.889	4.039	3.753	7.437	7.571	7.765
median	5.000	3.000	2.500	2.000	7.000	7.000	8.000
sd	6.509	6.430	6.197	5.363	6.451	6.691	6.224
Perception gap ²							
mean	1.944	2.894	3.636	2.924	1.405	1.423	-0.622
median	0.000	1.600	3.200	1.700	0.000	0.000	0.000
sd	5.830	6.148	6.865	6.185	4.426	4.703	5.229
Subjective standard deviation (Sd) ³							
mean	6.451	6.376	6.524	6.520	6.396	6.606	6.278
median	6.412	6.368	6.500	6.452	6.422	6.472	6.224
sd	4.161	4.218	4.098	4.173	4.086	4.151	4.229
Number of observations	14,249	2,356	2,364	2,395	2,396	2,382	2,356

Note: 1. "Prior" means expectations prior to information treatment. "Posterior" means expectations posterior to information treatment.

Range responses are transformed into point estimates by taking mid-values of the ranges.

3. Perception gap is equal to subjective information prior subtracted by true measure of treatment information.

4. Subjective standard deviation is estimated by using the responses on subjective probabilities for future inflation levels.

3.2 Comparison of treatment and control groups

We expect that both subjective priors and inflation expectations before information treatments are drawn from the same distribution for each of the treatment and control groups. We test this hypothesis as null. Table 2 shows the results of an ES characteristics function test, which indicate that the null hypothesis cannot be rejected for any group with regard to both subjective priors and expectations before treatments. This result clearly shows that both subjective priors and expectations before treatment are comparable between each individual treatment and control groups, and this is indicative of successful randomization across groups.

subjective probabilities.

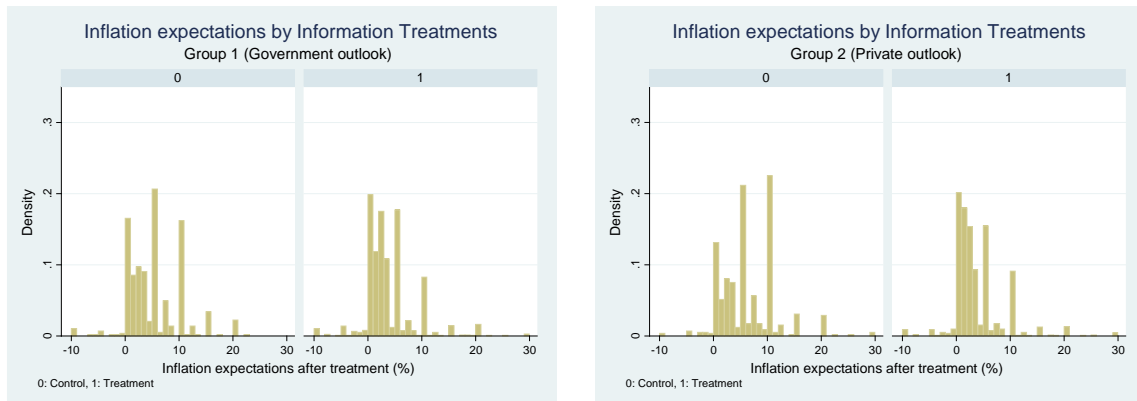
Table 2 Result of ES characteristic function test

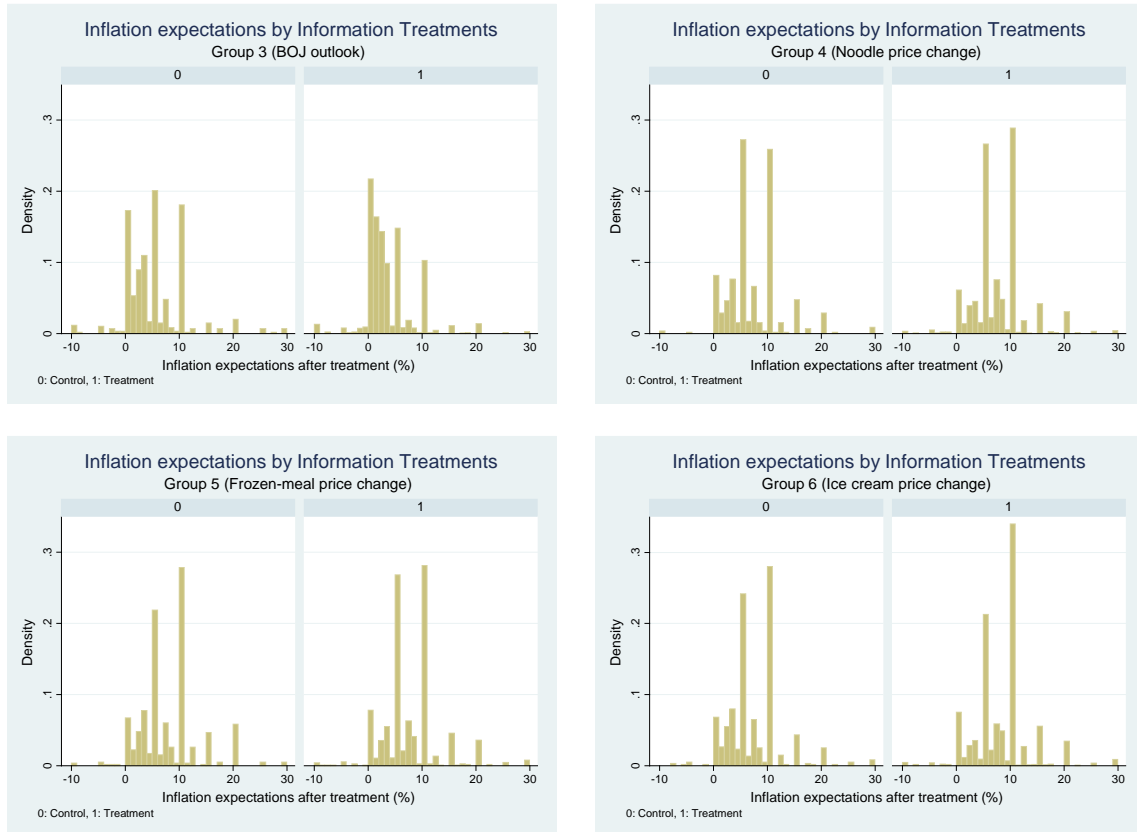
ES test p -value	Group					
	Government	Private	BOJ	Noodle	Frozen food	Ice cream
Inflation expectations (before information treatments)	0.531	0.145	0.641	0.102	0.355	0.983
Subjective priors of treatment information	0.140	0.509	0.665	0.828	0.757	0.784

Figure 2 compares the distributions of inflation expectations following information provision, between the treatment and control groups of each information group, with clear differences in the distribution between the two groups. Interestingly, the distribution of expectations in the control groups differs among groups 1–6, which implies the possibility that respondents’ expectations can be influenced by particular inflation-related keywords (e.g., “BOJ,” “scheduled price change of noodles”), even when they are not informed on true measures. Possible interpretations are that people are either 1) quite sensitive to these keywords, assuming a certain prior knowledge of what they imply, or 2) simply reactive to the information provided right before being asked about their expectations, without judging whether the provided information is important to the future inflation development. While this is an interesting issue in investigating the formation of inflation expectations, we do not pursue it further in this study.

Another feature to be noted from Figure 2 is a distinct peak of responses at 0%, 5%, 10%, 15%, etc. (i.e., multiples of five in a positive region). These peaks are particularly obvious among prior expectations and posterior expectations of groups 4-6. This issue will be further discussed in the following section.

Figure 2 Inflation expectations after treatments (by group and by information treatment)





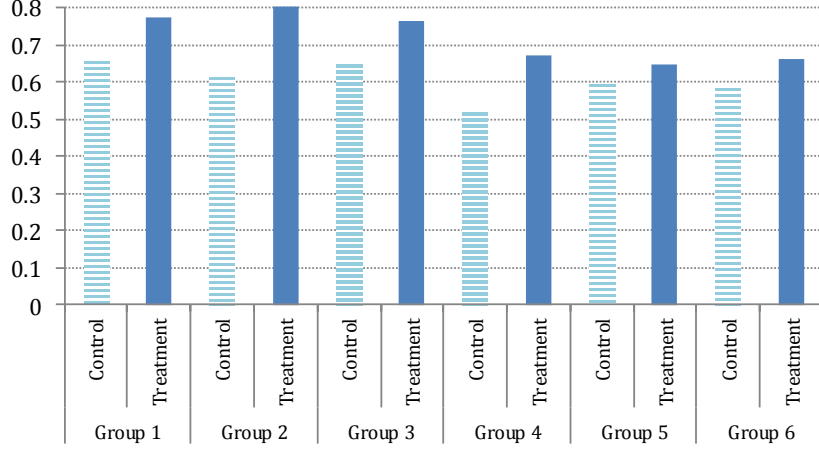
3.3 Impact of treatment information on inflation expectations

3.3.1 Updates of expectations

As explained, respondents are asked twice to provide his or her views on future inflation. Although we pose several questions not directly linked to inflation expectations, and provide information treatments between the two questions, the survey respondents do answer the exact same questions within a short time interval. However, the proportion of individuals who updated their expectations in response to the second question is surprisingly high: at least a majority of the respondents in each group changed their views (Figure 3). As these proportions are higher among the treatment groups than the control groups, we argue that information provision should influence expectations, particularly when people consider the information reliable and relevant vis-à-vis future inflation developments¹³. Concurrently, we note that the percentage of updates is high among the control groups; in particular, the differences between the control and treatment groups are limited in groups 5 and 6.

¹³ We tested a hypothesis that our treatment (i.e., information provision) induces respondents to change their expectations from the first question to the second one, via Probit analysis with a control of respondents' attributes. The estimation results clearly indicate the positive impact of treatment on the probability of updates for all six groups.

Figure 3 Proportion of respondents who updated their expectations after information treatment, by group



3.3.2 A framework to estimate Bayesian updating scheme

In this subsection, we present a theoretical framework to analyze consumers' expectation formation. Suppose a signal of true inflation of the next period, (π_{t+1}) , available at time t , S_t , contains noise ε_t , which is normally distributed with mean 0 and variance $\sigma_{\varepsilon,t}^2$:

$$S_t = \pi_{t+1} + \varepsilon_t,$$

$$\varepsilon_t \sim N(0, \sigma_{\varepsilon,t}^2).$$

Also, assume that prior belief of next period inflation, π_{t+1}^0 , follows normal distribution with mean μ_{t+1}^0 and variance $\sigma_{\pi,0}^2$.

$$\pi_{t+1}^0 \sim N(\mu_{t+1}^0, \sigma_{\pi,0}^2).$$

From the standard discussion of Bayesian updating, given the signal individuals update their inflation expectations to form posterior expectations, π_{t+1}^1 :

$$E[\pi_{t+1}^1 | S_t] = \frac{\sigma_{\varepsilon,t}^2}{\sigma_{\varepsilon,t}^2 + \sigma_{\pi,0}^2} \mu_{t+1}^0 + \frac{\sigma_{\pi,0}^2}{\sigma_{\varepsilon,t}^2 + \sigma_{\pi,0}^2} S_t. \quad (1)$$

Our experiment dataset contains the information of a set of prior and posterior expectation of future

inflation $(\pi_{t+1}^0, \pi_{t+1}^1)$ for a large number of consumers, indexed by i ($i = 1, \dots, N$), where N is the number of observations.

Under the full information rational expectation hypothesis (FIRE), all the consumers form expectations by solving the common (true) data generating process using all available information. Under FIRE, all the prior expectations, π_{t+1}^0 , must be identical for all i , which can be easily rejected given cross-section heterogeneity of expectations. Following previous research, we introduce the difference in the available information for each individual to allow for cross-section heterogeneity of expectations. Note that if we assume μ_{t+1}^0 is heterogeneous, it is natural to assume that $\sigma_{\pi,0}^2$ is also heterogeneous across individuals.

Usually, econometricians cannot observe the individual specific information set. Thus, if we try to estimate the Bayesian update formula (1), the information term will be absorbed in the error term as follows:

$$\begin{aligned} \pi_{t+1,i}^1 &\equiv E[\pi_{t+1}|S_{t,i}] = \omega_{t,i}\pi_{t+1,i}^0 + h_{t,i}, \quad (2) \\ \omega_{t,i} &= \frac{\sigma_{\varepsilon,t}^2}{\sigma_{\varepsilon,t}^2 + \sigma_{\pi,0}^2}. \end{aligned}$$

Because $\omega_{t,i}$ is consumer specific and is likely to be correlated with $h_{t,i}$, the regression coefficient of the prior belief is neither a consistent nor an unbiased estimate of $\omega_{t,i}$.¹⁴

Although the individual information set is not observable for researchers, with the help of an experiment, it is possible to investigate the formation of inflation expectations. In our survey experiment, the inflation expectations can be compared between survey participants who are randomly assigned to receive some information related to inflation (treatment) and participants who are not assigned to do so (control). As consumers in a control group do not get any new information, their posterior must be the same as their prior; in other words their weight for the prior, $\omega_{t,i}$, should be equal to unity. Therefore, the Bayesian updating rule can be described as follows:

$$\begin{aligned} \text{Treatment: } \pi_{t+1,i}^1 &= \omega_{t,i}\pi_{t+1,i}^0 + h_{t,i}; \\ \text{Control: } \pi_{t+1,i}^1 &= \pi_{t+1,i}^0; \\ \omega_{t,i} &= \frac{\sigma_{\varepsilon,t}^2}{\sigma_{\varepsilon,t}^2 + \sigma_{\pi,0}^2}; \\ h_{t,i} &= (1 - \omega_{t,i})S_t. \end{aligned}$$

Combining these rules of treatment and control, we get

¹⁴ Previous literature, such as Kandel and Zilberfarb (1999), assumes orthogonality between $\omega_{t,i}$ and $\pi_{t+1,i}^0$.

$$\pi_{t+1,i}^1 = \pi_{t+1,i}^0 \left(1 + (\omega_{t,i} - 1) \times I_i(\text{Treatment}) \right) + h_{t,i} \times I_i(\text{Treatment}),$$

where $I_i(\text{Treatment})$ is an indicator function that takes the value 1 if consumer i is in a treatment group, otherwise 0.

