Updating Behavior of Inflation Expectations:
Evidence from Japanese Household Panel Data
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Abstract

This study provides insights into the expectation-updating behavior of Japanese households with regard to future inflation. Households do not renew their information set in every period, but they do so at a greater frequency than that argued in the literature. A more volatile inflation rate leads to improved accuracy vis-à-vis expectations, given higher attention levels—although greater volatility does make it more difficult to form precise forecasts. Additionally, the estimation results involving inflation reflect variation in consumption basket by household attributes and are consistent; these results are clearer than those involving the consumer price index, thus indicating the possibility that households indeed face variations in inflation rate, depending on their characteristics.

Keywords: Inflation, survey expectations, information stickiness, rational inattention, forecast error.

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1. Introduction

Attention has been called in Japan to the role of expectations in the economy, ever since the start of the Abe administration in 2012. Expectations for the future matter considerably in the principal decisions of economic agents, including in decisions pertaining to household consumption or savings, labor supply, and firms' pricing. Although important, expectations have not been analyzed directly in the literature, as their formation process is neither clear nor easily modeled; additionally, it is difficult to analyze their link to the real economy, particularly at the micro level.

In order to fill this gap in the literature, this study examines behavior pertaining to inflation expectations among Japanese households. It aims to identify the major motivations that trigger updating behavior vis-à-vis expectations at the individual-household level, using micro-level survey data[1]. Furthermore, it explores the macro and microeconomic factors that affect the accuracy of expectations as seen in updating behaviors.

This study has five major findings. First, as recent theoretical models have predicted, information about macroeconomic conditions diffuses slowly through the population; households, however, seem to update their expectations more frequently than previous studies have indicated. Second, the volatility of realized inflation in recent periods seems to affect the updating frequency positively; this finding is consistent with theoretical expectations that indicate that past volatility leads to higher attentiveness toward inflation development. This positive relationship is more distinct with regard to downward revisions; it is also more distinct among the lowest-income groups, in both upward and downward revisions. Third, respondents who updated their expectations more frequently generally became more accurate than those who did not. There is also evidence that persistence in forecast errors is quite limited, indicating that the error converges to zero in the very long term, while each update does not necessarily improve accuracy (i.e., updating in a staggered fashion). Fourth, at the beginning of the survey, a learning effect that connects greater attentiveness to more accurate forecasts exists, but this effect disappears after several survey waves. Finally, by using inflation data that reflect variation in the consumption basket by household income, this study derives results that show that past inflation volatility leads to expectations that are more accurate than those expected by theory. This may imply that inflation as observed by heterogeneous households indeed varies, and forecast errors should be derived based on inflation rates that reflect the main household attributes (e.g., income or age

[1] The micro-level dataset employed in this study has been provided by the Cabinet Office, Government of Japan under the framework set forth by the Statistics Law.

composition). On the other hand, once lagged forecast errors are controlled for, the negative relationship between past volatility and forecast errors is no longer clear. Such unstable results may be explained by the fact that households find it more difficult to form accurate expectations in a volatile period, despite their attention levels being higher than that in a stable period.

1.1 Literature review

The empirical analysis undertaken in this study has a basis in two major theoretical pricing models. The first is the sticky-information model introduced by Mankiw and Reis (2002). The essence of that model is that information about macroeconomic conditions diffuses sluggishly through the population, because of the cost of information acquisition or of reoptimization. The rigidity of this model is found in the probability of not updating new information for each period, despite the fact that prices change in every period. The second one is the noisy-information model of Mackowiak and Wiederholt (2009), in which agents receive information every period, but they need to decide whether they should focus on it carefully or less carefully, given finite attention and time. This latter model implies that agents update expectations in every period, but responses to new shocks are sticky and depend on the level of attention allocated to them.

One strand of research empirically analyzes the updating behaviors of economic agents with respect to their expectations; it also looks for evidence of information friction, as proposed by the theoretical model of Mankiw and Reis (2002). This research has been undertaken by Carroll (2003) and Coibion and Gorodnichenko (2012), each of whom find supportive evidence in the case of US households, and by Hori and Kawagoe (2011), for Japanese households. Overall, the empirical literature provides evidence of information friction.

The model of Mackowiak and Wiederholt (2009) has been extended into the discussion of Drager and Lamla (2013) on expectation-updating behavior vis-à-vis inflation expectations. Through this extension, they derive several empirical hypotheses with regard to the relationships between volatility measures and expectation-updating behavior.

Another strand of relevant literature is that which analyzes the relationships between expectations and household attributes. It is natural to expect that there are certain relationships, as inflation expectations should closely association with consumption decisions—the latter of which will vary in line with household characteristics (e.g., income level, or the ages of household members). Among other factors, income level has been found to negatively correlate with expectation levels in many countries, including Japan (e.g., Bryan and Venkatu (2001) and Pfajfar and Santoro (2008) for the United States, Blanchflower and MacCoille (2009) for the United Kingdom, and Malgarini (2008) for Italy). This result is intuitive and easily interpreted: households with lower incomes usually have higher consumption propensities and lower wealth, and so they are often more responsive to possible signs of future inflation.

Based on a discussion of literature, the contribution of the current study can be summarized as follows. (1) Using a new dataset, it undertakes a thorough analysis of expectation updating and of the background of various expectation levels. No study within the literature uses a panel dataset with a sufficiently long time-horizon to analyze the frequency of updates or any convergence in expectation level. (2) It undertakes dynamic analysis that takes into account both information rigidity and possible persistence in expectation levels. (3) It undertakes detailed analysis by income group or by several indicators of "realized inflation," to examine the accuracy of expectations. The results of detailed micro-level analysis provide support for the assertion that there is a deviation in rational expectations with respect to households' inflation expectations.

2. Model

This section introduces two models derived from the literature. The first is the model of information rigidity argued by Mankiw and Reis (2002). The current study, meanwhile, follows the formulation of Coibion and Gorodnichenko (2012) (henceforth CG).

In the model of Mankiw and Reis (2002), agents are inattentive and they update their information sets in each period with a probability of $(1-\delta)$; however, they do not acquire new information with a probability of δ, and so δ is an indicator of information rigidity. The average forecast of the *h*-period ahead *x* at time *t*, $F_t x_{t+h}$, is a weighted average of the current and past full-information rational expectations of the *h*-period ahead *x* at time *t*, $E_t x_{t+h}$. Thus, at period *t*, the current average forecast can be expressed as a weighted average of the full-information rational expectation at period *t* and the average forecast at period *t* – 1, as follows:

$$F_t x_{t+h} = (1-\delta) E_t x_{t+h} + \delta F_{t-1} x_{t+h}. \quad (1)$$

$F_t x_{t+h}$: average forecast of the *h*-period ahead *x* at time *t*

$E_t x_{t+h}$: full-information rational expectation of the *h*-period ahead *x* at time *t*

According to the definition of the full-information rational expectation, $E_t x_{t+h}$ can be described as:

$$E_t x_{t+h} = x_{t+h} - v_{t+h,t}. \text{ (2)}$$

$v_{t+h,t}$: full-information rational expectations error

By combining (1) and (2), one derives the relationship between the *ex post* mean forecast error and the *ex ante* forecast revision as:

$$x_t - F_t x_{t+h} = \frac{\delta}{1-\delta}(F_t x_{t+h} - F_{t-1} x_{t+h}) + v_{t+h,t}. \text{ (3)}$$

From the dataset, one can actually observe $(F_t x_{t+h} - F_{t-1} x_{t-1+h})$ (i.e., the change in the individual one-year-ahead forecast, from the previous month to the current month) instead of $(F_t x_{t+h} - F_{t-1} x_{t+h})$ in (3) (individual forecast revision for the same month). This gives rises to error-term persistence. Following the thinking of CG, I employ contemporaneous innovation in gasoline prices, defined as the residuals of the AR(2) model of the first difference of the log of the nominal gasoline price[2].
Regarding the model of an individual updating his or her expectations, I base the discussion on the model of rational inattention to price setting (see Wiederholt (2010), following the discussion of Drager and Lamla (2013)). Similar to the idea underpinning the rational inattention model of Wiederholt (2010), consumers must decide how to allocate their attention in the face of the costs of both forecast errors and information collection. Let π_i^e denote the inflation expectations of consumer *i* at period *t*. Setting inflation expectations to π_i^e—which differs from the full-information rational expectation π^{e*}—incurs a loss for consumers. The full-information rational expectation equals

$$\pi^{e*} = \phi x, \text{ (4)}$$

where *x* is a normally distributed random variable with mean 0 and variance σ_x^2. *x* represents the aggregate shock that affects the inflation rate, and ϕ is a parameter. Paying attention to the variable *x* is modeled as receiving an individual signal $s_i = x + \varepsilon_i$, where the noise ε_i is independent of *x* and normally distributed with mean 0 and variance σ_ε^2. Thus, an individual's inflation forecast can be described as

$$\pi_i^e = E[\pi^{e*} | s_i]. \text{ (5)}$$

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[2] See the discussion in section 4.1 for details.

The individual chooses the amount of attention κ devoted to the variable *x*, and faces a marginal cost of attention $\mu > 0$. By assuming this individual incurs a loss stemming from his or her forecast error and that it is equal to $\frac{\omega}{2}(\pi_i^e - \pi^{e*})^2$ (where ω is some parameter value), the problem of choosing the optimal attention level for each individual can be described as follows.

At each period, consumers decide whether to update their expectations, meaning that they face a simple static problem described as follows:

$$\min_{\sigma^2_{x|s_i},\kappa>0} E_{x,s_i}\left[\frac{\omega}{2}(\pi_i^e - \pi^{e*})^2\right] + \mu\kappa, \ (6)$$[3]

subject to (4) and (5) and to an information constraint[4]:

$$\frac{1}{2}\log_2(2\pi e\sigma_x^2) - \frac{1}{2}\log_2\left(2\pi e\sigma^2_{x|s_i}\right) \leq \kappa. \ (7)$$

By using the law of iterated expectations, the problem for each consumer (6) can be transformed into the following:

$$\min_{\sigma^2_{x|s_i},\kappa>0} \frac{\omega}{2}\left(\phi^2\sigma^2_{x|s_i}\right) + \mu\kappa.$$

From the first-order condition from the Lagrangian and the information constraint (7), the optimal level of attention κ^* is given by

$$\kappa^* = \begin{cases} \frac{1}{2}\log_2\left(\frac{\sigma_x^2\omega\phi^2 ln2}{\mu}\right) & if \ \left(\frac{\sigma_x^2\omega\phi^2 ln2}{\mu}\right) \geq 1 \\ 0 & otherwise \end{cases}. \ (8)$$

The ratio $\left(\frac{\sigma_x^2\omega\phi^2 ln2}{\mu}\right)$ is the marginal benefit of devoting attention to the variable *x* at $\kappa = 0$, divided by the marginal cost of devoting attention to the variable *x* (Wiederholt 2010). Further, the expected inflation rate set by the consumer equals[5]

$$\pi_i^e = \left(1 - 2^{-2\kappa^*}\right)\phi(x + \varepsilon_i). \quad (9)$$

[3] The idea that agents minimize the expected value of squared forecast errors (plus the marginal cost of collecting information) might not be so straightforward, if we consider the loss or gain caused by the income effect and the loss incurred by the substitution effect in solving the utility maximization problem in intertemporal consumption decision-making, where consumption decisions are made based on individuals' inflation expectations. The current study follows a model from the literature to focus on the main interest of frequency and the direction expectation updates.