We then assume reporting error exists in the expectation data. Specifically, let the observed prior expectation be described as follows:

$$\begin{aligned} \tilde{\pi}_{t+1,i}^0 &= \pi_{t+1,i}^0 + v_{t,i}^0, \\ \tilde{\pi}_{t+1,i}^0 &\sim N(\mu_{t+1}^0, \sigma_{\pi,0}^2 + \sigma_v^2), \end{aligned}$$

where $v_{t,i}^j, j = 0,1$ is assumed to be i.i.d. among individuals, independent from the true belief, and to follow a certain identical distribution with variance σ_v^2 . Although these reporting errors correspond to the classical measurement error, we allow for non-zero covariance between the reporting error of prior expectation and that of posterior expectation for the same individuals.

Since consumers know their true prior belief, their updating rule is

$$\pi_{t+1,i}^1 = \frac{\sigma_{\varepsilon,t}^2}{\sigma_{\varepsilon,t}^2 + \sigma_{\pi_{t,i}^0}^2} \pi_{t+1,i}^0 + \frac{\sigma_{\pi_{t,i}^0}^2}{\sigma_{\varepsilon,t}^2 + \sigma_{\pi_{t,i}^0}^2} S_t.$$

where $\sigma_{\pi_{t,i}^0}^2$ is the variance of true prior expectation of consumer i .

For the econometrician, the observed prior and posterior expectations contain reporting errors,

$$\tilde{\pi}_{t+1,i}^1 = \frac{\sigma_{\varepsilon,t}^2}{\sigma_{\varepsilon,t}^2 + \sigma_{\pi_{t,i}^0}^2} (\pi_{t+1,i}^0 + v_{t,i}^0) + \frac{\sigma_{\pi_{t,i}^0}^2}{\sigma_{\varepsilon,t}^2 + \sigma_{\pi_{t,i}^0}^2} S_t + v_{t,i}^1.$$

Thus, the updating rule becomes:

$$\begin{aligned} \text{Treatment: } \pi_{t+1,i}^1 &= \omega_{t,i} (\pi_{t+1,i}^0 + v_{t,i}^0) + h_{t,i} + v_{t,i}^1; \\ \text{Control: } \pi_{t+1,i}^1 &= (\pi_{t+1,i}^0 + v_{t,i}^0) + v_{t,i}^1; \\ \omega_{t,i} &= \frac{\sigma_{\varepsilon,t}^2}{\sigma_{\varepsilon,t}^2 + \sigma_{\pi_{t,i}^0}^2}; \end{aligned}$$

$$h_{t,i} = (1 - \omega_{t,i})S_t.$$

The regression coefficient of $\pi_{t+1,i}^0$ of control group is no longer 1 because of the noise in reported prior expectations. The expected value of the regression coefficient of the reported prior expectation of a control group is

$$\frac{\sigma_{\pi_{t,i}^0}^2}{\sigma_{v,t}^2 + \sigma_{\pi_{t,i}^0}^2} + \frac{Cov(v_{t,i}^0, v_{t,i}^1)}{\sigma_{v,t}^2 + \sigma_{\pi_{t,i}^0}^2}$$

and that of a treatment group is

$$\frac{\sigma_{\pi_{t,i}^0}^2}{\sigma_{v,t}^2 + \sigma_{\pi_{t,i}^0}^2} \omega_{t,i} + \frac{Cov(v_{t,i}^0, v_{t,i}^1)}{\sigma_{v,t}^2 + \sigma_{\pi_{t,i}^0}^2}.$$

Since the covariance terms are identical between control and treatment groups, by taking the difference of the two estimates, we can remove the bias caused by the correlation in the reporting errors, which is nothing but the coefficient for the pooled regression treatment dummy. Specifically, consider the following estimation model:

$$\pi_{t+1,i}^1 = (\pi_{t+1,i}^0 + v_{t,i}^0) \left(\beta_i + (\omega_{t,i} - \beta_i) * I_i(Treatment) \right) + h_{t,i} * I_i(Treatment) + v_{t,i}^1. \quad (3)$$

The expected values of the regression coefficients for the prior and the interaction term of the prior and the treatment dummy become:

$$E(\hat{\beta}_i) = \frac{\sigma_{\pi_{t,i}^0}^2}{\sigma_{v,t}^2 + \sigma_{\pi_{t,i}^0}^2} + \frac{Cov(v_{t,i}^0, v_{t,i}^1)}{\sigma_{v,t}^2 + \sigma_{\pi_{t,i}^0}^2}, \quad (4)$$

$$E(\widehat{\omega_{t,i} - \beta_i}) = \frac{\sigma_{\pi_{t,i}^0}^2}{\sigma_{v,t}^2 + \sigma_{\pi_{t,i}^0}^2} (\omega_{t,i} - 1). \quad (5)$$

Although the serial correlation of the reporting errors does cause biases for the coefficient of the prior, it does not cause it for the interaction term of the prior and treatment dummy. Note that even though full identification of $\omega_{t,i}$ and $\frac{\sigma_{\pi_{t,i}^0}^2}{\sigma_{v,t}^2 + \sigma_{\pi_{t,i}^0}^2}$ is impossible without knowledge of information each consumer used when making his/her prior belief, we can show that $E(\widehat{\omega_{t,i} - \beta_i})$ is always non positive, which can be tested without knowing the information set each consumer used.

3.3.3 Measuring Individual Level Uncertainty and Rounding Practices

When estimating (3), one of the crucial variables is $\sigma_{\pi_{t,i}}^2$, the variance of the prior, which is assumed heterogeneous across consumers. If each consumer faces the same degree of uncertainty, it is possible to use cross sectional variance of the prior as the individual uncertainty level, but we cannot take this approach in this study. We need to construct a proxy that captures individual level of heterogeneity in the degree of uncertainty, which we denote as $x_{t,i}$. By linearizing the estimation model in terms of $\sigma_{\pi_{t,i}}^2$ near $\sigma_{\pi_{t,i}}^2 = 0$, and denoting $\sigma_{\pi_{t,i}}^2 = x_{t,i}$, we obtain

$$\begin{aligned} \tilde{\pi}_{t+1,i}^1 = & (\beta_0 + \beta_1 x_{t,i}) \tilde{\pi}_{t+1,i}^0 + (\gamma_0 + \gamma_1 x_{t,i}) \tilde{\pi}_{t+1,i}^0 \times I_i(Treatment) \\ & + (\phi_0 + \phi_1 x_{t,i}) \times I_i(Treatment) \quad (6) \end{aligned}$$

and we expect $\beta_1 > 0, \gamma_1 < 0$.¹⁵

In this study, we construct three different proxies for the $\sigma_{\pi_{t,i}}^2$, the degree of the informedness or uncertainty: (1) subjective standard deviation, (2) perception gap, and (3) a measure based on rounding practices in recent literature (Binder, 2015). The first measure is straightforward: the extent of respondents' certainty of their expectations evaluated by the standard deviation of inflation expectations estimated from subjective probabilities (henceforth, subjective Sd¹⁶). More specifically, we asked consumers about the probability distribution of their prior belief on future inflation. The individual level standard deviation is a direct measure for the uncertainty.

As the second measure, we use the responses of consumers' priors of future-inflation related information. As previously explained in section 2, at the second stage, we ask people for the subjective priors of their perceptions, not their inflation expectations, with regard to randomly assigned treatment information (e.g., inflation forecasts published by authorities or expected price change of particular food items). If the subjective prior deviates from the treatment information, we consider the respondent is less informed on the future inflation development. To estimate an uncertainty measure we define the difference between these subjective priors on treatment information (τ) and the true measure of the treatment (τ^*) as a perception gap, in line with

¹⁵ For the proof of $\beta_1 > 0$, right-hand side of (3) is increasing in $\sigma_{\pi_{t,i}}^2$ by using $\sigma_{v,t}^2 > Cov(v_{t,i}^0, v_{t,i}^1)$. It is easy to show the right-hand side term of (4) is nonpositive, and $\frac{\sigma_{\pi_{t,i}}^2}{\sigma_{v,t}^2 + \sigma_{\pi_{t,i}}^2}$ is positive and increasing in $\sigma_{\pi_{t,i}}^2$, while $(\frac{\sigma_{\varepsilon,t}^2}{\sigma_{\varepsilon,t}^2 + \sigma_{\pi_{t,i}}^2} - 1)$ is negative and decreasing in $\sigma_{\pi_{t,i}}^2$, which implies a negative sign of γ_1 .

¹⁶ Economists have long recognized the importance of measuring uncertainty surrounding people's expectations. Since the 1990s, they have attempted to collect survey-based measures of uncertainty of inflation or income, and confirmed the feasibility of elucidating consumers' subjective probability distribution of future inflation or wage (Manski, 2004; Pesaran and Weale, 2006). Among a number of studies that followed Manski (2004), Bruin de Bruin et al. (2011) find individuals are willing and able to provide probabilistic information about future inflation, and their responses show considerable heterogeneity and are systematically correlated with respondent characteristics.

discussions in the literature. As this gap becomes smaller in absolute terms, we assume that the agent becomes more informed about the future development of inflation.

Specifically, the perception gap of respondent i , (PG_i), is defined as follows:

$$PG_i = \tau_i - \tau^*.$$

This perception gap is one of the key concepts in our research.

Previous studies, including Branch (2004), explore the dispersion of survey responses on inflation expectations and investigate the characteristics of processes that might account for this dispersion. When a researcher observes the distribution of survey responses, it is obvious that it can have structures that are more complicated than distributions such as a simple normal density. Instead of imposing strong assumptions on the choice of models of expectation formation, recent work of Binder (2015) discusses that there are two types of consumers; “type-h consumers”, who round their expectations to a multiple of five because of high uncertainty for their responses, and “type-l consumers”, with less uncertainty, who report their forecast to the nearest integer. We employ this measure (henceforth, “Binder measure”) as our third uncertainty measure to identify different types of consumers according to their rounding practices. As previous literature indicates, researchers cannot directly observe why respondents give rounded figures;¹⁷ some may round their responses to simplify communication although they have clearer ideas, while others may feel they are unable to provide precise responses, as they perceive the future as ambiguous (Manski & Molinari, 2010). Although rounding practices may not directly be linked to uncertainty, we assume they can be related, thus part of respondents with multiples of five figures (henceforth, “M5,” i.e., perform gross rounding) can be of an uncertain type, compared with the rest of the respondents (i.e., provide refined responses). We label the former group of consumers as “H-type,” and the latter group as “L-type.”

Table 4 reports the change in the share of H-type consumers before and after the treatment by information groups. Interestingly, the posterior shares differ to a fair extent among groups 1-3 and groups 4-6. Based on the discussion in the previous section, we infer that the decrease in H-type is linked to lower expectations (and vice-versa) and interpret the fact that consumers become more uncertain by learning ambiguous, seemingly irrelevant new information, while they turn to be less uncertain when learning authoritative information. In Appendix 2, we discuss the details of the construction of Binder measures.

¹⁷ Recent literature pointed out that survey respondents tend to provide round numbers to convey uncertainty in various contexts including consumption expenditures, earnings, or inflation expectations (e.g., Pudney (2008)).

**Table 4 Change in the share of M5 responses
(comparison between prior and posterior responses)**

Group	Prior (A)	Posterior(B)	(B)-(A)
1	0.626	0.523	-0.102
2	0.612	0.496	-0.116
3	0.633	0.516	-0.117
4	0.623	0.700	0.077
5	0.635	0.718	0.083
6	0.638	0.716	0.077
Total	0.628	0.612	-0.016

4. Empirical analysis of updating behavior

4.1. Estimation based on Bayesian updating

In this section, we undertake a parametric analysis of updating behavior to examine whether our data is consistent with Bayesian updating. We estimate a simple structural model of expectation revision based on the framework of Bayesian updating in Section 3.3.2. In our experiment, we provide the randomly assigned individuals in a treatment group with different information simultaneously, which enables us to estimate the structural parameters of the updating model. Summary statistics of the variables employed in the estimation are shown in Table A-2 in the Appendix.

At the first stage, we estimate the following basic updating model:

$$\pi_{t+1,i}^1 = \beta_0 \tilde{\pi}_{t+1,i}^0 + \gamma_0 \tilde{\pi}_{t+1,i}^0 \times I_i(Treatment) + \phi_0 \times I_i(Treatment) + v_{t,i}^1, \quad (8)$$

where $I_i(Treatment)$ is an indicator variable that equals 1 if respondent i is in a treatment group, and 0 otherwise, $v_{t,i}^1$ is a term of reporting error and $\beta_0, \gamma_0, \phi_0$ are parameters to be estimated. The sign of γ_0 is expected to be negative.

From the discussion in section 3.3.2, considerations of the reporting errors are needed because most parameters, such as β_0 and γ_0 , are subject to the attenuation biases. Therefore, we run both an ordinary least squares (OLS) and a two stage least squares (2SLS) regression to estimate (8), using a couple of individual traits and respondents' perception of the realized inflation as instrument variables that are typically correlated with inflation expectations, but are not expected to be correlated with reporting errors.¹⁸

Table 5 compares the OLS and 2SLS estimates for each information group. All OLS estimates of β_0 are positive but much smaller than unity, while they get closer to unity in 2SLS estimates. Only the 2SLS results of BOJ group pass both weak IV test and over-identification test, with Hausman test result rejecting the equality of the OLS and 2SLS estimates. In this group, γ_0 of 2SLS estimate is negative and smaller than the OLS counterpart is, which is consistent with the expected effects of the reporting errors.