[4] For the derivation of this information constraint, please refer to Drager and Lamla (2013). The first term on the left-hand side of the inequality corresponds to the entropy of a random variable *x*, and the second term corresponds to that of the conditional entropy of *x*, given signal *si*. The constraint implies that a decrease in entropy as a result of obtaining the signal cannot exceed the information level.

[5] Mackowiak and Wiederholt (2009) provide the details of the derivation of (9).

From (8), I can infer that the larger the cost of a mistake in setting inflation expectations and the greater the variance of the realized inflation rate (i.e., the larger the ω and the larger the $\phi^2\sigma_x^2$, respectively), the more the attention devoted to variable *x*. This leads to a greater response of inflation expectation π_i^e to changes in *x*. If the marginal cost exceeds the marginal benefit described in (8), the optimal inflation expectation rate chosen by the consumer is $\pi_i^e = 0$; however, the assumption is that this would not happen, given that μ is relatively smaller than the marginal benefit of devoting attention at $\kappa = 0$.

Further, (9) can be transformed as

$$\pi_i^e - \pi^{e*} = \left(-2^{-2\kappa^*}\right)\phi x + \left(1 - 2^{-2\kappa^*}\right)\phi\varepsilon_i.$$

Thus, more attention being devoted to *x* leads to a smaller change in the absolute value of the forecast error in response to changes in *x*. If the attention level is sufficiently high, the forecast error more closely approaches the level of $\phi\varepsilon_i$, where ε_i is noise independent of *x*. These findings can be summarized into several hypotheses on rational inattention, all of which can be tested empirically.

(H1) Under rational inattention, greater volatility in inflation expectations under a full-information rational expectation yields a higher attention level, which leads to more frequent updates in inflation expectations[6].

(H2) Under rational inattention, greater variance in aggregate shocks on the inflation expectations under a full-information rational expectation (and the resulting higher attention level) leads to a smaller forecast error in the expectation.

(H3) Under rational inattention, a higher attention level leads to a smaller response of forecast errors to changes in the inflation expectations under a full-information rational expectation.

(H4) Under rational inattention, a higher attention level leads to a greater response of inflation expectation to changes in inflation expectations, under a full-information rational expectation.

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[6] (9) implies that the inflation expectation π_i^e should reflect changes in either the optimal attention level or the observed signal. However, changes in expected inflation rate in response to changes in observed signals should be very small when the optimal attention is positive but close to 0. In such cases, it is assumed that no updates in inflation expectations are observed in the data, assuming that the respondent remained within the same response category.

3. Dataset

3.1 Data

This study makes use of data captured through the Consumer Confidence Survey published by the Cabinet Office of the government of Japan. The survey covers all households in Japan (around 50 million households). Each survey captures data on 6,720 households (single, 2,016; nonsingle, 4,704) and is executed on a monthly basis. Surveyed households are asked to respond to the questionnaire over 15 consecutive months; thus, the survey results provide a rotating panel dataset for the period from April 2006 to June 2011. Non-negligible number of households were dropped during the 15-month period, or otherwise failed to complete a questionnaire from time to time during this period. The data structure is fairly unbalanced, while the majority of households responded to the questionnaire in each of the 15 months. The average response rate has been around 75% since fiscal year 2006 (FY2006).

The survey asked each respondent household the question, "How do you expect the price level of the goods frequently purchased by your household to change in one year's time?"[7]; I used the answer as a proxy for the inflation expectation of each household. The response was provided through the respondent's selection of one of the following 10 options: (a) decrease by more than 10%, by 5–10%, by 2–5%, or by 0–2%; (b) unchanged; or (c) increase by more than 10%, by 5–10%, by 2–5%, or by 0–2%[8]; or (d) unknown. I take the mid-value of the selected response and consider it the household's inflation expectation.

In addition to the data captured through the Consumer Confidence Survey, I employ several datasets available at an aggregate level: one is the consumer price index (CPI) and the other is the ESP forecast survey.

The CPI is published by the Ministry of Internal Affairs and Communications on a monthly basis. The CPI is calculated and used to measure the price fluctuations of goods and services that are purchased by households nationwide. The CPI reflects changes in the cost of purchased goods and services in a fixed "market basket"; the current base year is 2010. Each month's data are released at the end of the following month. For empirical analysis, I employ CPI by age group, and CPI by income group. Data on CPI by five income categories[9] are published on a monthly basis; CPI by age is

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[7] I note here that the survey actually asks the future price level of those items that are purchased frequently (i.e., does not include the price levels of durable goods).

[8] Before March 2009, the options were limited to seven: they did not include the options "increase/decrease of more than 10%." Instead, they were included in the category of "increase/decrease of more than 5%."

[9] As my data provide only categorical information on household income level, this classification does not perfectly match the five categories used in the CPI. Although there are some gaps among the classifications, I match income "<3 million" to the first category, "3–4 million" and "4–5.5 million" to the second category, "5.5–7.5 million" to the third category, "7.5–9.5 million" to the fourth category, and "9.5–12 million" and ">12 million" to the fifth.

not a published indicator, but I estimate it by using the “CPI by consumption” field with the various weights of the consumption baskets by age, which are synthesized based on data captured through the “Household Survey.”[10] By taking into account variation in the consumption basket by age group, I control for differences in the inflation level faced by households that have a variety of attributes. However, Kitamura (2008) argues that inflation rates by household vary to a substantial extent, although they do have a distribution that approximates the normal distribution. As I do not have micro-level data that provide information on both inflation expectations and actual price levels for each household, I employ data on the CPI, CPI by age, or CPI by income, given the fact that the distribution of household inflation asymptotically follows the normal distribution.
The ESP forecast survey is a monthly survey executed by the Japan Center for Economic Research, starting in May 2004. The Survey covers around 40 economists and institutions in the private sector who are engaged in short-term forecasts of the Japanese economy. The survey asks questions that prompt respondents’ projections of the CPI growth rate in the upcoming year. From the survey results, I construct two volatility indicators of the CPI. One is a gap in the one-year-ahead forecasts, between the values of the institutions with the top eight averages and the values of those with the bottom eight averages. I assume that this gap would increase when the recent CPI has been more volatile[11]. Another is the squared sum of the monthly changes of the average forecast during the preceding 12 months, which is calculated in a manner similar to the volatility measure of realized inflation rates.
Throughout this study, I define the forecast error as being equal to the realized inflation rate, minus the expected inflation rate. To examine the accuracy of expectations, I often take an absolute value for this value, which I call the absolute forecast error (henceforth, AFE).

3.2 Main features of inflation expectations

Before discussing the major features of the dataset, I wish to note the arguments within the literature that the aggregate (or average) data of inflation expectations can be misleading, given the existence of heterogeneity in the expectations level, as well as the rotating composition of the sample households (Engelberg et al. 2011). However, the size of the dataset I employ is sufficiently large for each period. Furthermore, the proportion of the rotation is limited (i.e., 6–7%) and the rotation proceeds in a gradual

[10] This survey is also executed by the Ministry of Internal Affairs and Communications on a monthly basis. Surveyed households are asked to provide detailed information on their monthly expenses in the form of a housekeeping book.
[11] Indeed, the correlation between the volatility measure of CPI in the previous 12 months and this gap is quite high (0.70); this is significant at the 1% level.

manner; thus, I assume that providing an overview of the average level of forecast errors and other statistics would be rather useful to understanding the general picture of the forecast errors of inflation expectations.

Table 3-1 provides the summary statistics of the frequency of updates, and the resulting forecast errors[12]. Throughout the 15-month survey period, households updated their expectations an average of 3.2 times; this corresponds to around 23% of all responses that each household provided[13]. For each survey, close to 60% of households were updating their expectations.

Figure 3-1 shows the trend in average AFE, by survey month. In this subsection, the forecast error is derived from CPI by age[14]. First, the average AFE always ranges between 2% and 2.5% points, indicating that household expectations always differ from CPI by age[15]. On average, the figure does not show a clear trend throughout the 15-month survey period: the average AFE has its peak at the 12th month and declines in the final three months. The figure does not imply that the aggregate forecast error converges to zero as the survey evolves and as the households have more opportunities to update their previous expectations. Figure 3-2 describes the trend in cumulative AFEs, by survey month. Although the average AFE varies from month to month, cumulative errors generally increase almost linearly throughout the survey period, although they do have a small kink in the 12th month and take a gentler slope in the subsequent months. The median number of expectation updates throughout the survey period is two; this indicates that there are many respondents who never update their expectations or, if ever, only once. Thus, I divide the sample into two subsamples: those who frequently updated their expectations (i.e., more than once; the "more frequent group") and those who rarely updated their expectations (i.e., none or once; the "less frequent group").

Figure 3-3 shows that the majority of households update their expectations around the beginning of the survey period, and the ratio remains stable after the 6th month; this ratio is much higher in the more frequent group than the less frequent group. I also calculate the average AFE by month, for each group. Figure 3-4 describes the trends of both groups; the level itself is always higher in the less frequent group than in the more frequent group; in fact, the gap between the two groups continues to grow and becomes the largest at around the 12th month. In addition, the average AFE for both groups continues to increase up to the 12th month, but this is more obvious in the less frequent

[12] The summary statistics of the other variables employed in the estimation are provided in the Appendix (Table A-1).
[13] Note that this result is derived from a dataset containing households that dropped out before the end of the usual survey period.
[14] Parallel analysis based on the CPI basically shows similar results.
[15] Ueno and Namba (2014) discuss the possible origins of these positive errors in detail.

group; this implies that the AFE increases mainly because of a lack of updates. However, I note that more frequent updates do not necessarily lead to smaller errors. When I compare the variance of AFEs between these two groups, it increases up to around the 12th month within the less frequent group, while the variance remains at almost the same level within the more frequent group (Figure 3-5). Some members of the less frequent group have small AFEs, although they rarely update their expectations.

Table 3-1 Summary statistics of expectation updates (per household)

	Mean	SD	Skewness	Median
Number of updates	3.174	2.789	0.842	3.0
Number of updates/Survey length	0.231	0.198	0.730	0.2
Proportion of respondents updated expectations	0.589	0.055	-0.518	0.603

Note: Sample period is 2006.4-2011.6. “Number of updates” stands for the number of updates per household during the survey period of 15 months. “Survey length” is the number of months each household participated in the survey (maximum 15). “Proportion of respondents updated expectations” is the share of households that updated their expectations in each survey.