As we have three proxies of respondents' informedness before treatment, we next estimate the model with information measures:

¹⁸ We use respondents' gender, educational level, and age (all dummy variables) and an additional dummy variable that indicates if a respondent perceives the realized inflation rate for the preceding year was positive. Basic individual characteristics are correlated with inflation expectations (e.g., Bryan and Venkatu, 2010). Furthermore, inflation perceptions can affect expectations when expectations are formed in an adaptive manner.

$$\pi_{t+1,i}^1 = (\beta_0 + \beta_1 x) \tilde{\pi}_{t+1,i}^0 + (\gamma_0 + \gamma_1 x) \tilde{\pi}_{t+1,i}^0 \times I_i(Treatment) + (\phi_0 + \phi_1 x) \times I_i(Treatment) + v_{t,i}^1, \quad (9)$$

where $I_i(Treatment)$ is an indicator variable that equals 1 if respondent i is in a treatment group, and 0 otherwise, $v_{t,i}^1$ is a term of reporting error, and $\beta_j, \gamma_j, \phi_j$ ($j = 0,1$) are parameters to be estimated. As discussed in section 3.3.3, the sign of β_1 is expected to be positive, while that of γ_1 is negative, with $\beta_1 > 0, \gamma_1 < 0$.

Table 5 Bayesian updating model without information measure

	Government		Private		BOJ	
	OLS	OLS-IV	OLS	OLS-IV	OLS	OLS-IV
Prior (β_0)	0.461 *** (0.0503)	0.506 *** (0.162)	0.300 ** (0.124)	0.702 *** (0.234)	0.516 *** (0.0835)	0.839 *** (0.176)
Prior*T (γ_0)	-0.174 ** (0.0691)	-0.184 (0.189)	-0.0580 (0.131)	-0.244 (0.272)	-0.264 *** (0.0893)	-0.418 ** (0.195)
Treatment (T) (ϕ_0)	-0.210 (0.412)	-0.148 (1.270)	-1.489 * (0.881)	0.0541 (1.958)	-0.0610 (0.567)	1.009 (1.317)
Number of observations	2,356		2,364		2,395	
R-squared	0.085	0.084	0.073	0.013	0.126	0.083
Cragg-Donald Wald F statistic	16.952**		8.531		14.079**	
Sargan statistic	12.321		16.736		11.043	
p-value	0.1375		0.033		0.1999	
Hausman chi2	0.22		5.59		7.96	
p-value	0.975		0.133		0.047	
	Noodle		Frozen food		Ice cream	
	OLS	OLS-IV	OLS	OLS-IV	OLS	OLS-IV
Prior (β_0)	0.611 *** (0.0695)	0.385 (0.317)	0.622 *** (0.0596)	0.913 *** (0.171)	0.579 *** (0.0764)	0.880 *** (0.239)
Prior*T (γ_0)	-0.217 *** (0.0801)	0.504 (0.338)	-0.129 (0.0816)	-0.129 (0.208)	-0.158 * (0.0905)	0.0953 (0.265)
Treatment (T) (ϕ_0)	1.555 *** (0.497)	-3.133 (2.168)	0.737 (0.533)	0.878 (1.484)	1.678 *** (0.564)	-0.0561 (1.722)
Number of observations	2,396		2,382		2,356	
R-squared	0.146	0.006	0.197	0.138	0.156	-0.034
Cragg-Donald Wald F statistic	6.035		12.558*		12.314*	
Sargan statistic	13.378		5.927		4.672	
p-value	0.0995		0.6555		0.7919	
Hausman chi2	19.49		9.32		27.17	
p-value	0.000		0.025		0.000	

Standard errors in parentheses.

***, **, * indicates statistical significance at 1%, 5%, and 10% level, respectively.

**, * if F statistic is greater than Stock-Yogo weak ID test critical values (5% maximal IV relative bias and 10% maximal IV relative bias, respectively)

Note: In Model OLS-IV, excluded instruments are female dummy, household income, age dummy (young or not), education dummy (high school graduates or not), dummy for the perception of past price increase, and the interaction terms of each of these variables with T.

Constant terms are included in all specifications.

Table 6 summarizes basic statistics of three uncertainty measures (see section 3.3.3) by group, as well as their correlations. The statistics of the share of H-type and subjective *Sd* are similar among information groups, ascertaining that initial randomized grouping is proper. On the other hand, those of absolute *PG* vary probably due to the differences in the type of information we gave each treatment group. Correlations between H-type measure and either absolute *PG* or subjective *Sd* are not high in their levels (0.034-0.077 and 0.095-0.125, respectively), but *p*-values are always zero. Correlations between absolute *PG* and subjective *Sd* of most groups but ice cream exceed 0.2 with zero *p*-values. If we control multiple information measures at the same time when estimating (9), these statistics indicate the possibility of multicollinearity; we consider it can be beneficial to control multiple measures simultaneously because of the complementarity among the three uncertainty measures.

Table 6 Basic characteristics of three information measures

	Total	Government	Private	BOJ	Noodle	Frozen food	Ice cream
H-type¹							
mean	0.385	0.385	0.377	0.388	0.382	0.387	0.390
median	0.000	0.000	0.000	0.000	0.000	0.000	0.000
sd	0.487	0.487	0.485	0.487	0.486	0.487	0.488
Absolute perception gap (PG)²							
mean	3.391	4.140	4.690	4.098	2.294	1.941	3.204
median	1.200	1.600	3.200	1.700	1.000	0.000	3.000
sd	5.125	5.389	6.193	5.478	4.038	4.514	4.180
Subjective standard deviation (Sd)³							
mean	6.451	6.376	6.524	6.520	6.396	6.606	6.278
median	6.412	6.368	6.500	6.452	6.422	6.472	6.224
sd	4.161	4.218	4.098	4.173	4.086	4.151	4.229
Correlation							
H-type and PG	0.065	0.061	0.077	0.077	0.077	0.075	0.034
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
H-type and Sd	0.110	0.120	0.095	0.111	0.109	0.098	0.125
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PG and Sd	0.215	0.230	0.268	0.302	0.212	0.222	0.049
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of observations	14,249	2,356	2,364	2,395	2,396	2,382	2,356

Note: 1. H-type indicates the type of respondents who formed prior expectations in a rough manner. We estimate the statistics related to H-type by bootstrapping (N=50). Thus the number of observations is 50 times the number of original observations.

2. Absolute perception gap is equal to the absolute value of subjective information prior subtracted by true measure of treatment information.

3. Subjective standard deviation is estimated by using the responses on subjective probabilities for future inflation levels.

Table 7 shows the estimation results of four specifications, with either one of the three proxy-measures (models (1)-(3)) and with all three measures (model (4)).¹⁹ As the information

¹⁹ To address the issue of attenuation bias, 2SLS provides better estimation results. However, for the specification of

measure, model (1) employs consumer types, assuming H-type consumers are less uncertain with limited information. Model (2) uses the absolute level of perception gaps (PG_i) as people's information level. In model (3), we use the subjective standard deviation Sd_i as the information measure. Finally, model (4) contains a set of all the information measures. These measures are expected to capture the degree of uncertainty of the consumers when they provide their prior expectations.

In Table 7, we show that the estimates of β_1 , the interaction term between the absolute perception gap and the prior, are positive and statistically significant at 1% level in both model (2) and model (4). The estimates of the coefficient β_1 of the interaction term between subjective standard deviation (Sd) and prior expectations (model (3) and model (4)) are estimated to be positively significant in the majority of the results, while it has the opposite sign in model 4 for the BOJ case. In contrast, in Table A-2,²⁰ the auxiliary specification with the control of two information measures, that is, consumer types and subjective standard deviations (model (6)), has an estimate of positive β_1 of the interaction term between subjective Sd and prior expectations.

Although the results with the information measures of absolute perception gaps and/or subjective standard deviations are rather consistent with our theoretical expectation, the estimates of β_1 with consumer-type measures have small but positive results (only model (4) of BOJ group and model 1 of ice cream group). In total, at least two of the information measures (i.e., absolute perception gap and subjective standard deviation) provide evidence consistent with the Bayesian updating with reporting errors, and another measure of consumer types is inconsistent with this updating framework.

The size of the regression coefficient of β_1 is also economically significant. Summary statistics in Table A-2 show that the mean values of absolute PG are between 2.29 and 4.69, while their standard deviations are between 4.04 and 6.19 among all six information groups. Thus, a change in absolute PG by one standard deviation (i.e., 5.48) in model (4) of BOJ group, raises posterior expectations by 1.62% points on average, which is 43.2% of the mean value of the posterior expectations, 3.75%. The extent is more modest for the ice cream group; the change by one standard deviation raises the posterior expectations by 0.91% points on average,²¹ relative to the mean posterior expectation level of 7.77%.

Table 7 also shows that the estimates of γ_1 are negative in almost all results in case of absolute perception gaps. However, the results are weaker in the case of subjective standard deviation with opposite signs in model 4 of government and BOJ groups. We suspect that this reflects multicollinearity among the three information measures. In case of consumer-type measures,

(9) appropriate IVs were not feasible.

²⁰ Table A-2 contains the results of supplementary specifications (i.e., combination of two of the information measures), and presents consistent results with those of Table 9.

²¹ If we estimate these average effects by using the estimation results of subjective Sd , they are much lower; in BOJ case this is even negative ($\blacktriangle 0.07\%$ points) and in ice cream group it is 0.47% points (see Table 8).

the estimate is negative only in model 4 of the BOJ group. If we focus on the results with information measures of absolute PG , the results of γ_1 endorses the arguments from β_1 estimates and indicates consistency with our discussion of Bayesian updating. In other words, people tend to be more responsive to the information treatment if the provided treatment conveys more reliable or more precise information (smaller variance of the noise, $\sigma_{\varepsilon,t}^2$).

By comparing the results among information groups, R -squared is the greatest in BOJ group when absolute perception gaps are included as information measures. Overall model fit is the best with BOJ treatment than the others, particularly compared with the treatments of government or private forecasts. Interestingly, our Bayesian updating framework seems to be consistent with the information group not only for the government, Bank of Japan, or professional forecasts, but also for the future food prices (i.e., noodle, frozen food, and ice cream groups). Our prediction was that people tend to be greatly influenced by the authoritative information, but to a lesser extent when they receive food information, which is too specific to be relevant to the overall inflation development. However, Table 7 implies that people are influenced by not only the former type of information but also the latter under the Bayesian updating scheme.

We then estimate the impact of the increase in the extent of uncertainty on posterior expectations via the term $(\gamma_1 x) \tilde{\pi}_{t+1,i}^0 \times I_i(Treatment)$ with x proxied by absolute PG . Taking as an example model (4) results of the BOJ group again, a change in absolute PG by one standard deviation (i.e., 5.48) decreases the posterior expectations by 1.47% points on average, which is about 39.3% of the average posterior level. Table 8 shows the estimated average effects through the two interaction terms, $(\gamma_1 x) \tilde{\pi}_{t+1,i}^0$ and $(\gamma_1 x) \tilde{\pi}_{t+1,i}^0 \times I_i(Treatment)$. The total impacts of information treatment through uncertainty are generally negative, implying that consumers change their posterior from their prior to a greater extent when they receive new information. This is consistent with the prediction of Bayesian updating.

Table 7 Bayesian updating model with information measures

Explained=Posterior expectation								
	Government				Private			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Prior (β_0)	0.475 *** (0.032)	0.156 *** (0.067)	0.339 *** (0.077)	0.131 *** (0.026)	0.271 *** (0.079)	0.156 (0.126)	-0.0497 (0.285)	-0.182 *** (0.050)
Prior*T (γ_0)	-0.219 *** (0.053)	0.0603 (0.097)	-0.199 (0.128)	-0.0962 *** (0.039)	-0.0487 (0.084)	-0.00293 (0.135)	0.101 (0.298)	0.124 ** (0.058)
T (ϕ_0)	-0.088 (0.243)	-1.213 *** (0.553)	-0.422 (0.502)	-1.126 *** (0.184)	-1.479 *** (0.266)	-2.774 *** (0.872)	-2.084 ** (1.063)	-2.604 *** (0.217)
Information measure								
1) Type								
Prior*High (β_1)	-0.019 (0.046)			-0.0402 (0.044)	0.0566 (0.124)			0.0345 (0.099)
Prior*High*T (γ_1)	0.076 (0.093)			0.100 (0.086)	-0.021 (0.137)			-0.011 (0.119)
High*T (ϕ_1)	-0.130 (0.524)			-0.177 (0.480)	-0.0155 (0.444)			-0.241 (0.427)
2) Perception gap								
Prior*PG (β_1)		0.0405 *** (0.009)		0.0402 *** (0.000)		0.0169 *** (0.007)		0.0164 *** (0.001)
Prior*PG*T (γ_1)		-0.0364 *** (0.012)		-0.0515 *** (0.001)		-0.0232 ** (0.011)		-0.0125 *** (0.001)
PG*T (ϕ_1)		0.165 (0.123)		0.486 *** (0.002)		0.387 *** (0.096)		0.365 *** (0.002)
3) Subjective standard deviation								
Prior*Sd (β_1)			0.0125 *** (0.007)	0.00561 *** (0.001)			0.0345 (0.021)	0.0319 *** (0.002)
Prior*Sd*T (γ_1)			-5.85e-06 (0.015)	0.0140 *** (0.001)			-0.0184 (0.024)	-0.0181 *** (0.002)
Sd*T (ϕ_1)			0.0532 (0.071)	-0.0308 *** (0.007)			0.0809 (0.091)	0.0193 *** (0.006)
R-squared	0.087	0.125	0.091	0.243	0.077	0.159	0.092	0.235
Number of observations			2,356				2,364	

Note: Model (1),(4): Bootstrap standard errors are in parentheses (100 times). R squared is an average value of the results from bootstrapping. ***, **, * indicates statistical significance at 1%, 5%, and 10% level, respectively.

Prior means prior expectations, High means dummy of H-type respondents. PG stands for absolute values of perception gap. Sd is subjective standard deviation, estimated from subjective probabilities.