Figure 3-1 Average level of AFE

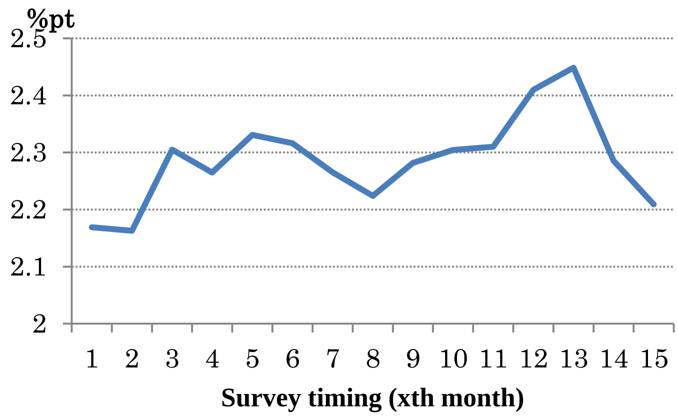


Figure 3-2 Average cumulative errors

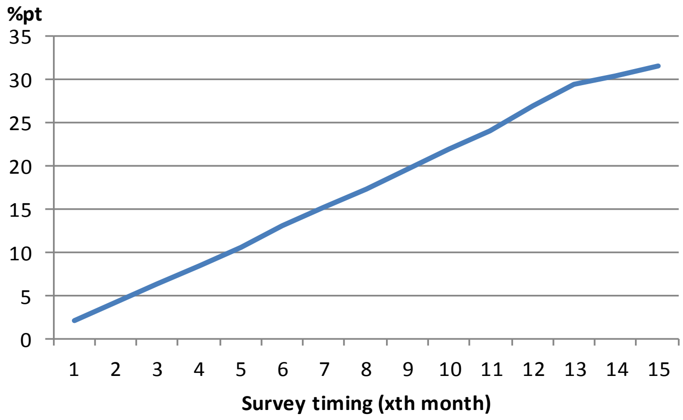


Figure 3-3 Proportion of households that updated their expectation, by survey month

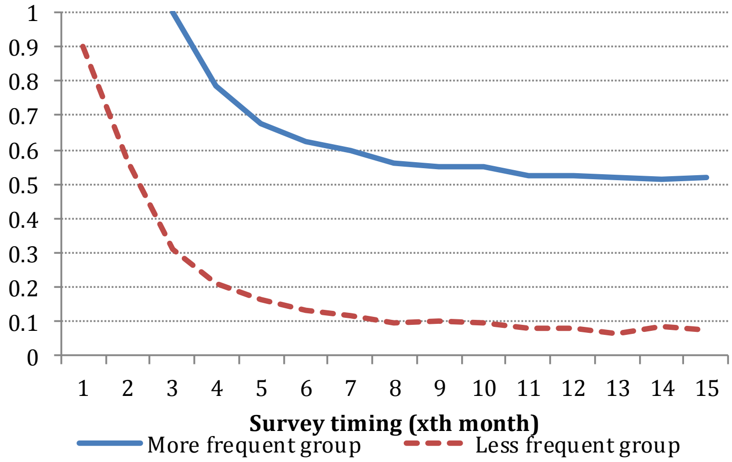


Figure 3-4 Average AFE, by survey month

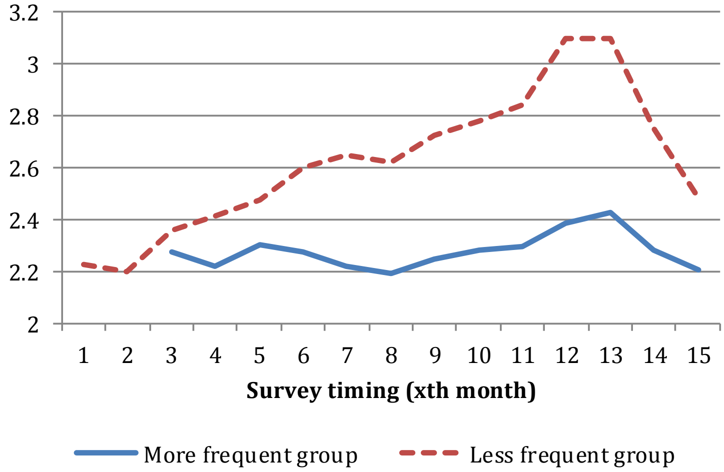
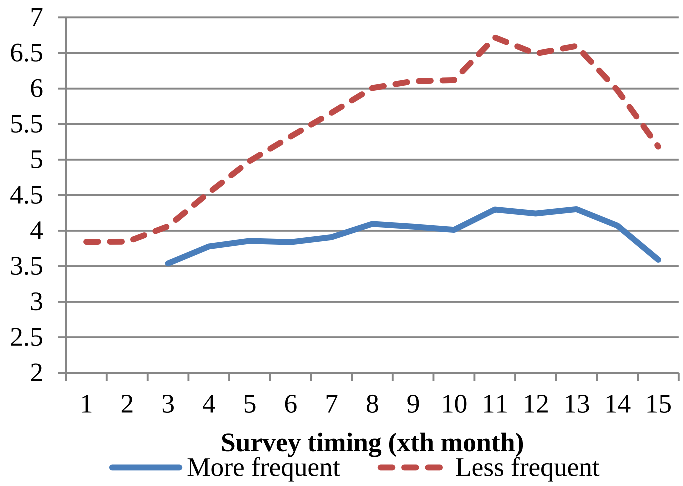


Figure 3-5 Variance of AFE, by survey month



3.2.1 Descriptive micro-level evidence of inflation expectations

Thus far, I focused on variation in inflation expectations by survey month. I also examined whether there is obvious cross-sectional variation in update frequency or forecast error by household composition. Based on the available data, I categorize the surveyed households into nine types, and summarize the descriptive statistics thereof (Table 3-2). In this Table, I see no particular patterns linking household typology to statistical variation.

Table 3-2 Descriptive statistics on rigidity and precision of expectations

	N	Age	Income	Expected inflation rate	Forecast error	Forecast error (absolute values)	Number of updates	Frequency of updates	Share of frequent updaters
Average household	33,740	57.9	493.0	1.52	-1.64	2.33	3.17	0.23	65.2%
1 Single, non-employed	4,962	71.2	311.9	1.58	-1.78	2.42	3.28	0.25	65.3%
2 Couple, non-employed	4,549	72.6	365.0	1.63	-1.71	2.37	3.26	0.23	66.0%
3 Single, employed or self-employec	5,210	45.5	401.4	1.38	-1.52	2.31	2.97	0.23	62.8%
4 Couple (no kids, single worker), employed or self-employed	2,141	59.5	517.7	1.53	-1.61	2.31	3.18	0.23	64.8%
5 Couple (no kids, two workers), employed or self-employed	1,953	57.8	560.8	1.45	-1.53	2.27	3.22	0.23	65.9%
6 Couple + someone (single worker), employed or self-employed	3,896	44.7	589.4	1.55	-1.64	2.29	3.02	0.22	64.1%
7 Couple + someone (two workers), employed or self-employed	4,896	50.3	647.2	1.54	-1.62	2.31	3.15	0.23	65.7%
8 Couple + someone (more than two workers), employed or self-employed	2,859	58.6	753.7	1.53	-1.60	2.32	3.20	0.23	66.2%
9 Others	3,274	60.4	497.3	1.49	-1.68	2.37	3.38	0.25	67.1%

Note: N is the number of households within each category. “Share of frequent updaters” is the proportion of households in the “more frequent group,” as discussed above. Except for this share, all statistics are mean values.

Although there are no particular differences in expectation by household type, it could be expected that the income and price effects of future inflation/deflation would vary across income, savings, or wealth distributions. Possibly, households with higher income or more wealth exhibit smaller responses to expected changes in real income because they can use their wealth to smooth shifts in real income. On the other hand, households below the median or at the end of the distribution might be more responsive to information that suggests future inflation. Therefore, in the following section that discusses the empirical results, I include those estimation results that relate to variation by household income level.

4. Estimation results

4.1 Information rigidity

CG offer the sticky-information model, which describes a positive correlation between the average level of forecast revision and that of forecast error for each period, as follows (section 2):

$$x_t - F_t x_{t+h} = \alpha + \beta(F_t x_{t+h} - F_{t-1} x_{t+h-1}) + \varepsilon_{t+h,t}. \quad (10)$$

As the time-series length of the dataset used here is limited, I test this relationship between averages for all samples (the whole country), subsamples (the prefecture level), and individuals. As CG discuss, the error term of this specification $\varepsilon_{t+h,t}$ consists of both errors of full-information rational expectations and the discrepancy caused by the gap in the forecast period (i.e., $\beta(F_{t-1} x_{t+h-1} - F_{t-1} x_{t+h})$). This discrepancy is likely to introduce error-term persistence. Following the approach of CG, I thus employ generalized method of moments (GMM) and use contemporaneous innovations in gasoline prices[16] as instruments. Since gasoline prices have significant effects on CPI

[16] The innovations are derived residuals of the AR(2) model of the first difference of logged gasoline prices, which should not correlate with the information available before the period *t* – 1 or with the rational-expectations error.

inflation[17], the estimated innovations are statistically significant predictors of contemporaneous changes in inflation expectations, and can account for an important share of their volatility (Table 4-1, models (2)–(4)).

Table 4-1 Test of information rigidity (1)

	(1)		(2)		(3)		(4)	
Forecast revision $(E_t(\pi_{t+12})\text{-}E_{t\text{-}1}(\pi_{t+11}))$	2.115		2.081	***	2.232	***	2.302	***
	(2.671)		(0.104)		(0.105)		(0.113)	
Constant	-1.697	***	-1.709	***	-1.713	***	-1.727	***
	(0.233)		(0.017)		(0.016)		(0.015)	
N	59		2,773		2,773		243,741	
First stage F-statistics	11.94		741.74		169.12		128.94	
Wald $\chi^2(1)$	0.63		400.76		449.15		416.98	
Prob > $\chi^2(1)$	0.428		0.000		0.000		0.000	
Hansen's J $\chi2(5)$	-		-		19.78		54.99	
Prob > $\chi^2(5)$	-		-		0.001		0.000	

Note: Instrumental variable (henceforth, IV) regression by GMM. Forecast revisions are instrumented with the shock of gasoline price. Column (1) regresses the average forecast error of the full sample on the average forecast revision from the previous month. Column (2) does the same estimation for each subsample, by prefecture. Column (3) is the same as (2), in that it uses as instruments the shock of the gasoline price and the average demographic attributes of the households. Column (4) shows the results at an individual level; individual forecast revision is instrumented with the same controls as (3).

Robust standard errors/clustered standard errors shown in parentheses. *** significant at the 1% level.

Table 4-1 shows the estimation results of the test for information rigidity. First, at an aggregate level (model (1)), forecast revisions are proxied by the changes in the average expectations from the previous month to the current month. In this model, the coefficient of the forecast revision is positive but not significant, as in a previous study on the US case (Drager and Lamla 2013)[18]. Next, I test for rigidity in a similar manner, at the prefecture level. I find the estimated coefficient to be close to that of model (1), but this time, it is significantly positive. If prefecture-level forecast revisions were instrumented not only with gasoline price shocks but also with the average demographic

[17] According to the “Guide to CPI Base Year 2010,” gasoline is classified as one of the items that are “most frequently purchased” (i.e., purchased over 15 times per year); it has a weight of 229/10,000 (2.3%) among all purchased items and of 229/1,166 (19.6%) among the frequently purchased items.

[18] In my estimation, the sample size in the time-series direction is limited in order to yield stable model performance. It is important to note that the sample period contains the month of the Great East Japan Earthquake and its aftermath, when the absolute level of forecast errors surged.

attributes of the respondents, the coefficient would once again be significantly positive, and slightly greater than the previous model (model (3)). Finally, the micro-level test result (i.e., household level) is consistent with that at the prefecture level (model (4)). These results indicate that the null hypothesis of the existence of information rigidity cannot be rejected. However, I must note that the additional demographic instruments are likely to correlate with the error in the second stage, leading to the rejection of Hansen's overidentification tests (models (3) and (4)). Fortunately, the estimated coefficients are both significantly positive and at a level similar to those of the results of (2).

The estimated coefficient is greater than that seen in the literature (Drager and Lamla 2013, CG). The difference between the current study and the studies within the literature in terms of data frequency actually implies lower information rigidity among the households in my dataset than among the US households who took part in the University of Michigan Survey of Consumers. For example, the parameter $\hat{\beta} \approx 2.3$ of model (4) implies that δ in formulation (3) is around 0.697; thus, households update their information, on average, once every 3.3 months[19].

Furthermore, I investigate whether information rigidity differs with survey timing: Figure 3-3 indicates that patterns in the updating of expectations appear to change as the survey proceeds. I divide the sample into two subsamples—namely, those taking part near the beginning of the survey process (i.e., households at an early stage) and those in the mid- or final stage of the survey process (i.e., households at a later stage)[20]—and apply the same estimation formulation (10), as before.

[19] By using one of their estimation results—and based on the sticky-information model—CG argue that agents in the survey sample update their information sets every six to seven months.

[20] I divide the sample at the threshold of the 6th survey month, as the proportion of households who updated their expectations is almost flat after this month (Figure 3-3).

Table 4-2 Test of information rigidity (2)

	Households at an early survey stage				Households at a latter survey stage			
	(5)		(6)		(7)		(8)	
Forecast revision $(E_t(\pi_{t+12})-E_{t-1}(\pi_{t+11}))$	1.492	***	1.415	***	2.711	***	3.119	***
	(0.141)		(0.138)		(0.197)		(0.219)	
Constant	-1.655	***	-1.745	***	-1.759	***	-1.725	***
	(0.019)		(0.016)		(0.017)		(0.021)	
N	2,746		109,076		2,489		115,709	
First stage F-statistics	46.96		56.23		63.30		57.98	
Wald $\chi^2(1)$	111.44		104.69		188.73		202.76	
Prob > $\chi^2(1)$	0.000		0.000		0.000		0.000	
Hansen's J $\chi 2(5)$	11.36		93.24		11.97		62.43	
Prob > $\chi^2(5)$	0.045		0.000		0.035		0.000	

Note: IV regression by GMM. Columns (5) and (6) contain the results of surveyed households at an early stage (i.e., up to 6th month of the survey). Column (5) regresses the average forecast error of the subsamples by prefecture on the average forecast revision from the previous month of the subsamples by prefecture. Forecast revisions are instrumented with the shock of gasoline price, as well as the average demographic attributes. Column (6) shows the results at an individual level; individual forecast revision is instrumented with the same controls as (5). Columns (7) and (8) are the estimation results that correspond to (5) and (6), respectively, but with the surveyed households at a later stage of the survey (i.e., from the seventh to the 15th survey month).

Table 4-2 indicates that information rigidity changes as the survey proceeds. Notwithstanding the estimation method, the results imply that rigidity is higher at later stages of the survey period. Although the size of the greatest coefficient (i.e., 3.12 from model (8)) implies that households update their information every 4.1 months—which is not a large change from the results seen with the full sample—I need some interpretation as to why households become more reluctant to update their information set. As households do not observe the realized forecast errors up to the very final stage of the survey, it is not the case that households update their expectations frequently based on the realized forecast errors around the beginning. This survey is a sentiment survey to which households can reply in a casual manner, without involving any "serious" information collection. Therefore, particularly during any "close-to-zero inflation" period and after becoming accustomed to being asked about their expectations (i.e. after having experienced several survey waves), households might implicitly assume that future inflation rates would not evolve overly much, and thus refrain from updating their information sets. To examine whether more stable price levels would lead to less frequent updates in information and vice versa, I divide the sample into two subsamples by period: one comprises those households facing “close-to-zero inflation,” while the other comprises households facing either “inflation” or “deflation” (i.e., a volatile period[21,22]). I then implement the same estimation with each, but add an interaction term between a dummy for volatile period and forecast revision. As expected, the estimated coefficient of this interaction term is negative, indicating more frequent updates to the information set (Table 4-3); however, it is significant only at the 10% level in case of estimation at the individual level. Further, the sum of the coefficient of forecast revision and that of the interaction term is even negative for the prefecture-level estimation, which is not consistent with the model of information rigidity. In a subsequent section, I further investigate the possible impact of volatility in inflation expectations on forecast updates as well as forecast errors.

Table 4-3 Test of information rigidity (3)

	(1)		(2)	
Forecast revision $(E_t(\pi_{t+12})-E_{t-1}(\pi_{t+11}))$	10.198	***	4.640	***
	(2.943)		(1.410)	
$(E_t(\pi_{t+12})-E_{t-1}(\pi_{t+11}))*I^{volatile}$	-13.137	***	-3.371	*
	(4.695)		(2.036)	
Constant	-1.387	***	-1.672	***
	(0.116)		(0.036)	
N	2,773		243,741	
First stage F-statistics	55.51		67.88	
Wald $\chi^2(1)$	51.35		468.16	
Prob > $\chi^2(1)$	0.000		0.000	
Hansen's J $\chi2(5)$	9.645		43.75	
Prob > $\chi^2(5)$	0.047		0.000	

Note: IV regression by GMM. $I^{volatile}$ is an indicator of the period of deflation or inflation. Column (1) regresses the average forecast error of the subsamples by prefecture on the average forecast revision from the previous month of the subsamples by prefecture. Forecast revisions are instrumented with the shock of gasoline price, as well as with the average demographic attributes. Column (2) shows the results at an individual level; individual forecast revision is instrumented with the same controls as (1).

4.2 Updates to inflation expectations

[21] I set the threshold inflation rates to –0.6% and 0.6%, which correspond to 25% and 75% of the entire distribution, respectively. The median value is zero.

[22] I also use another indicator of volatility: the squared sum of the inflation rate in the preceding three months. In this case, I could not obtain statistically significant implications.

4.2.1 Test of H1

(H1) Under rational inattention, greater volatility in inflation expectations under a full-information rational expectation yields a higher attention level, which leads to more frequent updates in inflation expectations.

First, I examine whether households update their expectations more frequently when there is an increase in the observed volatility of inflation rates. For this purpose, I specify a binary response model of the process that underlies expectation updating at each household, as follows:

$$y_{it} = \begin{cases} 1 & if\ y_{it}^* > 0 \\ 0 & if\ y_{it}^* \leq 0 \end{cases}, \quad i = 1, \ldots, N \quad t = 2, \ldots, 15, \quad (11)$$

where y_{it}^* is the latent variable that accounts for household expectation updating. The binary variable y_{it} takes the value 1 if the *i*th household updates its expectation at period *t*, and the value 0 if the *i*th household does not update it. The latent variable y_{it}^* is explained by various factors, including the volatility of inflation rates:

$$y_{it}^* = \alpha + \beta\pi_{t-1} + \gamma\sigma_{t-1} + \delta X_i + u_{it}, \quad (12)$$

where α is a constant, π_{t-1} is the realized inflation rate last observed, X_i is a vector of sociodemographic characteristics of the *i*th household[23], and σ_{t-1} is the volatility of realized inflation as observed by households.

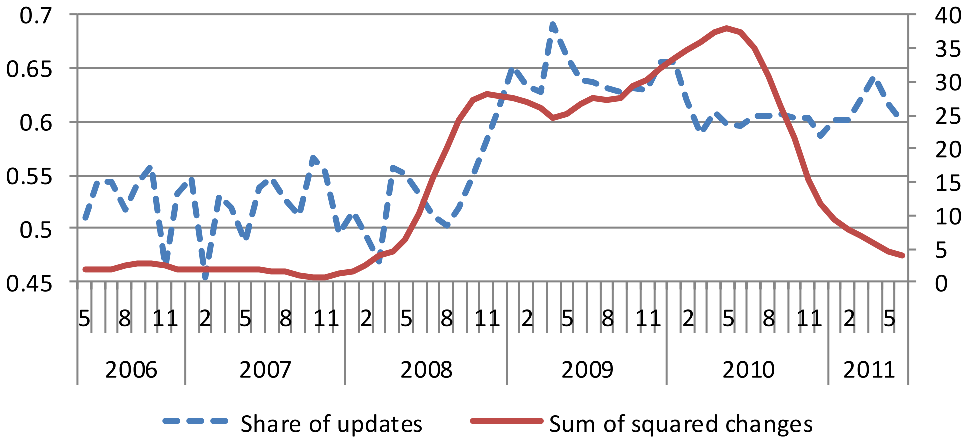
As a measure of such volatility, I follow Drager and Lamla (2013) and use the sum of squared changes of inflation for the preceding one year (i.e., from *t* – 12 to *t* – 1). For this volatility measure, I use either the actual inflation rate, the average forecast inflation rate made by professional forecasters, or the average inflation expectations among households. I also use the gap in professional forecasts in inflation in one year's time—between those institutions with the eight highest forecasts, and those with the eight lowest forecasts—as a measure of expected uncertainty. Further, I check whether the inaccuracy of one's own previous forecast positively affects the probability of the updates in the current period. For this test, since households know their realized forecast errors only 12 months after the forecast point, I either limit the sample to the households that have already recognized their former forecast errors, or use instruments without

[23] I use a variety of variables: age of household head, household income, number of family members, and survey months. I employ the same set of sociodemographic controls in the analyses of H1–H4.

limiting the sample. Inconcrete, lagged AFEs are instrumented with the lagged error of the professionals' forecasts that have already been realized[24].

Figure 4-1 describes the trends of one of the volatility measures (squared changes of realized inflation for one year) and the share of respondents who updated their expectations. The correlation between the two series is high (0.667, *p*-value 0.000), whereas the positive correlation seems not to be stable in 2011[25].

Figure 4-1 Expectation updating and volatility measure (1)



Note: Share of updates is plotted on the left-hand axis, and volatility measure on the right-hand axis. Share of updates is adjusted for FY2006–FY2008, given the obvious impact of using two different survey methods.