T is treatment.

Constant terms are included in all specifications.

Explained=Posterior expectation

	BOJ				Noodle			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Prior (β_0)	0.491 *** (0.046)	0.0471 (0.069)	0.302 *** (0.113)	0.0208 (0.022)	0.636 *** (0.046)	0.361 *** (0.085)	0.445 *** (0.106)	0.340 *** (0.031)
Prior*T (γ_0)	-0.193 *** (0.052)	0.172 ** (0.078)	-0.120 (0.131)	0.136 *** (0.033)	-0.226 *** (0.062)	-0.0229 (0.096)	-0.0102 (0.147)	-0.0271 (0.043)
T (ϕ_0)	-0.438 *** (0.142)	-2.585 *** (0.492)	-1.121 * (0.580)	-2.759 *** (0.136)	1.376 *** (0.271)	0.143 (0.565)	-0.00825 (0.625)	-0.220 (0.190)
Information measure								
1) Type								
Prior*High (β_1)	0.0421 (0.082)			0.0887 * (0.046)	-0.0397 (0.075)			-0.0100 (0.069)
Prior*High*T (γ_1)	-0.129 (0.090)			-0.141 ** (0.063)	0.00326 (0.107)			-0.0380 (0.093)
High*T (ϕ_1)	0.709 *** (0.247)			0.412 (0.299)	0.590 (0.549)			0.527 (0.431)
2) Perception gap								
Prior*PG (β_1)		0.0447 *** (0.006)		0.0454 *** (0.001)		0.0354 *** (0.012)		0.0352 *** (0.001)
Prior*PG*T (γ_1)		-0.0573 *** (0.009)		-0.0447 *** (0.001)		-0.0426 *** (0.015)		-0.0513 *** (0.001)
PG*T (ϕ_1)		0.420 *** (0.100)		0.425 *** (0.001)		0.478 *** (0.107)		0.728 *** (0.003)
3) Subjective standard deviation								
Prior*Sd (β_1)			0.0207 * (0.011)	-0.00273 *** (0.001)		0.0158 (0.011)	0.00292 ** (0.001)	
Prior*Sd*T (γ_1)			-0.0193 (0.014)	0.0033 *** (0.001)		-0.0270 * (0.016)	-0.0071 *** (0.002)	
Sd*T (ϕ_1)			0.165 *** (0.048)	0.0811 *** (0.004)		0.249 *** (0.066)	0.144 *** (0.006)	
R-squared	0.129	0.258	0.141	0.375	0.148	0.215	0.157	0.297
Number of observations			2,395				2,396	

Note: Model (1),(4): Bootstrap standard errors are in parentheses (100 times). R squared is an average value of the results from bootstrapping. ***, **, * indicates statistical significance at 1%, 5%, and 10% level, respectively.

Prior means prior expectations, High means dummy of H-type respondents. PG stands for absolute values of perception gap. Sd is subjective standard deviation, estimated from subjective probabilities.

T is treatment.

Constant terms are included in all specifications.

Explained=Posterior expectation	Frozen food				Ice cream			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Prior (β_0)	0.598 *** (0.037)	0.399 *** (0.085)	0.412 *** (0.098)	0.212 *** (0.040)	0.510 *** (0.027)	0.426 *** (0.061)	0.374 *** (0.116)	0.245 *** (0.021)
Prior*T (γ_0)	-0.147 ** (0.066)	-0.0368 (0.098)	-0.0706 (0.127)	0.0774 (0.059)	-0.124 ** (0.052)	-0.0220 (0.114)	-0.0173 (0.140)	-0.0762 * (0.040)
T (ϕ_0)	0.847 *** (0.319)	0.0167 (0.601)	-0.376 (0.560)	-0.941 *** (0.253)	1.558 *** (0.256)	1.444 ** (0.677)	0.421 (0.534)	2.212 *** (0.189)
Information measure								
1) Type								
Prior*High (β_1)	0.0396 (0.062)			0.0344 (0.073)	0.0828 ** (0.032)			0.0239 (0.032)
Prior*High*T (γ_1)	0.0347 (0.117)			0.0408 (0.115)	-0.0391 (0.078)			0.0142 (0.075)
High*T (ϕ_1)	-0.245 (0.620)			-0.433 (0.568)	0.0599 (0.493)			-0.159 (0.471)
2) Perception gap								
Prior*PG (β_1)		0.0406 *** (0.011)		0.0402 *** (0.001)		0.0353 *** (0.011)		0.0333 *** (0.000)
Prior*PG*T (γ_1)		-0.0407 *** (0.015)		-0.0479 *** (0.001)		-0.0327 (0.021)		-0.0418 *** (0.000)
PG*T (ϕ_1)		0.451 (0.127)		0.681 *** (0.005)		0.00113 (0.118)		0.551 *** (0.002)
3) Subjective standard deviation								
Prior*Sd (β_1)			0.0199 *** (0.009)	0.0160 *** (0.001)		0.0206 (0.014)		0.0171 *** (0.000)
Prior*Sd*T (γ_1)			-0.0123 (0.013)	-0.0240 *** (0.001)		-0.0221 (0.018)		-0.0135 *** (0.001)
Sd*T (ϕ_1)			0.209 *** (0.061)	0.243 *** (0.007)		0.234 *** (0.067)		0.139 *** (0.010)
R-squared	0.200	0.274	0.214	0.341	0.158	0.165	0.173	0.318
Number of observations			2,382				2,356	

Note: Model (1),(4): Bootstrap standard errors are in parentheses (100 times). R squared is an average value of the results from bootstrapping. ***, **, * indicates statistical significance at 1%, 5%, and 10% level, respectively. Prior means prior expectations, High means dummy of H-type respondents. PG stands for absolute values of perception gap. Sd is subjective standard deviation, estimated from subjective probabilities. T is treatment. Constant terms are included in all specifications.

4.2. Robustness check

In this section, we add several variables that do not appear in equation (9) to check the robustness of the structural estimation. Theoretically, if we include variables outside the Bayesian updating framework, the coefficient must be zero. However, the scatterplot between perception gaps and posterior expectations indicates a clear positive relationship notwithstanding the content of information treatment (correlations and p-values are shown in Table A-5 in the Appendix).

Even if the role of the perception gaps remains unclear in the Bayesian updating, to check the robustness of the results in the previous section, we additionally include these gaps in

the original specification of (9) and examine whether the signs of the coefficients of interest remain significant and with the same signs. The results are included in the Appendix, Table A-6.

Table 8 Average effect of the increase in uncertainty-related terms by one-standard deviation on posterior expectations (% points)

Proxies for the degree of informedness	Government			Private			BOJ		
1) Type									
Prior*High (β_1)	-	-	-0.129	-	-	0.112	-	-	0.281 *
Prior*High*T (γ_1)	-	-	0.320	-	-	-0.035	-	-	-0.448 **
2) Perception gap									
Prior*APG (β_1)	1.435 ***	-	1.425 ***	0.703 ***	-	0.683 ***	1.594 ***	-	1.620 ***
Prior*APG*T (γ_1)	-1.290 ***	-	-1.825 ***	-0.962 **	-	-0.518 ***	-2.044 ***	-	-1.596 ***
3) Subjective standard deviation									
Prior*SSd (β_1)	-	0.347 ***	0.156 ***	-	0.947	0.878 ***	-	0.564 *	-0.074 ***
Prior*SSd*T (γ_1)	-	-1.E-04	0.387 ***	-	-0.506	-0.497 ***	-	-0.524	0.090 ***

Proxies for the degree of informedness	Noodle			Frozen food			Ice cream		
1) Type									
Prior*High (β_1)	-	-	-0.032	-	-	0.113	-	-	0.076
Prior*High*T (γ_1)	-	-	-0.120	-	-	0.134	-	-	0.045
2) Perception gap									
Prior*APG (β_1)	0.931 ***	-	0.926 ***	1.240 ***	-	1.228 ***	0.963 ***	-	0.907 ***
Prior*APG*T (γ_1)	-1.119 ***	-	-1.351 ***	-1.243 ***	-	-1.465 ***	-0.892	-	-1.140 ***
3) Subjective standard deviation									
Prior*SSd (β_1)	-	0.420	0.078 **	-	0.560 **	0.451 ***	-	0.569	0.471 ***
Prior*SSd*T (γ_1)	-	-0.720 *	-0.190 ***	-	-0.345	-0.675 ***	-	-0.610	-0.373 ***

Note: 1. Based on the estimation results of Table 4. ***, **, * indicates statistical significance of estimated coefficients at 1%, 5%, and 10% level, respectively.
2. "-" means the terms are not included in the models. The estimated effects are based on Model (2), (3), and (4) from the left column of each of six groups.
3. Prior means prior expectations, High means dummy of H-type respondents. APG stands for absolute values of perception gap. SSd is subjective standard deviation, estimated from subjective probabilities.
T is treatment.

Even with the control of the perception gaps, β_1 is often estimated to be positive and γ_1 to be negative with less significance in case of information measures of absolute perception gaps and subjective standard deviations. Table 9 compares the estimated average effect with and without the control of perception gaps, based on the results of model (4). Although the effects become more limited than the original specification, the results remain consistent with our expectations, which confirm the robustness of the results in Table 7, even with the control of the "puzzle" effect.

Table 9 Comparison of the average effect with and without perception gaps

	Government		Private		BOJ	
	w/ Gap	w/o Gap	w/ Gap	w/o Gap	w/ Gap	w/o Gap
1) Type						
Prior*High (β_1)	-0.024	-0.129	0.017	0.112	0.030	0.281 *
Prior*High*T (γ_1)	0.053	0.320	-0.005	-0.035	-0.056 *	-0.448 **
2) Perception gap						
Prior*APG (β_1)	0.040 ***	1.425 ***	-0.065 ***	0.683 ***	0.118 ***	1.620 ***
Prior*APG*T (γ_1)	-0.101 ***	-1.825 ***	0.089 ***	-0.518 ***	-0.114 ***	-1.596 ***
3) Subjective standard deviation						
Prior*SSd (β_1)	0.039 ***	0.156 ***	0.118 ***	0.878 ***	-0.004	-0.074 ***
Prior*SSd*T (γ_1)	0.044 ***	0.387 ***	-0.061 ***	-0.497 ***	0.006 *	0.090 ***
	Noodle		Frozen food		Ice cream	
	w/ Gap	w/o Gap	w/ Gap	w/o Gap	w/ Gap	w/o Gap
1) Type						
Prior*High (β_1)	0.001	-0.032	0.016	0.113	0.014	0.076
Prior*High*T (γ_1)	-0.024	-0.120	0.021	0.134	0.005	0.045
2) Perception gap						
Prior*APG (β_1)	0.008 ***	0.926 ***	-0.021 ***	1.228 ***	0.014 ***	0.907 ***
Prior*APG*T (γ_1)	-0.073 ***	-1.351 ***	-0.115 ***	-1.465 ***	-0.049 ***	-1.140 ***
3) Subjective standard deviation						
Prior*SSd (β_1)	-0.003	0.078 **	0.072 ***	0.451 ***	0.056 ***	0.471 ***
Prior*SSd*T (γ_1)	-0.014 **	-0.190 ***	-0.105 ***	-0.675 ***	-0.041 ***	-0.373 ***

Note: Average effects are estimated by using the estimates of Model (4) of each information group with the control of PG (shown in Table A-3) [column w/Gap] and these without that control (shown in Table 9) [column w/o Gap]. Prior means prior expectations, High means dummy of H-type respondents. APG stands for absolute values of perception gap. SSd is subjective standard deviation, estimated from subjective probabilities. Gap corresponds to perception gaps.

T is treatment.

***, **, * indicates statistical significance of estimated coefficients at 1%, 5%, and 10% level, respectively.

5. Conclusions

In this study, we examine the features of expectation-updating behavior among survey respondents, based on an experiment that makes use of various information treatments. We aim to find clues as to how people process new information when updating expectations. We find this updating behavior to be consistent with the rational expectation with limited information. That is, the Bayesian Updating scheme with heterogeneous belief can explain some changes in consumers' belief

over future inflation. In particular, we confirm that (1) more uncertain consumers at a prior stage are influenced by new information largely in their updates, and (2) more reliable information for consumers affects them more. Even though consumers' updating behaviors are heterogeneous and seem to deviate from rationality at a glance, they actually are quite coherent with the simple Bayesian framework thus implying the possibility of rationality in their expectation formation.

Although consumers can respond to information that is not so relevant to the future inflation development, our model fits best in case of BOJ treatment. It would be encouraging for policymakers to find that information treatments are in general effective for consumers. However, we find that expectations can also be responsive to the information regarding future price changes among specific food items, even when the share of these items in their consumption basket is quite small. This implies the possibility that expectations can be volatile in response to price change news among various items in their basket. At the same time, we note that the analysis of expectations remains unclear to some extent. For example, the expectations of consumers after treatment are strongly and positively correlated with the level of informedness; this finding implies that the mechanism of information-processing should be more complicated than the usual learning model based on Bayes theorem, although this does not undermine consistency. Further investigation, particularly that uses data on uncertainty, is scope for future research.

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Appendix 1

The basic structure of the experiment consists of the following three stages.