Table 4-4 summarizes the estimation results for the probability of updating inflation expectations. The models contain various measures of inflation volatility[26], as well as individuals' previous forecast errors, as determinants of updating current inflation expectations. All models include as explanatory variables the demographic variables of the respondents, as well as the realized inflation rate of the previous period.

[24] At the time of the survey, households do not know their previous forecast errors; they do not learn of these until the 13th month of the survey period. I thus instrument the forecast error of the previous month with the forecast errors of the professionals with regard to their forecasts of the most recent quarter, which is realized at the survey timing. I consider this a valid instrument, since household inflation expectations highly correlate with trends in current inflation rates.

[25] Appendix Figure A-1 shows the correlation between the other volatility measures and the share of updates. Both correlations are positive and significant.

[26] According to the model, this should be a measure of the volatility of the inflation expectations under full-information rational expectations. I thus employ measures based on the realized values of inflation rates, as well as on professional economists' forecasts.

In general, the estimation results support (H1). Models (1), (2), and (4) all indicate that higher volatility in inflation rates in the most recent year—measured either by the actual inflation rates or by the inflation rates expected by professional forecasters—leads to a higher probability of updating inflation expectations. Model (3) is not consistent with the results of (1), (2), and (4), but the measure of volatility of household expectations is dependent on subjective factors and is not necessarily an appropriate one, compared to other measures. Models (5) and (6) show how previous forecast errors are reflected in updating behaviors; as expected, positive signs are derived for previous errors, indicating that a nonnegligible number of attentive households exists and that they update their forecasts when they had made great forecast errors in the past. The estimated marginal effect of the one-year lagged forecast error is 0.004 (model (5)), while that of the one-month lagged forecast error is 0.023—much greater than the effect of one-year lagged forecast (model (6)). Besides consistency with (H1), one interesting feature of the estimation results is that the updating probability is negatively influenced by the recent inflation rate: when the inflation rate increases, households tend to stay with their current expectation levels, as long as the inflation rate remains positive.

Table 4-4 Probability of updating inflation expectations

	(1)		(2)		(3)		(4)		(5)		(6)	
π_{t-1}	-0.0503	***	-0.0542	***	-0.0580		-0.0457	***	-0.0695	***	-0.0955	***
	(0.003)		(0.003)		(0.003)		(0.003)		(0.011)		(0.007)	
$\sigma^2(\pi_{t-1})$	0.00251	***										
	(0.000)											
$\sigma^2(\pi^{e,\ professional}_{t-1})$			0.00984	***								
			(0.002)									
$\sigma^2(\pi^{e,\ household}_{t-1})$					-0.0341	**						
					(0.014)							
$Gap(\pi^{e,\ professional}_{t-1})$							0.1325	***				
							(0.012)					
Forcast error (lagged)									0.0110	*	0.0570	***
									(0.006)		(0.010)	
N	287,646		287,646		225,533		255,504		23,028		268,487	
Demographic controls	yes		yes		yes		yes		yes		yes	
Wald	1626.15		1567.98		1362.53		1298.05		146.05		1269.09	
chi2>0	0.000		0.000		0.000		0.000		0.000		0.000	

Models (1)–(4): panel probit estimation (random effects model). Model (6): iv probit estimation. Note: For model (6), clustered standard errors are reported in parentheses[27]. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. $\sigma^2(\pi_{t-1})$ is the sum of squared changes of realized inflation over the previous 12 months. $\sigma^2(\pi^{e,\ professional}_{t-1})$ corresponds to the sum of squared

[27] In practice, if idiosyncratic errors are serially correlated when $T > 2$, the usual standard errors of the fixed-effects estimator are understated to a great extent.

changes of inflation expectations of professional forecasters over the previous 12 months. $\sigma^2(\pi^{e,\ household}_{t-1})$ is the sum of squared changes of mean inflation expectations of the "Consumer Confidence Survey" over the previous 12 months. Gap($\pi^{e,\ professional}_{t-1}$) is an indicator of future uncertainty; it is derived by subtracting the average inflation forecast (one year ahead) among the bottom eight institutions from that average forecasted by the top eight institutions, as discussed. In model (5), forecast errors with a one-year lag are included as an explanatory variable. In model (6), forecast errors with a one-month lag are included, but instrumented with the realized forecast errors of professional forecasters.

I then repeat the same analysis of model (1), by income group. Table 4-5 comprises the estimation results of panel probit estimation by income level. In these estimations, I distinguish upward revisions from downward revisions, and examine whether the recent level and volatility of realized inflation rates affect either or both of the revisions.

Table 4-5 Marginal effects on probability of updating inflation expectations (upward or downward), by income

[Panel A]

Updating expectations upwards														
Income	3million -		3-4 million		4-5.5million		5.5-7.5 million		7.5-9.5 million		9.5-12 million		12 million+	
π_{t-1}	-0.0241	***	-0.0256	***	-0.0270	***	-0.0271	***	-0.0295	***	-0.0265	***	-0.0328	***
	(0.002)		(0.002)		(0.002)		(0.003)		(0.003)		(0.004)		(0.005)	
$\sigma^2(\pi_{t-1})$	0.00068	***	-0.00016		-0.0010	***	-0.0006	***	-0.0012	***	-0.0012	***	-0.0005	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
N	105,318		47,983		43,093		36,482		22,181		13,065		9,242	
Demographic controls	yes		yes		yes		yes		yes		yes		yes	
Wald	767.3		234.03		279.12		172.99		141.88		61.23		81.41	
chi2>0	0.000		0.000		0.000		0.000		0.000		0.000		0.000	

[Panel B]

Updating expectations downwards														
Income	3million -		3-4 million		4-5.5million		5.5-7.5 million		7.5-9.5 million		9.5-12 million		12 million+	
π_{t-1}	0.0129	***	0.0043	**	0.0028		0.0035	*	0.0041		0.0054		0.0048	
	(0.004)		(0.002)		(0.006)		(0.002)		(0.003)		(0.003)		(0.004)	
$\sigma^2(\pi_{t-1})$	0.00228	***	0.00103	***	0.0059	***	0.0018	***	0.0016	***	0.0018	***	0.0015	***
	(0.000)		(0.000)		(0.001)		(0.000)		(0.000)		(0.000)		(0.000)	
N	105,318		47,983		43,093		36,482		22,181		13,065		9,242	
Demographic controls	yes		yes		yes		yes		yes		yes		yes	
Wald	196.16		103.6		179.47		141.48		69.96		44.71		28.84	
chi2>0	0.000		0.000		0.000		0.000		0.000		0.000		0.000	

Note: Marginal effects from panel probit estimation. Panel A corresponds to the case when the explained variable =1, if respondents changed their expectations upward; Panel B, meanwhile, corresponds to the case when the explained variable =1, if respondents changed their expectations downward.

With regard to the coefficients of CPI volatility, the signs are positive and significant for all income groups in the case of downward revision; however, the signs tend to be negative, but not necessarily consistently so, in the case of upward revision. Therefore, the previous conjecture that volatility leads to a higher attention level and more updates seems to hold particularly in the case of downward revision. As discussed in the previous section, households tend to have expectations that exceed the realized inflation rates; this finding could be consistent with (H1), since in general, if households become more attentive, they prefer to update their expectations to lower levels. At the same time, it is also interesting to find the coefficients of the recent CPI inflation rate all to be negative and significant in the case of upward revision (i.e., when actual prices have been increasing, households tend not to update their expectations upward), while the coefficients of the rate are all positive but not necessarily significant in the case of downward revision. Unfortunately, I see no clear relationship between income level and updating probability.

4.2.2 Test of H2

(H2) Under rational inattention, greater variance in aggregate shocks on the inflation expectations under a full-information rational expectation (and the resulting higher attention level) leads to a smaller forecast error in the expectation.

I then test whether more frequent updates in expectations lead to a lower absolute level of inflation expectations. Assuming that each update generally contributes to improvements in forecast accuracy, a greater number of previous updates should yield smaller forecast errors at the current survey point. I thus expect that, conditional on previous updates (i.e., at least more than one), the coefficient of update frequency up to the current survey point should have a negative sign with respect to the AFEs[28]. Further, as I observed that higher volatility in inflation rates leads to more frequent updates (H1), I also directly employ each volatility measure as an explanatory variable.

[28] Appendix Figure A-2 shows that there is no apparent relationship at an aggregate level between 1) the share of updated expectations and the average level of AFEs (Figure A-2, upper), or between 2) one of the volatility measures and the average AFEs (Figure A-2, lower). Note that these are only aggregate-level results, and so detailed micro-level analysis is required.

Table 4-6 AFEs and household attentiveness (1)

	(1)	(2)	(3)	(4)	(5)	(6)
Number of previous updates	-0.0722 ***					
	(0.007)					
Frequency of previous updates		-0.3239 ***				
		(0.082)				
$\sigma^2(\pi_{t-1})$			-0.00095			
			(0.001)			
$\sigma^2(\pi^{e,\ professional}_{t-1})$				-0.1087 ***		
				(0.006)		
$\sigma^2(\pi^{e,\ household}_{t-1})$					1.3460 ***	
					(0.033)	
$Gap(\pi^{e,\ professional}_{t-1})$						1.1283 ***
						(0.036)
N	123,423	123,423	121,376	121,376	95,598	124,084
Lagged inflation rate	yes	yes	yes	yes	yes	yes
Demographic controls	yes	yes	yes	yes	yes	yes
F	805.02	790.02	797.85	847.55	1063.92	1022.72
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000

Note: A fixed-effects model is selected for (1)–(6). Conditional on updates[29]. Clustered standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. "Frequency of previous updates" stands for the ratio of updates to the survey length up to the survey point. $\sigma^2(\pi_{t-1})$ is the sum of squared changes of realized inflation over the previous 12 months. $\sigma^2(\pi^{e,\ professional}_{t-1})$ corresponds to the sum of squared changes of inflation expectations of professional forecasters over the previous 12 months. $\sigma^2(\pi^{e,\ household}_{t-1})$ is the sum of squared changes of mean inflation expectations of the "Consumer Confidence Survey" over the previous 12 months. $Gap(\pi^{e,\ professional}_{t-1})$ is an indicator of future uncertainty; it is derived by subtracting the average inflation forecast (one year ahead) among the bottom eight institutions from that average forecasted by the top eight institutions, as discussed.

Table 4-6 shows estimation results derived by using various measures of household attentiveness. All explanatory variables are either exogenous or predetermined, and are known to the respondents at each survey point. Fixed-effects models are selected in all cases. First, with regard to the frequency of previous updates, the coefficients have negative signs; generally, more frequent updates in the past lead to a lower level of current value among AFEs. Second, the signs of the coefficients of the volatility measures are mixed; as expected, the sign is negative with volatility among forecasters'

[29] Parallel estimation results from the full sample are consistent and similar, with the same signs and similar coefficient levels.

expectations (negative but not significant with the volatility of actual inflation rates), but they are positive with household inflation expectations, as well as with the uncertainty measure of forecaster expectations. This might imply that when the realized inflation rates have been volatile, it is difficult for households to make accurate expectations, despite having an increased attention level.