1. Eliciting inflation expectations from each subject (first question on inflation expectations)

2. Eliciting the prior perceptions of the information related to future inflation developments (subjective priors)

Respondents in each Group are asked a question about either the inflation outlooks of professional institutions or scheduled price changes in particular grocery items as below.

a. Group 1 (Government outlook group): In the “government outlook group,” respondents are asked: “The Japanese government publishes around January each year the inflation outlook for the upcoming fiscal year. How high do you think the most recent rate of expected inflation by the Japanese government is?”

b. Group 2 (Private outlook group): In the “professional-forecasters outlook group,” respondents are asked: “A group of professional economists in the private sector regularly reports its expectations of future inflation. How high do you think the most recent rate of expected inflation by the professional economists is?”

c. Group 3 (BOJ outlook group): In the “BOJ group,” respondents are asked: “The members of the Policy Board of the Bank of Japan predict future inflation on a regular basis. How high do you think the most recent rate of expected inflation by the BOJ is?”

d. Group 4 (Noodle group): For the “noodle group,” the survey explains: “Major producers of instant noodles announced this month increases in the price levels of their products, because of an increase in the costs of transportation, raw materials, or personnel expenses.” Then respondents are asked: “What do you think will be the extent of such price changes, in percentage points?”

e. Group 5 (Frozen meal group): For the “frozen meal group,” the survey explains: “Major producers of frozen meals announced this month planned increases in the price levels of their household products, because of an increase in the costs of transportation, raw materials, or personnel expenses.” Then respondents are asked: “What do you think will be the extent of such price changes, in percentage points?”

f. Group 6 (Ice cream group): For the “ice cream group,” the survey explains: “Major confectionery companies announced planned increases in the price levels of some of their ice cream products, because of an increase in the costs of raw materials, or wrapping.” Then, the respondents are asked: “What do you think is the extent of such price changes, in percentage points?”

3-1. Providing subjects in the treatment group with true measures of the aforementioned information would constitute a signal to the subject in the formation of expectations; in the case of the control group, the subject receives no signal (information treatment)

3-2. Eliciting inflation expectations from each subject again (second question on inflation

expectations)

Only respondents in the treatment groups are provided with the correct answer to the question posed in the previous stage as follows.

- a. **Group 1:** “According to the government outlook published this month, the government forecasts a CPI inflation rate of **1.4%** over 2015FY.”
- b. **Group 2:** “According to the outlook by professional forecasters in the private sector, they expect the future inflation rate over the next fiscal year (2015FY) to be **0.2–1.8%**, with a mean value of **0.84%**.”
- c. **Group 3:** “According to the outlook of the policy board members of the BOJ, they expect the future inflation rate over the next fiscal year (2015FY) to be **0.4–1.3%**, with a median value of **1.0%**.”
- d. **Group 4:** “According to the news release, several large food manufacturers that produce instant noodles intend to increase their product prices by **5–8%** this January. In addition, major noodle companies announced that they intend to increase the prices of chilled noodles by **4–9%** next March.”
- e. **Group 5:** “According to the news release, several large food manufacturers announced that they intend to increase the prices of frozen meals for households by **3–10%** next February.”
- f. **Group 6:** “According to the news release, several large confectionary manufacturers announced that they intend to increase the prices of some ice cream products by **8–10%** next March.”

Appendix 2 Construction of Binder Measures

As discussed in section 3.3.3, the third measure of the uncertainty degree is Binder measure (Binder, 2015). Suppose consumers are classified as two types, 1) well informed consumers and 2) uninformed consumers. Although we cannot directly observe such consumer types, by estimating the finite mixture model, it is possible to classify our sample to fit the two types. The basic idea is quite simple. Consumers with greater uncertainty are likely rounding their estimates at 0, 5, 10, etc., while well-informed consumers do not round their estimates.

Formally, we replace each response of consumer i at timing t , R_{it} , with an interval $[R_{it}^L, R_{it}^U]$ ($i=1,2,\dots,N$), (t = prior, posterior), where N is the total number of respondents. L and U stand for lower bound and upper bound, respectively. Given the response R_{it} , $[R_{it}^L, R_{it}^U]$ is formed as follows:

$$\begin{aligned} \text{If } R_{it} = M5, \text{ then } [R_{it}^L, R_{it}^U] &= [R_{it} - 2.5, R_{it} + 2.5], \\ \text{otherwise, } [R_{it}^L, R_{it}^U] &= [R_{it} - 0.5, R_{it} + 0.5]. \end{aligned}$$

We assume that R_{it} for each t of both H-type and L-type consumers is drawn from the normal distributions, $N(\mu_{Ht}, \sigma_{Ht}^2)$, and $N(\mu_{Lt}, \sigma_{Lt}^2)$, respectively. Following the discussion of Binder (2015), the distribution of R_{it} for each t is assumed to be a mixture of two probability mass functions (pmfs). The pmfs ϕ_t^L, ϕ_t^H for L-type and H-type, respectively, can be expressed as the discretized normal distributions as follows:

$$\begin{aligned} \phi_t^L &= P(R_{it} = j | i \text{ is L-type}) = \int_{j-0.5}^{j+0.5} \frac{1}{\sqrt{2\pi\sigma_{Lt}^2}} e^{-\frac{(x-\mu_{Lt})^2}{2\sigma_{Lt}^2}} dx, j = \dots 0, 1, 2, \dots \\ \phi_t^H &= P(R_{it} = j | i \text{ is H-type}) = \int_{j-2.5}^{j+2.5} \frac{1}{\sqrt{2\pi\sigma_{Ht}^2}} e^{-\frac{(x-\mu_{Ht})^2}{2\sigma_{Ht}^2}} dx, j = \dots 0, 5, 10, \dots \end{aligned}$$

The density function of 2-component finite mixture can be described:

$$\phi_t(R | \mu_{Ht}, \mu_{Lt}, \sigma_{Ht}^2, \sigma_{Lt}^2, \pi_{Ht}, \pi_{Lt}) = \sum_{kt=Lt, Ht} \pi_{kt} \times \phi_t^k,$$

where π_{kt} is the share of k -type responses ($k = L, H$), with $0 < \pi_{kt} < 1$ and $\sum_{k=L, H} \pi_{kt} = 1$. Denoting the number of observations at t as N_t for the observed prior/posterior responses $\{R_{it}\}_{i=1}^{N_t}$, we estimate the five unknown parameters $\mu_{Ht}, \mu_{Lt}, \sigma_{Ht}, \sigma_{Lt}, \pi_{Ht}$ by maximizing the following likelihood function:

$$\max_{\theta_{jt}, \pi_{Ht}} \ln L_t = \sum_{i=1}^{N_t} \left(\log \left(\sum_{k=L,H} \pi_{kt} \times \phi_t^k \right) \right). \quad (7)$$

As Table 4 indicates, the shares of two types of respondents vary among information groups, particularly with regard to posterior responses. In addition, summary statistics of inflation expectations in Table 1 reveal that the mean and variances of the Normal distributions from which consumers are drawn should be different among information groups. Therefore, we estimate the unknown parameters for each information group. Further, we separately estimate these parameters for control and treatment of each group, assuming our treatment can affect the dynamics of type changes for each respondent before and after the treatment.

Table A2-1 below summarizes the maximum likelihood estimates of mixture distribution parameters from (7), that is, the means (μ_{Ht}, μ_{Lt}) , the standard deviations $(\sigma_{Ht}, \sigma_{Lt})$, the share of H-type respondents π_{Ht} , as well as bootstrap standard errors. In case of prior responses, the means of H-type consumers are slightly greater than those of L-type ones, with standard deviations around the same level. As expected from the previous discussion (see section 3.2), all parameters look similar among information groups.

Posterior means become smaller for both H-type and L-type consumers in groups 1-3 and greater for H-type consumers in groups 4-6. Information treatment actually leads to increased standard deviations for both H and L types, while this change is distinct among posterior H-type treated consumers in groups 1-3. In this regard, one remarkable exception is L-type consumers who are treated in group 3 (BOJ), whose standard deviation diminishes although to a limited extent. Shares of H-type consumers diminish in case of posterior responses for groups 1-3, while it is more distinct among those who are treated. In contrast, these shares increase largely among those in groups 4-6, who are provided with not so relevant inflation-related information.

Table A2 Maximum likelihood estimates of mixture distribution parameters

Government

	mean		sd		share of H-type
	L-type	H-type	L-type	H-type	
prior	6.577 (0.116)	7.343 (0.158)	5.459 (0.183)	5.832 (0.253)	0.385 (0.004)
posterior, all samples	3.889 (0.128)	5.031 (0.235)	6.414 (0.494)	8.138 (0.748)	0.344 (0.004)
posterior, control	4.872 (0.215)	5.891 (0.330)	5.253 (0.253)	5.547 (0.367)	0.371 (0.008)
posterior, treatment	3.562 (0.165)	4.690 (0.317)	6.724 (0.674)	8.880 (1.006)	0.334 (0.005)

BOJ

	mean		sd		share of H-type
	L-type	H-type	L-type	H-type	
prior	6.514 (0.104)	7.188 (0.147)	5.094 (0.160)	5.306 (0.251)	0.387 (0.004)
posterior, all samples	3.753 (0.108)	4.934 (0.195)	5.342 (0.219)	6.441 (0.341)	0.340 (0.005)
posterior, control	5.165 (0.262)	6.096 (0.396)	6.188 (0.458)	6.924 (0.630)	0.380 (0.008)
posterior, treatment	3.276 (0.114)	4.434 (0.215)	4.933 (0.244)	6.152 (0.409)	0.326 (0.005)

Frozen food

	mean		sd		share of H-type
	L-type	H-type	L-type	H-type	
prior	6.768 (0.111)	7.441 (0.158)	5.550 (0.186)	5.966 (0.265)	0.388 (0.004)
posterior, all samples	7.572 (0.156)	8.337 (0.203)	6.674 (0.474)	7.186 (0.623)	0.418 (0.003)
posterior, control	7.893 (0.185)	9.076 (0.241)	6.601 (0.304)	7.015 (0.430)	0.407 (0.006)
posterior, treatment	7.467 (0.154)	8.111 (0.202)	6.694 (0.461)	7.222 (0.603)	0.421 (0.003)

Private

	mean		sd		share of H-type
	L-type	H-type	L-type	H-type	
prior	6.708 (0.122)	7.403 (0.243)	5.381 (0.184)	5.887 (0.282)	0.380 (0.004)
posterior, all samples	4.039 (0.133)	5.544 (0.259)	6.179 (0.426)	7.848 (0.675)	0.332 (0.005)
posterior, control	5.620 (0.288)	6.437 (0.432)	6.711 (0.526)	7.619 (0.748)	0.386 (0.008)
posterior, treatment	3.505 (0.136)	5.121 (0.286)	5.894 (0.504)	7.924 (0.825)	0.311 (0.006)

Noodles

	mean		sd		share of H-type
	L-type	H-type	L-type	H-type	
prior	6.516 (0.109)	7.143 (0.159)	5.385 (0.186)	5.851 (0.275)	0.384 (0.004)
posterior, all samples	7.437 (0.146)	8.133 (0.186)	6.435 (0.558)	6.697 (0.619)	0.412 (0.004)
posterior, control	7.229 (0.265)	8.104 (0.356)	7.137 (0.477)	7.931 (0.626)	0.411 (0.006)
posterior, treatment	7.505 (0.148)	8.144 (0.187)	6.186 (0.560)	6.224 (0.638)	0.412 (0.004)

Ice cream

	mean		sd		share of H-type
	L-type	H-type	L-type	H-type	
prior	6.529 (0.111)	7.169 (0.158)	5.278 (0.186)	5.632 (0.265)	0.390 (0.004)
posterior, all samples	7.765 (0.151)	8.440 (0.183)	6.205 (0.461)	5.968 (0.358)	0.417 (0.004)
posterior, control	7.196 (0.286)	8.413 (0.391)	5.658 (1.144)	5.677 (1.505)	0.401 (0.007)
posterior, treatment	7.961 (0.150)	8.450 (0.179)	6.371 (0.441)	6.056 (0.346)	0.422 (0.004)

Note: Std. errors are estimated from bootstrapping (N=1,000), and are shown in parentheses.

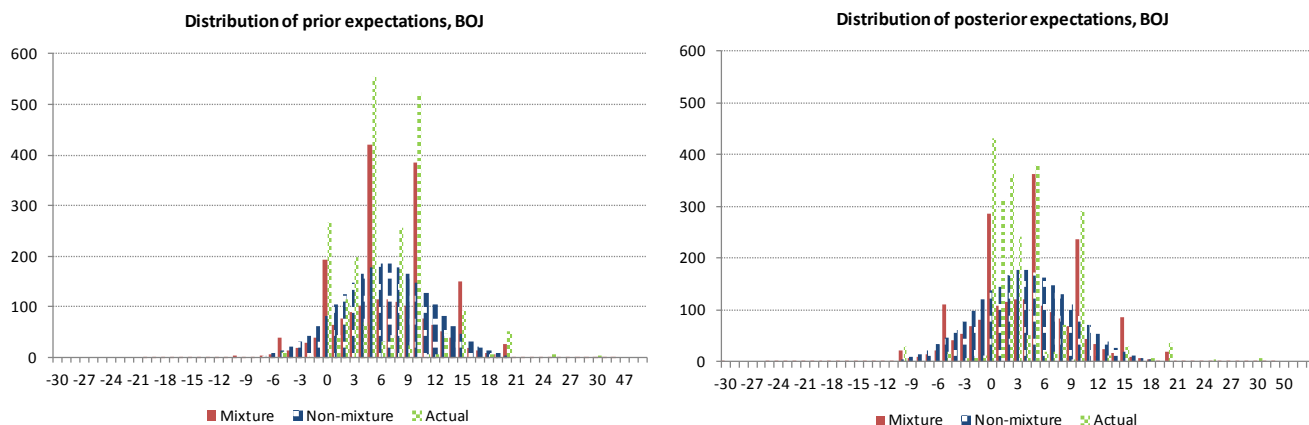
(Testing goodness of model fit)

From Figure 2, we can observe the distribution of inflation expectations responses is more complicated than a simple Normal distribution. We thus apply a mixture model with two types of respondents, assuming people may be characterized by their rounding practices in providing their responses. In this subsection, we formally test goodness of model fit by comparing a simple Normal model with a mixture model, and examine whether we could reject the null hypothesis that the distribution would fit a normal model than a mixture model.

Figure A2 below compares the shape of the histograms for both prior and posterior expectations with the fitted Normal (non-mixture) and mixture models, by using the example of the BOJ group. Table 6 compares the test statistics (Chi-squared statistic and BIC) between mixture and non-mixture

models for prior and posterior expectations of BOJ group.²² All test statistics support mixture models rather than the non-mixture one, which is particularly the case of prior expectations with more distinct peaks at M5 numbers (e.g., 0, 5, 10%) (Table A2-2).

Figure A2 Histogram and fitted distribution (BOJ group)



Note: “Mixture” shows the distribution of fitted mixture model, “Non-mixture” shows the fitted Normal distribution, and “Actual” shows a histogram of survey responses.

Table A2-2 Goodness of fit test results (BOJ group)

prior, BOJ	Mixture	Non-mixture	posterior, BOJ	Mixture	Non-mixture
chi-sq	3.32.E+07	7.12.E+08	chi-sq	2.46.E+03	3.46.E+05
BIC	2,669	5,219	BIC	3,463	4,605

Note: 1. “chi-sq” is the Chi-squared statistic defined as $\chi^2 = \sum_{i=1}^N \frac{(O_i - E_i)^2}{E_i}$, where O_i is the observed frequency for bin i , and E_i is the expected frequency for bin i , which is $E_i = F(x_{i+1}) - F(x_i)$, where F is CDF of the probability distribution of being tested, and x_{i+1} and x_i are limits for bin i .

2. Statistics are calculated by using responses without outliers (i.e., expectations with the absolute values greater than 30), as Chi-squared statistics become infinity because of the very small level of expected frequency for such outliers.

²² Figures and Tables of all information groups are included in the Appendix 3 (Figure A-1 and Table A-6).

Appendix 3 (Tables and Figures)

Table A-1 Summary statistics of respondents' attributes (by group)

	Group						
	All	1	2	3	4	5	6
Treatment group	0.749 (0.433)	0.750 (0.433)	0.747 (0.435)	0.747 (0.435)	0.753 (0.431)	0.754 (0.431)	0.744 (0.436)
Female	0.484 (0.500)	0.477 (0.500)	0.488 (0.500)	0.477 (0.500)	0.487 (0.500)	0.497 (0.500)	0.481 (0.500)
Mortgage	0.272 (0.445)	0.263 (0.440)	0.282 (0.450)	0.267 (0.442)	0.278 (0.448)	0.269 (0.444)	0.271 (0.445)
Age (20s-30s)	0.363 (0.481)	0.354 (0.478)	0.361 (0.480)	0.355 (0.479)	0.371 (0.483)	0.374 (0.484)	0.365 (0.481)
Age (40s-50s)	0.433 (0.496)	0.450 (0.498)	0.437 (0.496)	0.441 (0.497)	0.433 (0.496)	0.418 (0.493)	0.422 (0.494)
Age (60s)	0.203 (0.402)	0.196 (0.397)	0.203 (0.402)	0.204 (0.403)	0.196 (0.397)	0.208 (0.406)	0.213 (0.410)
Not married	0.351 (0.477)	0.360 (0.480)	0.343 (0.475)	0.351 (0.477)	0.365 (0.482)	0.341 (0.474)	0.349 (0.477)
Household annual income per capita (ten thousand JPY)	254.162 (136.444)	258.116 (134.011)	254.094 (135.837)	256.359 (138.289)	254.038 (139.589)	246.813 (131.361)	255.594 (139.214)
Education (high school or below)	0.259 (0.438)	0.256 (0.437)	0.274 (0.446)	0.266 (0.442)	0.259 (0.438)	0.255 (0.436)	0.247 (0.431)
Education (college)	0.284 (0.451)	0.295 (0.456)	0.265 (0.442)	0.279 (0.449)	0.293 (0.455)	0.302 (0.459)	0.270 (0.444)
Education (university or above)	0.456 (0.498)	0.449 (0.497)	0.461 (0.499)	0.455 (0.498)	0.448 (0.497)	0.442 (0.497)	0.483 (0.500)
Number of family members	2.845 (1.288)	2.815 (1.285)	2.843 (1.302)	2.841 (1.314)	2.853 (1.292)	2.872 (1.263)	2.842 (1.271)
Number of children (17 years old or younger)	0.468 (0.816)	0.463 (0.800)	0.470 (0.824)	0.484 (0.839)	0.451 (0.803)	0.487 (0.826)	0.452 (0.803)
Number of observations (N)	14,249	2,356	2,364	2,395	2,396	2,382	2,356

Note: Standard deviations are in parentheses.

Table A-2 Summary statistics of the variables used in the estimation equations (8) and (9)

	Government			Private			BOJ		
	mean	p50	sd	mean	p50	sd	mean	p50	sd
Prior ¹	6.577	5.000	5.481	6.708	5.000	5.403	6.514	5.000	5.117
Posterior ¹	3.889	3.000	6.430	4.039	2.500	6.197	3.753	2.000	5.363
H-type (H) ²	0.385	0.000	0.487	0.377	0.000	0.485	0.388	0.000	0.487
Treatment (T)	0.750	1.000	0.433	0.747	1.000	0.434	0.747	1.000	0.435
H*T	0.287	0.000	0.452	0.276	0.000	0.447	0.294	0.000	0.456
Prior*T	4.953	5.000	5.721	4.857	5.000	5.355	4.824	5.000	5.259
Prior*H	2.896	0.000	5.330	2.868	0.000	5.387	2.873	0.000	5.210
Prior*H*T	2.152	0.000	4.863	2.019	0.000	4.622	2.162	0.000	4.749
Perception gap ³	2.894	1.600	6.148	3.636	3.200	6.865	2.924	1.700	6.185
Perception gap (absolute value), (PG)	4.140	1.600	5.389	4.690	3.200	6.193	4.098	1.700	5.478
PG*T	3.125	1.400	5.189	3.502	0.200	5.764	3.056	0.700	5.061
Prior*PG	34.821	10.500	72.369	42.205	12.800	92.359	35.813	8.500	76.519
Prior*PG* T	26.537	4.200	68.608	31.040	1.800	81.602	26.330	3.400	67.175
Subjective standard deviation (Sd) ⁴	6.376	6.368	4.218	6.524	6.500	4.098	6.520	6.452	4.173
Sd*T	4.819	4.461	4.599	4.799	4.366	4.485	4.910	4.684	4.634
Prior*Sd	51.689	31.488	63.734	52.932	33.440	62.748	51.406	33.750	59.377
Prior*Sd*T	39.425	12.297	62.080	7.325	0.000	28.909	7.242	0.000	27.595
Number of observations	117,800			118,200			119,750		

	Noodle			Frozen food			Ice cream		
	mean	p50	sd	mean	p50	sd	mean	p50	sd
Prior ¹	6.516	5.000	5.407	6.768	5.000	5.572	6.529	5.000	5.301
Posterior ¹	7.437	7.000	6.451	7.571	7.000	6.691	7.765	8.000	6.224
H-type (H) ²	0.382	0.000	0.486	0.387	0.000	0.487	0.390	0.000	0.488
Treatment (T)	0.753	1.000	0.431	0.754	1.000	0.431	0.744	1.000	0.436
H*T	0.289	0.000	0.453	0.294	0.000	0.455	0.292	0.000	0.455
Prior*T	4.954	5.000	5.504	5.012	5.000	5.538	4.900	5.000	5.514
Prior*H	2.781	0.000	5.257	2.961	0.000	5.453	3.139	0.000	5.625
Prior*H*T	2.142	0.000	4.760	2.186	0.000	4.802	2.371	0.000	5.128
Perception gap ³	1.405	0.000	4.426	1.423	0.000	4.703	-0.622	0.000	5.229
Perception gap (absolute value), (PG)	2.294	1.000	4.038	1.941	0.000	4.514	3.204	3.000	4.180
PG*T	1.722	1.000	3.522	1.424	0.000	3.886	2.396	0.000	3.990
Prior*PG	21.221	5.000	61.115	21.171	0.000	76.438	22.865	2.500	63.015
Prior*PG* T	16.023	0.000	50.730	16.007	0.000	71.417	17.835	0.000	60.591
Subjective standard deviation (Sd) ⁴	6.396	6.422	4.086	6.606	6.472	4.151	6.278	6.224	4.229
Sd*T	4.836	4.630	4.493	4.945	4.704	4.580	4.655	3.746	4.544
Prior*Sd	50.823	31.342	63.709	54.636	33.945	65.932	50.728	31.686	63.090
Prior*Sd*T	8.723	0.000	33.340	8.852	0.000	31.854	7.257	0.000	26.642
Number of observations	119,800			119,100			117,800		

Note: 1. "Prior" means expectations prior to information treatment. "Posterior" means expectations posterior to information treatment.

Range responses are transformed into point estimates by taking mid-values of the ranges.

2. H-type indicates the type of respondents who formed prior expectations in a rough manner.

We estimate the statistics related to H-type by bootstrapping (N=50). Thus the number of observations is 50 times the number of original observations.

3. Perception gap is equal to subjective information prior subtracted by true measure of treatment information.

4. Subjective standard deviation is estimated by using the responses on subjective probabilities for future inflation levels.

Table A-3 Supplementary results of Bayesian updating with information measures (1)

	Government			Private			BOJ		
	(5)	(6)	(7)	(5)	(6)	(7)	(5)	(6)	(7)
Prior	0.180 *** (0.029)	0.355 *** (0.027)	0.108 (0.088)	0.125 * (0.075)	-0.0497 (0.054)	-0.180 (0.295)	-0.003 (0.026)	0.284 *** (0.040)	0.0641 (0.105)
T	-1.026 *** (0.233)	-0.300 (0.201)	-1.258 *** (0.450)	-2.630 *** (0.255)	-1.988 *** (0.223)	-2.707 ** (1.077)	-2.826 *** (0.166)	-1.364 *** (0.129)	-2.518 *** (0.494)
Prior*T	0.000800 (0.050)	-0.236 *** (0.043)	-0.0496 (0.119)	-0.00783 (0.081)	0.0775 (0.062)	0.134 (0.306)	0.249 *** (0.039)	-0.067 (0.047)	0.0640 (0.117)
Information measure									
1) Type									
Prior*High	-0.0362 (0.044)	-0.0286 (0.046)		0.0589 (0.116)	0.0316 (0.106)		0.087 * (0.045)	0.036 (0.082)	
Prior*High*T	0.103 (0.091)	0.0828 (0.093)		0.008 (0.131)	0.0149 (0.122)		-0.135 ** (0.065)	-0.101 (0.091)	
High*T	-0.250 (0.536)	-0.206 (0.519)		-0.362 (0.426)	-0.154 (0.442)		0.341 (0.324)	0.494 * (0.254)	
2) Perception gap									
Prior*PG	0.0407 *** (0.000)		0.0401 *** (0.009)	0.0168 *** (0.001)		0.0165 ** (0.007)	0.0451 *** (0.001)		0.0449 *** (0.00559)
Prior*PG*T	-0.0367 *** (0.001)		-0.0513 *** (0.011)	-0.0231 *** (0.001)		-0.0126 (0.008)	-0.0577 *** (0.001)		-0.0441 *** (0.00755)
PG*T	0.166 *** (0.006)		0.486 *** (0.061)	0.389 *** (0.005)		0.365 *** (0.046)	0.420 *** (0.003)		0.424 *** (0.0492)
3) Subjective standard deviation									
Prior*Sd		0.0129 *** (0.001)	0.00515 (0.007)		0.0330 *** (0.002)	0.0334 (0.022)		0.0205 *** (0.001)	-0.00187 (0.00856)
Prior*Sd*T		-0.00119 (0.002)	0.0154 (0.014)		-0.0173 *** (0.002)	-0.0194 (0.025)		-0.0187 *** (0.001)	0.00220 (0.0109)
Sd*T		0.0571 *** (0.008)	-0.0348 (0.066)		0.084 *** (0.006)	0.0177 (0.092)		0.159 *** (0.005)	0.0855 * (0.0457)
R-squared	0.127	0.093	0.241	0.162	0.094	0.233	0.260	0.143	0.373
Number of observations		2,356			2,364			2,395	

Note: Model (1),(4): Bootstrap standard errors are in parentheses (100 times). R squared is an average value of the results from bootstrapping. ***, **, * indicates statistical significance at 1%, 5%, and 10% level, respectively.

Prior means prior expectations, High means dummy of H-type respondents. PG stands for absolute values of perception gap. Sd is subjective standard deviation, estimated from subjective probabilities.

T is treatment.

Constant terms are included in all specifications.