I check the robustness of the estimation results by using the forecast errors that are based on the CPI estimated for age groups, and on CPI by income groups (Appendix Tables A-2 and A-3). Overall, the estimation results are quite consistent with those discussed above: the update frequency negatively affects the AFE, and volatility in recent inflation rates has a mixed effect on the AFE, depending on the measures involved.

I then examine whether the behaviors of the positive and negative forecast errors are symmetric. The above estimation results treat positive and negative forecast errors in a symmetric way, by taking absolute values of forecast errors. I divide the sample into two subsamples: one comprises those who overestimated inflation in the previous month, and the other comprises those who underestimated it. By looking at these two subsamples separately, I examine whether the estimated signs are consistent with previous ones. Table 4-7 shows the results, with the volatility of past inflation and the forecasts of professionals as measures; it indicates that both signs (i.e., in case of overestimation and underestimation) are consistent with regard to the responsiveness of AFEs.

Table 4-7 AFEs and household attentiveness (2)

Last period's performance	Overestimation				Underestimation			
	(1)		(2)		(3)		(4)	
$\sigma^2(\pi_{t-1})$	0.00889	***			0.0029	**		
	(0.001)				(0.001)			
$\sigma^2(\pi^{e,\ professional}_{t-1})$			-0.1041	***			-0.0274	***
			(0.008)				(0.008)	
N	62,252		62,252		59,124		59,124	
Lagged inflation rate	yes		yes		yes		yes	
Demographic controls	yes		yes		yes		yes	
F	904.74		913.45		284.18		285.80	
Prob>F	0.000		0.000		0.000		0.000	

Note: A fixed-effects model is selected for (1)–(4). Conditional on updates.

4.2.3 Dynamic panel analysis

The null hypothesis of no information rigidity is rejected in the previous subsection, so that there can be persistence or inertia[30] to a certain extent in the forecast errors. However, conditional on updates, this is not overly obvious in the literature, since many studies argue that households update their expectations in a rather staggered fashion. To check the persistence, I add the lagged AFEs as an explanatory variable to the previous set of explanatory variables, and undertake dynamic panel analysis.

The estimation model is provided as follows:

$$FE_{jt} = \alpha FE_{jt-1} + \beta A_{jt-1} + \gamma X_{jt} + \mu_j + \varepsilon_{jt}, \quad (13)$$

where FE_{jt} is the AFE of household j at period t, A_{jt-1} is a measure for household j's attentiveness up to the previous period (this can be proxied by a volatility measure of inflation up to the previous period), X_{jt} is individual household characteristics, μ_j is individual-specific characteristics, and ε_{jt} is an idiosyncratic shock. $\alpha, \beta,$ and γ are the parameters to be estimated.

Although the explanatory variables (*A*s and *X*s) are either exogenous or predetermined, FE_{jt-1} and μ_j would be correlated from the structure of this model. In addition, unobservable macro-level shocks may be included in ε_{jt} and are likely to correlate with the regressors. Thus, I use the system GMM of Arellano and Bover (1995) and Blundell and Bond (1998), which reduces potential bias and imprecision associated with the usual difference estimator by combining the regression in differences with the regression in levels[31]. Table 4-8 below comprises the estimation results by income group, with recent inflation volatility included as a regressor. As explained variables, I use both forecast errors and AFEs.

[30] At an aggregate level, the estimated coefficient of the AR(1) model is significant, and approximates 1.5.

[31] I used a Stata code provided as xtabond2 (Roodman 2009a).

Table 4-8 Determinants of forecast errors in inflation expectations

[Panel A: Explained = AFEs]

	All households	By income						
		3million-	3-4million	4-5.5million	5.5-7.5million	7.5-9.5million	9.5-12million	12million-
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AFE_{t-1}	-0.276 ***	-0.298 ***	-0.292 ***	-0.281 ***	-0.298 ***	-0.221 ***	-0.240 ***	-0.207 ***
	(0.010)	(0.02)	(0.024)	(0.028)	(0.026)	(0.032)	(0.054)	(0.061)
$\sigma^2(\pi_{t-1})$	0.216 ***	0.104	0.142 ***	0.211 *	0.184 ***	0.237 ***	0.250 ***	0.265 **
	(0.033)	(0.094)	(0.053)	(0.121)	(0.052)	(0.064)	(0.078)	(0.112)
N	60,124	19,864	10,521	9,216	8,005	5,052	2,968	2,174
Hansen test of over-identification (p-value)	0.000	0.072	0.237	0.956	0.101	0.062	0.226	0.007
Test for first-oreder serial correlation (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Test for second-oreder serial correlation (p-value)	0.892	0.355	0.361	0.759	0.188	0.354	0.368	0.328

Note: Conditional on updates[32]. AFE_{t-1} stands for the absolute forecast error of the previous period. Instruments used in level equations: ΔAFE_{t-1}, ΔCPI_{t-1}, $\Delta\sigma^2(\pi_{t-1})$, and Δgasoline_price_innovation$_{t-1}$; instruments used in first-difference equations: $AFE_{t-2, t-3, t-4, t-5}$, $CPI_{t-2, t-3, t-4, t-5}$, $\sigma^2(\pi_{t-2, t-3, t-4, t-5})$, gasoline_price_innovation$_{t-1, t-2, t-3, t-4}$, survey timing, and time dummies. "Gasoline_price_innovation" is estimated innovation in gasoline prices (see footnote 13). Collapsed GMM[33].

[Panel B: Explained = Forecast errors]

	All households	By income						
		3million-	3-4million	4-5.5million	5.5-7.5million	7.5-9.5million	9.5-12million	12million-
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FE_{t-1}	-0.213 ***	-0.247 ***	-0.194 ***	-0.215 ***	-0.273 ***	-0.169 ***	-0.150 ***	-0.142 ***
	(0.01)	(0.021)	(0.024)	(0.032)	(0.029)	(0.030)	(0.052)	(0.052)
$\sigma^2(\pi_{t-1})$	-0.322 ***	-0.248 ***	-0.263 ***	-0.341 ***	-0.244 ***	-0.400 ***	-0.318 ***	-0.350 *
	(0.046)	(0.066)	(0.052)	(0.068)	(0.091)	(0.084)	(0.113)	(0.203)
N	60,124	19,864	10,521	9,216	8,005	5,052	2,968	2,174
Hansen test of over-identification (p-value)	0.000	0.172	0.306	0.811	0.019	0.305	0.272	0.679
Test for first-oreder serial correlation (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Test for second-oreder serial correlation (p-value)	0.147	0.866	0.156	0.267	0.389	0.212	0.623	0.239

Note: Conditional on updates. FE_{t-1} stands for the forecast error of the previous period. Other notes are the same as Panel A, except that the corresponding values of the forecast errors are used in place of the instruments of lagged or differenced AFEs.

[32] For both Panels A and B, the results remain consistent when I limit the sample to households with more than two updates.

[33] Roodman (2009b) raises the issues related to instrument proliferation; he suggests the combination of instruments into smaller sets, to reduce the number of instruments overall.

The results in Panels A and B are consistent. With regard to the signs of the estimated coefficients of volatility measure, they are the opposite, since a higher level of volatility is likely to push up inflation expectations[34]; thus, the gap between expected and realized inflation expands, reducing forecast errors (i.e., increasing them in an absolute sense)[35]. Such relationships are more obvious among higher-income groups, in a general sense. Interestingly, the estimated coefficients of lagged (absolute) forecast errors are all negative, ranging between –0.1 and –0.2; this indicates that the suggested persistence in (absolute) forecast errors is quite limited and even significant with a negative sign. The implication here is that higher volatility indeed leads to more frequent updates, whereas higher volatility results in a "pushing up" of inflation expectations with greater AFEs. In other words, volatility does not necessarily improve forecast accuracy. Interestingly, higher-income groups seem to be more attentive to past volatility, but this does not necessarily mean that their forecasts are more accurate than those of others.

4.2.4 Learning effects throughout the survey period

Furthermore, I examine whether there is any variation in the slopes of the update frequency or past inflation volatility, depending on the survey timing. As most updates concentrate around the beginning of the survey period (Figure 3-3), and as the average AFEs increase in the middle of the survey period, I expect the response of the AFE to the update frequency or to inflation volatility to be more distinct around the beginning of the survey period than in the middle or at the end. Thus, I add the interaction terms between update frequency (or inflation volatility) and the dummies that relate to survey timing.

[34] See Appendix Table A-6. I note that while the estimated coefficients of volatility are positive, some of them are not statistically significant.

[35] This result is not necessarily consistent with the results seen in Table 4-5 (i.e., higher volatility enhances the probability of revising expectations upward). This may relate to the fact that the results in Table 4-8 are those with a control for the previous performance of expectations.

Table 4-9 AFEs and household attentiveness (3)

	(1)		(2)	
(A)				
Number of previous updates	-0.005	*		
$\sigma^2(\pi_{t-1})$			0.0172	***
Interaction-terms with (A) and survey-point dummies				
First month	-		-	
Second month	-		-	
Third month	-0.071	***	-	
Fourth month	-0.060	***	-0.003	***
Fifth month	-0.065	***	-0.003	***
Sixth month	-0.046	***	-0.006	***
Seventh month	-0.019	***	-0.007	***
Eighth month	-0.036	***	-0.009	***
Ninth month	-0.019	***	-0.011	***
Tenth month	-0.012	***	-0.013	***
Eleventh month	-0.014	***	-0.013	***
Twelfth month	-0.007	***	-0.015	***
Thirteenth month	-0.004		-0.017	***
Fourteenth month	-0.005	*	-0.017	***
Fifteenth month	-		-0.020	***
N	213,028		214,350	
Lagged inflation rate	yes		yes	
Demographic controls	yes		yes	
F	1829.98		521.56	
Prob>F	0.000		0.000	

Note: Conditional on at least one update in previous months. The other notes are the same as those in Table 4-6.

Table 4-9 summarizes the estimation results with the interaction terms, conditional on previous changes. The results of models (1) and (2) clearly indicate that the responses vary with survey timing, and that the absolute number of responses to the past updating frequency are greater at the beginning of the survey, but quickly approaches a small value around the seventh month of the survey period. Thus, after that time, additional updates no longer contribute overly much to a reduction in AFEs. It may be that learning effects exist around the beginning of the survey period. Regarding marginal responses to inflation volatility, the results of model (2) imply that around the beginning of the period, they are positive (as already discussed), but they gradually diminish toward the end of the survey period and ultimately approach zero. This may be interpreted as follows: there are learning effects at work and toward the end of the survey period, households tend to use updated information in a more efficient manner.

4.2.5 Test of H3

(H3) Under rational inattention, a higher attention level leads to a smaller response of forecast errors to changes in inflation expectations under a full-information rational expectation.

I then test H3. I test whether the variables that affect the probability of updates or the level of AFEs also have an impact on changes in individual-level AFEs. For this test, the explained variable is the changes in AFEs, and the explanatory variables are either the update frequency or the volatility in recent inflation rates. In this test, I undertake individual-level panel estimation to examine whether changes in individual-level errors are reduced by making repeated updates; however, I do so by examining only those households that had updated their expectations. The results are found in Table 4-10.