	Noodle			Frozen food			Ice cream		
	(5)	(6)	(7)	(5)	(6)	(7)	(5)	(6)	(7)
Prior	0.368 *** (0.043)	0.468 *** (0.034)	0.336 *** (0.115)	0.374 *** (0.044)	0.393 *** (0.036)	0.232 ** (0.118)	0.395 *** (0.024)	0.331 *** (0.023)	0.261 ** (0.104)
T	-0.066 (0.261)	-0.098 (0.218)	-0.0470 (0.651)	0.149 (0.292)	-0.197 (0.278)	-1.090 * (0.646)	1.415 *** (0.249)	0.409 ** (0.208)	2.188 *** (0.538)
Prior*T	-0.003 (0.061)	-0.025 (0.049)	-0.0441 (0.149)	-0.046 (0.065)	-0.096 (0.060)	0.0940 (0.143)	-0.024 (0.049)	-0.017 (0.045)	-0.0720 (0.127)
Information measure									
1) Type									
Prior*High	-0.008 (0.068)	-0.052 (0.077)		0.039 (0.072)	0.034 (0.064)		0.040 (0.032)	0.062 * (0.032)	
Prior*High*T	-0.046 (0.105)	0.030 (0.104)		0.029 (0.117)	0.057 (0.116)		0.001 (0.076)	0.014 (0.080)	
High*T	0.549 (0.512)	0.438 (0.514)		-0.389 (0.597)	-0.470 (0.613)		0.083 (0.491)	-0.179 (0.510)	
2) Perception gap									
Prior*PG	0.0354 *** (0.001)		0.0352 *** (0.0120)	0.0409 *** (0.001)		0.0400 *** (0.0109)	0.0347 *** (0.000)		0.0336 *** (0.0111)
Prior*PG*T	-0.0424 *** (0.001)		-0.0513 *** (0.0143)	-0.0412 *** (0.001)		-0.0475 *** (0.0155)	-0.0321 *** (0.001)		-0.0420 *** (0.0128)
PG*T	0.475 *** (0.008)		0.727 *** (0.0751)	0.452 *** (0.007)		0.681 *** (0.134)	0.000 (0.004)		0.552 *** (0.0645)
3) Subjective standard deviation									
Prior*Sd		0.0167 *** (0.001)	0.00257 (0.00912)		0.0199 *** (0.001)	0.0162 * (0.00863)		0.0199 *** (0.000)	0.0173 (0.0131)
Prior*Sd*T		-0.0277 *** (0.002)	-0.00713 (0.0143)		-0.0128 *** (0.001)	-0.0239 * (0.0137)		-0.0227 *** (0.001)	-0.0131 (0.0162)
Sd*T		0.244 *** (0.007)	0.150 ** (0.0610)		0.214 *** (0.008)	0.240 *** (0.0628)		0.245 *** (0.012)	0.133 ** (0.0605)
R-squared	0.217	0.159	0.295	0.277	0.217	0.339	0.167	0.175	0.317
Number of observations		2,396			2,382			2,356	

Note: Model (1),(4): Bootstrap standard errors are in parentheses (100 times). R squared is an average value of the results from bootstrapping. ***, **, * indicates statistical significance at 1%, 5%, and 10% level, respectively.

Prior means prior expectations, High means dummy of H-type respondents. PG stands for absolute values of perception gap. Sd is subjective standard deviation, estimated from subjective probabilities.

T is treatment.

Constant terms are included in all specifications.

Table A-4 Correlation between perception gaps and posterior expectations

	Total	Government	Private	BOJ	Noodle	Frozen food	Ice cream
Correlation between perception gaps and posterior expectations (p-value)	0.411 (0.000)	0.456 (0.000)	0.486 (0.000)	0.588 (0.000)	0.536 (0.000)	0.516 (0.000)	0.538 (0.000)
Number of observations	14,249	2,356	2,364	2,395	2,396	2,382	2,356

Table A-5 Supplementary results of Bayesian updating with information measures (2)

	Government							Private							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Prior	0.364 *** (0.026)	0.289 *** (0.061)	0.239 *** (0.063)	0.221 *** (0.022)	0.301 *** (0.025)	0.265 *** (0.022)	0.194 ** (0.0822)	0.183 *** (0.060)	0.235 ** (0.109)	-0.0944 (0.223)	-0.0367 (0.038)	0.240 *** (0.057)	-0.101 *** (0.039)	-0.0296 (0.183)	
T	-0.120 (0.232)	-0.00773 (0.488)	0.0130 (0.411)	-0.128 (0.180)	-0.467 ** (0.221)	0.149 (0.187)	-0.271 (0.470)	-1.308 *** (0.225)	-1.431 ** (0.686)	-1.481 * (0.878)	-0.807 *** (0.203)	-0.541 ** (0.239)	-1.399 *** (0.195)	-0.892 (0.818)	
Prior*T	-0.213 *** (0.048)	-0.0640 (0.092)	-0.248 ** (0.104)	-0.186 *** (0.038)	-0.078 * (0.046)	-0.297 *** (0.039)	-0.135 (0.114)	-0.0594 (0.066)	-0.124 (0.112)	0.0517 (0.237)	-0.0210 (0.050)	-0.156 ** (0.065)	0.0489 (0.049)	-0.0160 (0.201)	
Information measure															
1) Type															
Prior*High	-0.0385 (0.037)			-0.0492 (0.037)	-0.0426 (0.037)	-0.0463 (0.036)			0.0571 (0.094)			0.0349 (0.077)	0.0569 (0.090)	0.0349 (0.080)	
Prior*High*T	0.104 (0.088)			0.109 (0.083)	0.112 (0.084)	0.103 (0.086)			-0.0406 (0.110)			-0.0112 (0.101)	-0.0370 (0.110)	-0.0162 (0.101)	
High*T	-0.149 (0.508)			-0.177 (0.480)	-0.157 (0.490)	-0.173 (0.497)			-0.171 (0.396)			-0.241 (0.427)	-0.178 (0.422)	-0.225 (0.408)	
2) Perception gap															
Prior*PG	0.00348 (0.009)				0.00741 *** (0.000)	0.00837 *** (0.000)	0.00732 (0.011)		-0.00183 (0.006)		-0.0105 *** (0.000)		-0.0104 *** (0.001)	-0.0104 (0.007)	
Prior*PG*T	-0.00601 (0.011)				-0.0187 *** (0.001)	-0.0194 *** (0.001)	-0.0185 (0.013)		0.00192 (0.009)		0.0144 *** (0.001)		0.0153 *** (0.001)	0.0143 * (0.00770)	
PG*T	-0.150 * (0.090)				0.0380 *** (0.003)	0.0390 *** (0.003)	0.0381 (0.113)		0.0617 (0.100)		-0.200 *** (0.004)		-0.205 *** (0.005)	-0.201 (0.135)	
3) Subjective standard deviation															
Prior*Sd			0.0100 (0.006)	0.00921 *** (0.001)		0.0106 *** (0.001)		0.00859 (0.006)				0.0306 *** (0.017)	0.0287 *** (0.001)	0.0294 *** (0.001)	0.0297 *** (0.015)
Prior*Sd*T			0.00965 (0.013)	0.0104 *** (0.001)		0.00811 *** (0.001)		0.0119 (0.014)				-0.0134 (0.020)	-0.0148 *** (0.002)	-0.0122 *** (0.002)	-0.0158 (0.018)
Sd*T			-0.0287 (0.065)	-0.0308 *** (0.007)		-0.0247 *** (0.008)		-0.0348 (0.066)				-0.00484 (0.094)	0.0193 *** (0.006)	-0.004 (0.006)	0.0177 (0.092)
Perception gap	0.435 *** (0.001)	0.510 *** (0.056)	0.435 *** (0.043)	0.448 *** (0.002)	0.445 *** (0.002)	0.435 *** (0.001)	0.448 *** (0.095)	0.414 *** (0.001)	0.393 *** (0.047)	0.409 *** (0.042)	0.565 *** (0.004)	0.571 *** (0.004)	0.409 *** (0.001)	0.566 *** (0.127)	
	0.252	0.261	0.255	0.264 2,356	0.259	0.257	0.262	0.278	0.278	0.287	0.296 2,364	0.286	0.289	0.294	

Note: Model (1),(4): Bootstrap standard errors are in parentheses (100 times). R squared is an average value of the results from bootstrapping.

***, **, * indicates statistical significance at 1%, 5%, and 10% level, respectively.

Prior means prior expectations, High means dummy of H-type respondents. PG stands for absolute values of perception gap. Sd is subjective standard deviation, estimated from subjective probabilities.

T is treatment.

Constant terms are included in all specifications.

	BOJ							Noodle								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)		
Prior	0.347 *** (0.036)	0.126 * (0.065)	0.259 *** (0.091)	0.113 *** (0.022)	0.105 *** (0.026)	0.241 *** (0.031)	0.144 (0.092)	0.421 *** (0.035)	0.370 *** (0.072)	0.394 *** (0.090)	0.378 *** (0.026)	0.371 *** (0.036)	0.398 *** (0.025)	0.378 *** (0.091)		
T	-0.576 *** (0.153)	-1.494 *** (0.455)	-0.806 * (0.455)	-1.476 *** (0.136)	-1.187 *** (0.144)	-1.010 *** (0.143)	-1.251 *** (0.489)	1.333 *** (0.217)	1.472 *** (0.427)	0.474 (0.528)	0.292 (0.184)	0.919 *** (0.220)	0.287 * (0.172)	0.479 (0.537)		
Prior*T	-0.157 *** (0.043)	0.0598 (0.076)	-0.135 (0.104)	0.0432 (0.033)	0.086 ** (0.035)	-0.089 ** (0.040)	-0.0154 (0.106)	-0.184 *** (0.048)	-0.102 (0.078)	-0.116 (0.131)	-0.0651 * (0.039)	-0.04982 (0.050)	-0.0949 ** (0.037)	-0.0868 (0.131)		
Information measure																
1) Type																
Prior*High	0.0400 (0.063)			0.0622 (0.045)	0.0616 (0.044)	0.0372 (0.063)			-0.00662 (0.057)			0.00135 (0.059)	0.000795 (0.058)	-0.00882 (0.058)		
Prior*High*T	-0.101 (0.076)			-0.115 * (0.062)	-0.125 ** (0.060)	-0.089 (0.077)			-0.0611 (0.083)			-0.0493 (0.085)	-0.0568 (0.086)	-0.0474 (0.081)		
High*T	0.502 * (0.301)			0.412 (0.299)	0.516 * (0.287)	0.407 (0.311)			0.649 (0.437)			0.527 (0.431)	0.621 (0.445)	0.541 (0.413)		
2) Perception gap																
Prior*PG	0.0247 *** (0.006)				0.0216 *** (0.001)	0.0214 *** (0.001)	0.0212 *** (0.008)		0.00137 (0.009)		0.00204 *** (0.000)		0.00198 *** (0.000)		0.00198 (0.010)	
Prior*PG*T	-0.0322 *** (0.010)				-0.0209 *** (0.001)	-0.0205 *** (0.001)	-0.0204 *** (0.009)		-0.0125 (0.011)		-0.0182 *** (0.001)		-0.0195 *** (0.001)		-0.0181 (0.012)	
PG*T	0.134 (0.100)				-0.0689 *** (0.003)	-0.0633 *** (0.003)	-0.0711 (0.101)		-0.141 (0.106)		-0.0562 *** (0.004)		-0.0366 *** (0.005)		-0.0567 (0.227)	
3) Subjective standard deviation																
Prior*Sd			0.0109 (0.009)	-0.000948 (0.001)		0.0106 *** (0.001)		0.000356 (0.007)				0.00227 (0.008)	-0.000816 (0.001)		0.00251 ** (0.001)	0.000881 (0.008)
Prior*Sd*T			-0.0100 (0.011)	0.00152 * (0.001)		-0.0096 *** (0.001)		0.000686 (0.010)				-0.0149 (0.013)	-0.00340 ** (0.001)		-0.0148 *** (0.001)	-0.00368 (0.014)
Sd*T			0.0749 (0.046)	0.0811 *** (0.004)		0.0712 *** (0.004)		0.0855 * (0.046)				0.196 *** (0.053)	0.144 *** (0.006)		0.191 *** (0.006)	0.150 ** (0.061)
Perception gap	0.472 *** (0.001)	0.421 *** (0.046)	0.466 *** (0.040)	0.494 *** (0.003)	0.494 *** (0.003)	0.466 *** (0.001)	0.495 *** (0.089)	0.672 *** (0.002)	0.797 *** (0.102)	0.665 *** (0.069)	0.784 *** (0.003)	0.784 *** (0.003)	0.665 *** (0.002)	0.784 *** (0.002)	0.784 *** (0.214)	
	0.414	0.432	0.415	0.433 2,395	0.430	0.417	0.431	0.334	0.344	0.338	0.348 2,396	0.344	0.340	0.346		

Note: Model (1),(4): Bootstrap standard errors are in parentheses (100 times). R squared is an average value of the results from bootstrapping.

***, **, * indicates statistical significance at 1%, 5%, and 10% level, respectively.

Prior means prior expectations, High means dummy of H-type respondents. PG stands for absolute values of perception gap. Sd is subjective standard deviation, estimated from subjective probabilities.

T is treatment.

Constant terms are included in all specifications.

	Frozen food							Ice cream								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)		
Prior	0.473 *** (0.042)	0.561 *** (0.084)	0.316 *** (0.088)	0.318 *** (0.038)	0.493 *** (0.042)	0.298 *** (0.038)	0.338 *** (0.099)	0.353 *** (0.025)	0.365 *** (0.052)	0.255 *** (0.087)	0.219 *** (0.021)	0.334 *** (0.024)	0.232 *** (0.022)	0.238 *** (0.085)		
T	1.389 *** (0.290)	1.793 *** (0.567)	-0.355 (0.569)	-0.109 (0.256)	0.0370 (0.068)	0.0316 (0.069)	-0.256 (0.583)	1.682 *** (0.217)	1.982 *** (0.525)	0.923 ** (0.454)	0.940 *** (0.182)	0.0410 (0.031)	0.0332 (0.031)	0.926 * (0.559)		
Prior*T	-0.213 *** (0.065)	-0.250 *** (0.097)	0.00789 (0.118)	-0.0288 (0.059)	-0.191 *** (0.065)	-0.0097 (0.058)	-0.0113 (0.128)	-0.138 *** (0.042)	-0.119 (0.073)	-0.0828 (0.112)	-0.0504 (0.037)	-0.0723 * (0.043)	-0.0777 ** (0.036)	-0.0493 (0.112)		
Information measure																
1) Type																
Prior*High	0.0366 (0.069)			0.0318 (0.069)	0.0214 (0.117)	0.0412 (0.113)			0.0471 (0.030)			0.0283 (0.032)	-0.0196 (0.068)	0.0002 (0.066)		
Prior*High*T	0.0162 (0.114)			0.0434 (0.115)	1.226 *** (0.293)	-0.212 (0.247)			-0.0361 (0.064)			0.00973 (0.070)	1.535 *** (0.225)	0.908 *** (0.177)		
High*T	-0.212 (0.560)			-0.433 (0.568)	-0.252 (0.582)	-0.413 (0.548)			0.067 (0.440)			-0.159 (0.471)	-0.0270 (0.459)	-0.0980 (0.455)		
2) Perception gap																
Prior*PG			-0.0202 * (0.011)			-0.00476 *** (0.001)	0.594 *** (0.005)	0.589 *** (0.002)	-0.00498 (0.015)			0.00437 (0.014)	0.00331 *** (0.000)	0.562 *** (0.001)	0.534 *** (0.001)	0.00369 (0.014)
Prior*PG*T			0.0176 (0.015)			-0.00297 *** (0.001)	-0.0038 *** (0.001)			-0.00257 (0.018)			-0.00722 (0.016)	-0.0118 *** (0.001)	0.00411 *** (0.000)	-0.0121 (0.015)
PG*T			-0.257 (0.157)			0.0837 *** (0.007)	-0.0062 *** (0.001)			0.0827 (0.232)			-0.109 (0.107)	-0.00576 *** (0.002)	-0.0131 *** (0.001)	-0.00428 (0.091)
3) Subjective standard deviation																
Prior*Sd			0.0172 ** (0.008)	0.0174 *** (0.001)	0.116 *** (0.007)			0.0176 ** (0.008)			0.0141 (0.010)	0.0132 *** (0.000)	-0.00028 (0.002)			0.0135 (0.010)
Prior*Sd*T			-0.0288 ** (0.011)	-0.0254 *** (0.001)			0.0170 *** (0.001)	-0.0253 * (0.013)			-0.0141 (0.014)	-0.00964 *** (0.001)			0.0137 *** (0.000)	-0.00926 (0.014)
Sd*T			0.271 *** (0.049)	0.243 *** (0.007)			-0.0290 *** (0.001)	0.240 *** (0.063)			0.164 *** (0.058)	0.139 *** (0.010)			-0.0143 *** (0.001)	0.133 ** (0.061)
Perception gap	0.591 *** (0.002)	0.810 *** (0.116)	0.590 *** (0.070)	0.597 *** (0.004)			0.275 *** (0.008)	0.598 *** (0.190)	0.545 *** (0.001)	0.568 *** (0.051)	0.536 *** (0.054)	0.556 *** (0.001)			0.169 *** (0.010)	0.556 *** (0.064)
	0.348	0.354	0.359	0.364	0.352	0.361	0.361	0.340	0.346	0.348	0.353	0.345	0.349	0.352		
				2,382							2,356					