Table 4-10 Changes in AFEs and household attentiveness (1)

	(1)		(2)		(3)		(4)		(5)		(6)	
Number of previous updates	-0.0067											
	(0.007)											
Frequency of previous updates			-0.0288									
			(0.089)									
$\sigma^2(\Pi_{t-1})$					-0.0283	***						
					(0.001)							
$\sigma^2(\Pi^{e,\ professional}_{t-1})$							-0.1963	***				
							(0.006)					
$\sigma^2(\Pi^{e,\ household}_{t-1})$									0.5281	***		
									(0.036)			
$Gap(\pi^{e,\ professional}_{t-1})$											-0.7201	***
											(0.038)	
N	123,423		123,423		121,376		121,376		95,598		124,084	
Lagged inflation rate	yes		yes		yes		yes		yes		yes	
Demographic controls	yes		yes		yes		yes		yes		yes	
F	41.95		41.99		215.02		236.54		58.85		100.25	
Prob>F	0.000		0.000		0.000		0.000		0.000		0.000	

Note: A fixed-effects model is selected for (1)–(6). Conditional on updates. Clustered standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Other notes are the same as those of Table 4-6.

The implications derived from the contents of Table 4-10 can be summarized as follows. First, even if previous updates have been frequent, this does not seem to affect changes in AFEs significantly; there is also no clear evidence of convergence in errors through repeated updates. This finding does not align with (H3), which states that higher attention levels lead to more accurate forecasts, and thus to a limited extent of changes in the error level. On the other hand, the second implication is consistent with H3: with the exception of the measures of household dispersion, more volatile inflation leads to a higher attention level and thus to a limited extent of changes in AFEs. However, I note that more volatile inflation can lead to the limited extent of changes in AFEs, not because of higher attention but because of staggered updating. Indeed, in examining the results in Tables 4-4, 4-8 and 4-10 together, although they are mixed, some estimation results indicate that higher volatility induces frequent updates in expectations, but also a higher level of AFEs with a limited extent of changes in the forecast errors.

For H3, I again test the heterogeneity in the slopes of the explanatory variables by adding the interaction terms of update frequency/volatility measure with survey timing dummies (Appendix Table A-4). In the case of update frequency, all the coefficients of interaction terms were estimated to be significant. The variation in slopes clearly indicates a smaller absolute value of changes in expectations with more frequent updates around the beginning of the survey; toward the end of the survey, however, the trend goes in the opposite direction (i.e., more frequent updates mean even greater AFE in the current month than in the previous month, and thus, there is no conversion).

4.2.6 Test of H4

(H4) Under rational inattention, a higher attention level leads to a greater response of inflation expectation to changes in inflation expectations, under a full-information rational expectation.

H4 argues that a higher attention level yields a greater response to changes in the expectations themselves. To test this hypothesis, I regress the absolute changes in inflation expectations on the set of explanatory variables I employed for the previous tests with a fixed-effects model. Similar to the previous estimation, I expect such a response level to be dependent on survey timing; thus, I again add the interaction terms between the survey timing dummies and the measures of update frequency/volatility.

Table 4-11 Changes in inflation expectations and household attentiveness with updated expectations (1)

	(1)		(2)		(3)		(4)		(5)		(6)	
Number of previous updates	-0.018	***										
	(0.007)											
Frequency of previous updates			-0.186	**								
			(0.085)									
$\sigma^2(\pi_{t-1})$					-0.0027	***						
					(0.001)							
$\sigma^2(\pi^{e,\ professional}_{t-1})$							-0.034	***				
							(0.006)					
$\sigma^2(\pi^{e,\ household}_{t-1})$									0.322	***		
									(0.036)			
$Gap(\pi^{e,\ professional}_{t-1})$											0.323	***
											(0.035)	
N	123,423		123,423		121,376		121,376		95,598		124,084	
Demographic controls	yes		yes		yes		yes		yes		yes	
F	26.45		26.39		27.24		30.00		35.57		42.11	
Prob>F	0.000		0.000		0.000		0.000		0.000		0.000	

Note: A fixed-effects model is selected for (1)–(6). Conditional on updates. The other notes are the same as those for Table 4-6.

Table 4-11 summarizes the estimation results with updated expectations. From models (1) and (2), I observe that more frequent updates lead to smaller changes in expectations; this suggests that the level of inflation expectations itself becomes more stable by making repeated updates. Results with volatility measures are again mixed, and thus, it is difficult to conclude whether they are consistent with (H4); a more volatile inflation rate, and thus a higher attention level, leads to smaller changes in expectations (models (3) and 4)), but also to greater changes in expectations (models (5) and (6)).

Regarding possible parameter heterogeneity by survey timing, Table 4-12 contains estimation results with regard to inflation volatility upon updates in expectations[36].

[36] For most of the explanatory variables, estimation results with update frequencies do not have significant results; thus, I do not include those results in Table 4-12.

Table 4-12 Changes in inflation expectations and household attentiveness with updated expectations (2)

	(1)		(2)	
(A)				
$\sigma^2(\pi_{t-1})$	-0.011	***		
$\sigma^2(\pi^{e,\ professional}{}_{t-1})$			-0.081	***
Iteraction-terms with (A) and survey-point dummies				
First month	-		-	
Second month	-		-	
Third month	0.016	***	0.085	***
Fourth month	0.012	***	0.067	***
Fifth month	0.011	***	0.063	***
Sixth month	0.007	***	0.037	***
Seventh month	0.007	***	0.037	***
Eighth month	0.008	***	0.047	***
Ninth month	0.007	***	0.035	***
Tenth month	0.005	**	0.025	***
Eleventh month	0.005	***	0.023	***
Twelfth month	0.006	***	0.031	***
Thirteenth month	0.001		0.012	
Fourteenth month	0.002		0.018	**
Fifteenth month	-		-	
N	64,746		64,746	
Lagged inflation rate	yes		yes	
Demographic controls	yes		yes	
F	57.63		58.11	
Prob>F	0.000		0.000	

Note: Conditional on updates; other notes are the same as those for Table 4-9.

The estimation results indicate that around the beginning of the survey, households update their expectations upward, to a great extent in response to greater inflation volatility. As the survey proceeds, however, households tend to update their expectations downward, to a great extent with volatile inflation. This also indicates the possibility of learning effects toward the end of the survey (i.e., households use information efficiently).

5. Robustness checks by income group, with “CPI by income”

As stated in section 3, I have thus far employed the CPI of all items as a proxy for the inflation rate, although the actual inflation rate that each household faces may vary. Because of data limitations, I cannot determine the exact inflation rate of each household, although some published information is available on CPI by households’ major characteristics. As I am interested in the possible differences in expectation behavior among various income groups, I substitute the CPI of all items with CPI of all items by five income categories[37] and repeat the same estimation as that detailed in section 4. The level of inflation does not differ overly much among various income levels, but the volatility tends to be greater for lower-income households than for higher-income ones (Appendix Figures A-3 and A-4). Compared to the usual CPI, the distribution of volatility measured by the squared sum of previous inflation rates shifts rightward in the case of CPI by income; this reflects the fact that low-income households face much higher volatility in their price levels.

Table 5-1 shows the estimation results of the marginal effects of updating inflation expectations, by income level and by upward and downward revisions; as such, it comprises a parallel analysis of the results in Table 4-5. The results are consistent with the previous ones, although these are much clearer. The implications here are summarized as follows: (1) higher inflation in the previous period increases the probability of revising expectations downward and decreases the probability of revising expectations upward, (2) higher volatility is likely to lead to a downward updating of expectations and is less likely to lead to an upward updating of expectations, except in the lowest-income group. In addition, these features are more distinct among higher-income households than lower-income ones. In general, a greater absolute value of marginal effects of the volatility index among high-income households may imply that high-income households are relatively more attentive.

[37] To be more precise, I use in the analysis "CPI of all items, excluding imputed house rents."

Table 5-1 Marginal effects on probability of updating inflation expectations (upward or downward) by income (2)

Updating expectations upwards										
Income	3million -		3-5.5 million		5.5-7.5 million		7.5-9.5 million		9.5-million	
π_{t-1}	-0.0577	***	-0.0728	***	-0.0783	***	-0.0916	***	-0.0881	***
	(0.004)		(0.005)		(0.007)		(0.010)		(0.010)	
$\sigma^2(\pi_{t-1})$	0.00163	***	-0.00069	*	-0.0011	**	-0.0027	***	-0.0022	***
	(0.000)		(0.000)		(0.001)		(0.001)		(0.001)	
N	107,404		95,279		37,386		22,745		23,268	
Demographic controls	yes		yes		yes		yes		yes	
Wald	763.11		510.56		180.17		147.04		139.16	
chi2>0	0.000		0.000		0.000		0.000		0.000	

Updating expectations downwards										
Income	3million -		3-5.5 million		5.5-7.5 million		7.5-9.5 million		9.5-12 million	
π_{t-1}	0.0109	***	0.0114	***	0.0137	**	0.0238	**	0.0229	**
	(0.004)		(0.004)		(0.007)		(0.009)		(0.009)	
$\sigma^2(\pi_{t-1})$	0.00212	***	0.00427	***	0.0055	***	0.0052	***	0.0054	***
	(0.000)		(0.000)		(0.000)		(0.001)		(0.001)	
N	107,404		95,279		37,386		22,745		23,268	
Demographic controls	yes		yes		yes		yes		yes	
Wald	197.9		278.07		155.49		70.24		70.82	
chi2>0	0.000		0.000		0.000		0.000		0.000	

Note: Panel probit estimation; random effects model.

I then examine the relationships between inflation volatility and AFEs. Relating to the test in section 4, I divide the sample into (1) those respondents who revised their forecasts upward and (2) those who revised their forecasts downward. Table 5-2 below comprises these estimation results. Although the results based on the CPI of all items are difficult to interpret (Appendix Table A-5), the results below are easier to interpret. First, in the case of upward revision, higher volatility leads to smaller AFE, both in terms of the level and change level of AFEs. This finding aligns with (H2) and (H3). Second, in the case of downward revision, volatility again leads to smaller error, but higher volatility *increases* change levels, as these are likely to be negative. These findings are also consistent with (H2) and (H3). Along with the results in Table 5-1, these results can be summarized as follows: when inflation volatility has been high, households are more likely to revise their expectations downward. At the same time, higher volatility effectively decreases the level of AFEs to convergence, in cases of both upward and downward revisions. This can be considered evidence that supports the theoretical hypothesis that higher volatility induces a higher attention level, and thus more accurate expectations.

Appendix Table A-7 comprises the results of dynamic panel estimation. Contrary to the above results, these indicate that there are no significant relationships between volatility measures and forecast accuracy, once I control for the impact of lagged forecast errors. Similar to the previous results with the usual CPI, the coefficients of lagged forecast errors are all negative and significant; they are not, however, overly large in terms of absolute values. Thus, I find no indication of persistence among the AFEs.