Note: Model (1),(4): Bootstrap standard errors are in parentheses (100 times). R squared is an average value of the results from bootstrapping.

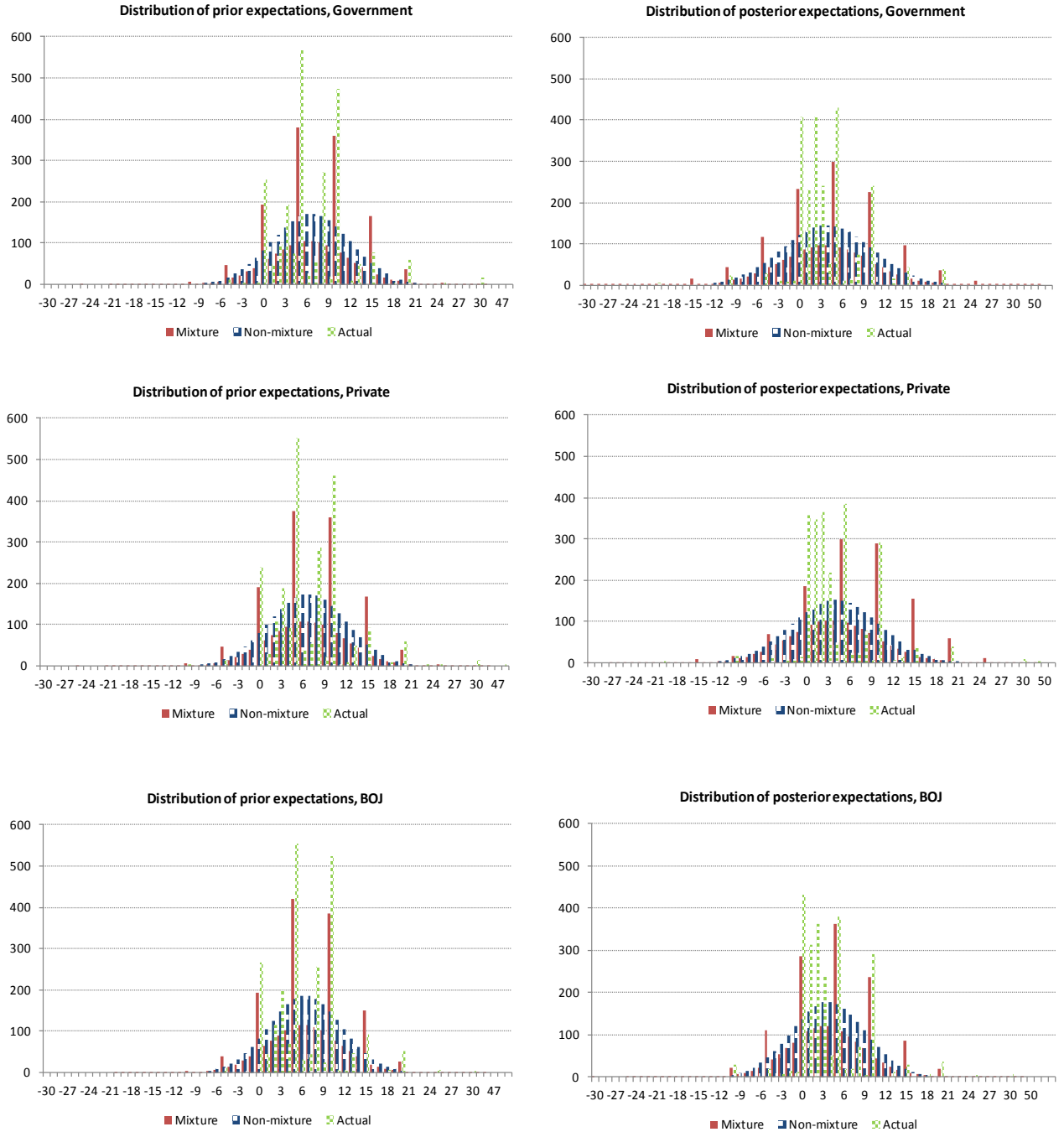
***, **, * indicates statistical significance at 1%, 5%, and 10% level, respectively.

Prior means prior expectations, High means dummy of H-type respondents. PG stands for absolute values of perception gap. Sd is subjective standard deviation, estimated from subjective probabilities.

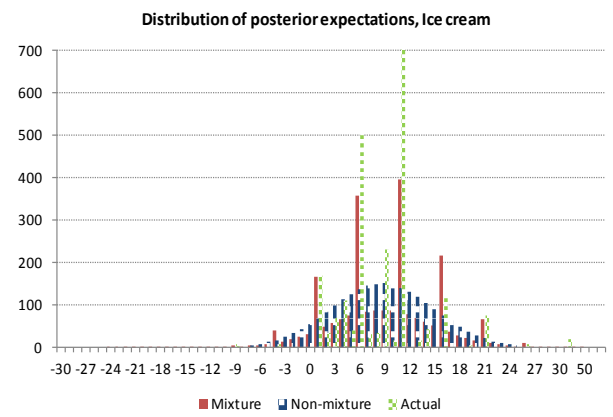
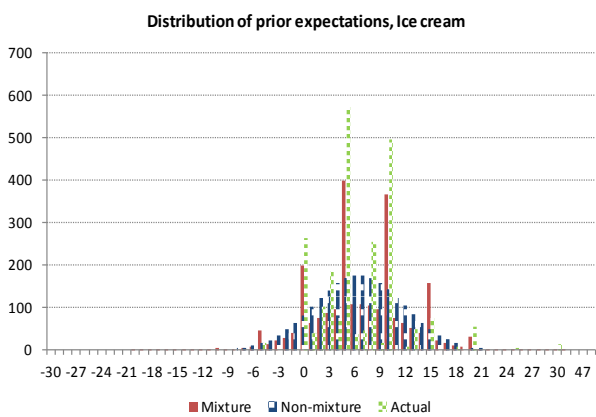
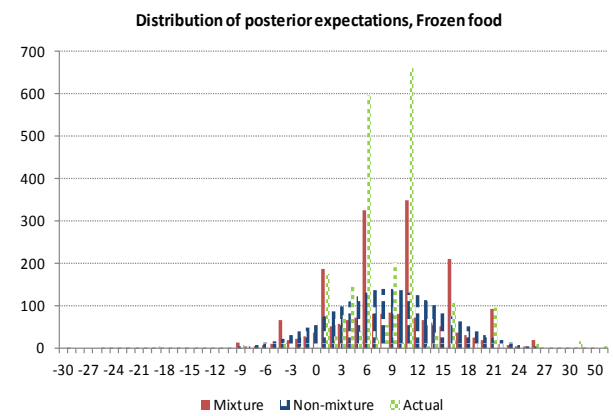
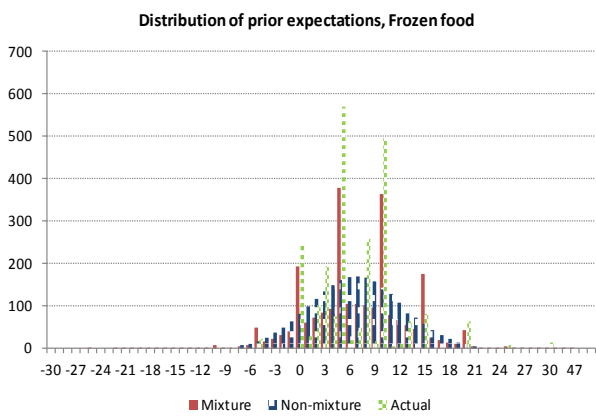
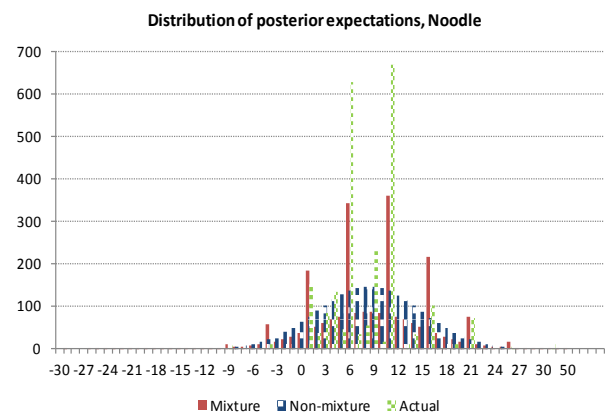
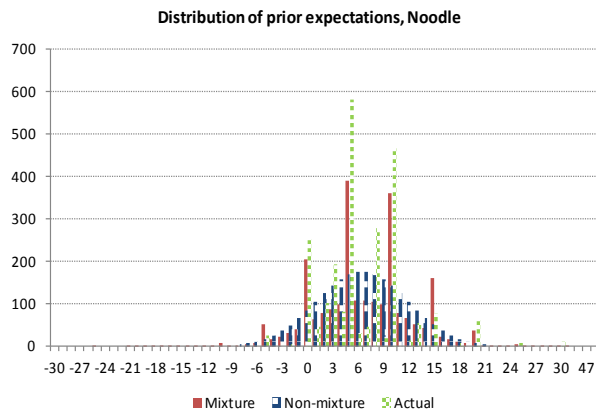
T is treatment

Constant terms are included in all specifications.

Figure A-1 Fitted mixture models
(all information groups, prior and posterior expectations)



Note: "Mixture" shows the distribution of fitted mixture model, "Non-mixture" shows that of fitted Normal distribution, and "Actual" shows a histogram of survey responses.



Note: “Mixture” shows the distribution of fitted mixture model, “Non-mixture” shows that of fitted Normal distribution, and “Actual” shows a histogram of survey responses.

**Table A-6 Goodness of model fit test results
(all information groups, prior and posterior expectations)**

prior, Government	Mixture	Non-mixture	posterior, Government	Mixture	Non-mixture
chi-sq	2.36E+03	2.06E+04	chi-sq	2.52.E+03	1.22.E+04
BIC	2,862	5,083	BIC	3,805	4,792
prior, Private	Mixture	Non-mixture	posterior, Private	Mixture	Non-mixture
chi-sq	2.08.E+03	2.13.E+04	chi-sq	2.56.E+03	3.41.E+04
BIC	2,783	4,924	BIC	3,713	4,581
prior, BOJ	Mixture	Non-mixture	posterior, BOJ	Mixture	Non-mixture
chi-sq	3.32.E+07	7.12.E+08	chi-sq	2.46.E+03	3.46.E+05
BIC	2,669	5,219	BIC	3,463	4,605
prior, Noodle	Mixture	Non-mixture	posterior, Noodle	Mixture	Non-mixture
chi-sq	1.61.E+03	1.20.E+04	chi-sq	1.58.E+03	6.58.E+03
BIC	2,851	5,114	BIC	3,907	6,287
prior, Frozen food	Mixture	Non-mixture	posterior, Frozen food	Mixture	Non-mixture
chi-sq	1.82E+03	1.25E+04	chi-sq	1.71.E+03	7.11.E+03
BIC	2,912	5,193	BIC	3,824	6,167
prior, Ice cream	Mixture	Non-mixture	posterior, Ice cream	Mixture	Non-mixture
chi-sq	2.58.E+03	2.79.E+04	chi-sq	1.72.E+03	9.05.E+03
BIC	2,748	5,169	BIC	3,662	6,288

Note: 1. “chi-sq” is the Chi-squared statistic defined as $\chi^2 = \sum_{i=1}^N \frac{(O_i - E_i)^2}{E_i}$, where O_i is the observed frequency for bin i , and E_i is the expected frequency for bin i , which is $E_i = F(x_{i+1}) - F(x_i)$, where F is CDF of the probability distribution of being tested, and x_{i+1} and x_i are limits for bin i .

2. Statistics are calculated by using responses without outliers (i.e., expectations with the absolute values greater than 30), as Chi-squared statistics become infinity because of the very small level of expected frequency for such outliers.