Table 5-2 AFEs and household attentiveness
by the direction of updates

[Panel A: Explained = AFEs]

Direction of updates	Upwards				Downwards			
	(1)		(2)		(3)		(4)	
$\sigma^2(\pi_{t-1})$	-0.0543	***			-0.0157	***		
	(0.001)				(0.001)			
$\sigma^2(\pi^{e,\ professional}_{t-1})$			-0.2589	***			-0.089	***
			(0.008)				(0.008)	
N	105,629		75,493		60,151		59,187	
Lagged inflation rate	yes		yes		yes		yes	
Demographic controls	yes		yes		yes		yes	
F	429.53		214.03		61.72		42.35	
Prob>F	0.000		0.000		0.002		0.000	

[Panel B: Explained = Change in AFEs]

Direction of updates	Upwards				Downwards			
	(1)		(2)		(3)		(4)	
$\sigma^2(\pi_{t-1})$	-0.0254	***			0.0376	***		
	(0.002)				(0.002)			
$\sigma^2(\pi^{e,\ professional}_{t-1})$			-0.2788	***			0.0548	**
			(0.008)				(0.009)	
N	63,933		62,189		60,151		59,187	
Lagged inflation rate	yes		yes		yes		yes	
Demographic controls	yes		yes		yes		yes	
F	67.91		193.66		154.05		58.90	
Prob>F	0.000		0.000		0.000		0.000	

Note: A fixed-effects model is selected for (1)–(4). Conditional on updates.

In general, replacing the CPI of all items with the CPI of all items by income yields basically consistent and clearer results. I consider this an indication of the advantage of taking into account the heterogeneity in inflation level that heterogeneous households face, although sufficient supporting data are not readily available.

6. Issues related to estimation methods

Thus far, I have sought to examine the response level of individual-level inflation expectations to macro-level shock information. All of these estimations implicitly assume homogeneity in response levels; if this assumption does not hold—because of heterogeneity in the parameter related to the cost of forecast errors, or because of idiosyncratic shocks that can be observed by individuals—the regression model will lead to inconsistent estimates (Pesaran and Smith 1995).

Additionally, I have thus far assumed that the error terms do not correlate among various household types. However, any cross-sectional dependence caused by the presence of unobserved and common macroeconomic factors that correlate with the included regressors can be problematic. Moscone and Tosetti (2009) assert that conventional ordinary least squares estimators are inefficient and estimated standard errors are biased when data contain cross-sectional dependence[38,39]. Hoyos and Sarafidis (2006) argue that substantial cross-sectional dependence among errors can be problematic in microeconomic applications, including cases where individuals respond similarly to common shocks or common and unobserved factors, on account of social norms, neighborhood effects, or herd behavior. The assumption that the residuals of individual expectation levels or forecast errors with demographic controls do not correlate among individuals can be violated, if there have been aggregate economy shocks (e.g., a new monetary policy adopted by a government) that are not necessarily observable but which affect individual expectations to a varied extent. In the context of expectation formation, Keane and Runkle (1990) analyze US professionals' inflation expectations and argue that the rejection of the hypothesis of unbiasedness is misleading, given the magnitude of aggregate shocks. They find that a large percentage of variance of forecast error from the regression that tests the rationality of expectations indicates that these errors are not independent among forecasters. Unlike professional forecasts, individual households are rather strongly affected by household-specific price information when forming inflation expectations, rather than unobserved macroeconomic factors. To examine the possible impact of cross-sectional dependence, I employ the common correlated effects (CCE) approach proposed by Pesaran (2006) to estimate panel data models that bear a multi-factor error structure. The CCE method is found to be robust to cross-sectional dependence among errors, and to the slope of

[38] Hoyos and Sarafidis (2006) point out that the impact of cross-sectional dependence in dynamic panel estimators is more severe than that of the usual panel estimators. If there is cross-sectional dependence in the disturbances, all the estimation procedures that rely on IV and GMM will be inconsistent with a large N and a fixed T.

[39] The Monte Carlo simulation of Pesaran (2006) shows substantial bias and size distortions in cases that ignore cross-sectional dependence.

heterogeneity. Some of the estimation results are included in Appendix Table A-8, which does not bear statistical significance[40].

6.1 Attrition[41]

Some of the households dropped out from the survey during the 15-month survey period[42]. If those households who dropped out differ systematically from those who stayed, then the dataset that consists of the continuing members would no longer be representative of the original population. If such attrition occurs in a nonrandom manner, any results based on the data of continuing members may be seriously affected by attrition bias. In my dataset, the proportion of households that dropped out increased as the survey period proceeded, finally reaching a nonneglible level. Ultimately, only 59.5% of the sample households in the panel dataset could be observed throughout the full survey period (i.e., 15 times), while a sizeable proportion of households (13.2%) dropped out near the end of the survey period (i.e., during the 13th and 14th months).
As a first step, I determine whether attrition is random. For this test, in addition to the usual demographic variables (i.e., age of household head, income, and number of household members), I include information on survey timing and two other variables, any of which may correlate with attrition. One of those variables is the lagged variable of the dependent variables (i.e., AFE and change in AFE), as is typically found in selection models; the other is the average attrition rate by prefecture, as an indicator of survey quality[43]. I implement two tests to examine randomness: attrition probits (Fitzgerald et al. 1998) and pooling tests, in which the equality of coefficients from the samples with and without attrition is tested (Becketti et al. 1998). In the latter, the dependent variable is an outcome variable from the first wave of the survey per household, while the independent variables include household variables as well as macro-level economic variables, an attrition dummy, and the interaction terms between the attrition dummy and the explanatory variables. The results of an F-test of the joint

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40 CCE estimation is an econometrically heavy task in the case of a large N dataset, and so I tried the estimation only in a couple of models. For technical reasons, I used only those households with a full set of observations (i.e., 15 observations), including those without updates. Unfortunately, the results indicate that model specification may be inappropriate. Further elaboration is required to obtain robust estimation results.

41 For the analysis in this subsection, I consulted a technical note by Baulch and Quisumbing (2011).

42 As is typical with a panel dataset, my dataset originally contained several respondents who had initially dropped out, but reappeared later in the survey period. As responses were collected directly from the households, the proportion of such samples is limited (3,832 observations, corresponding to 1.18% of the full sample). Thus, for this subsection's attrition-related analysis, I do not include those respondents who reappeared after dropping out.

43 For details, see Mallucio (2004). The government commission the execution of the Consumer Confidence Survey to a private survey company with branches at the prefecture level. Each month the polltakers hired by these branches visit the surveyed households to collect responses. Naturally, the attrition rate may well correlate with the quality (or skill) of the polltakers, who are hired and trained at the branch (i.e., prefecture) level.

significance of the attrition dummy and the interaction variables will help determine whether the coefficients from the explanatory variables differ between attritors and nonattritors.

If these tests indicate nonrandomness—except for identifying appropriate instrumental variables for selection models—another solution would be to estimate the inverse probability weights, which rely on auxiliary variables that relate to both attrition and the outcome variables (Fitzgerald et al. 1998). The thinking behind inverse probability weighting is that it gives more weight to households with initial characteristics similar to those of households that subsequently attrite, than to households with characteristics that make them more likely to continue throughout the survey period (Baulch and Quisumbing 2011).

6.2 Randomness test

The estimation results of attrition probits are summarized in Appendix Table A-9. The explanatory variables explain about 7.0% of panel attrition, implying that over 90% of the attrition remains unexplained; meanwhile, *z*-statistics and *p*-values indicate that most of the variables—except for income and city size—are statistically different from zero at the 1% significance level. The Chi-squared statistic 8,565.26, with 18 degrees of freedom, indicates that these variables are jointly statistically different from zero at the highest level of significance (*p*-value = 0.000). I thus conclude that these variables are significant predictors of attrition.

Next, the estimation results of a clustered regression for the test of Becketti et al. (1998) are shown in Table A-10. I implement an F-test to determine whether the attrition dummies and all the interaction terms are jointly equal to zero. The F-statistic of 96.18 (*p*-value 0.000) indicates that the null hypothesis of the randomness of attrition is rejected at the highest level of significance.

6.3 Inverse probability weight

Given that the above standard test results indicate that attrition is nonrandom in the estimation of AFEs, I calculate inverse probability weights for this model. For this estimation, I use as the auxiliary variables household demographic characteristics. The inverse probability weights vary from 0.8286 to 1.4932, with a mean value of 1.005. I compare the estimation results in the following section with and without these probability weights, and find there to be no substantial differences between the two estimations (Table A-11).

7. Conclusions

This study aimed to provide insights into the forecast-updating behavior of Japanese households with regard to the inflation rate. Similar to the findings in the literature, I detected information rigidity in inflation expectations; thus, it is clear that households do not renew their information set in each period. Although there is some rigidity, the estimation results indicate that they update their information once every 3.3 months; this is less rigid than the US case, for example. It is confirmed that more volatile inflation rates in a recent period will trigger more updates, particularly downwardly. With regard to the direction and extent of the updates, the theoretical model of rational inattention would prompt one to expect the accuracy of the expectations to improve along with the number of updates, and thus with recent volatility in the realized inflation rate. I obtained mixed results regarding the relationships between recent volatility and the level of forecast errors; making an accurate forecast would be more difficult during a volatile period, although households do tend to be more attentive during those times to inflation rate developments. However, there does appear to be a certain learning effect at work; thus, updates do indeed lead to greater accuracy, particularly from the middle of the survey period onward. Furthermore, if I use the realized inflation rate by household major attributes, the relationships between volatility and accuracy become clearer; this might imply that the realized inflation rate that each household faces varies to a certain extent, and hence, the estimation results with forecast errors based on the CPI of all items might bear ambiguous implications.

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Appendix (Tables and Figures)

Table A-1 Summary statistics (1)

Variable		Mean	SD	Min	Max	N
Based on CPI (all items)	error	-1.65	2.62	-7.9	7.8	297,200
	AFE	2.34	2.03	0.0	7.9	297,200
	D_AFE	0.02	1.59	-6.9	6.9	255,504
Based on CPI by income	error	-1.65	2.63	-7.9	8.0	297,200
	AFE	2.35	2.03	0.0	8.0	297,200
	D_AFE	0.02	1.60	-7.3	7.3	255,504
Based on CPI by age	error	-1.69	2.49	-7.4	7.1	297,200
	AFE	2.28	1.96	0.0	7.4	297,200
	D_AFE	0.02	1.58	-6.6	6.7	255,504
Other variables	Dpricex2	0.03	2.02	-10	10	255,504
	age	58.92	15.79	18	90	325,418
	income	494.29	252.78	300	1200	325,418
	number	2.56	1.51	1	12	325,418
	survey_month	6.92	4.17	1	15	325,418

Note: "error" stands for forecast error (realized inflation minus expected inflation). "AFE" stands for the absolute value of "error," and "D_AFE" is the change in AFE from the previous month. "Dpricex2" is the change in inflation expectations from the previous month; "number" is the number of household members, and "survey_month" is the timing of the survey (xth month of a 15-month survey).

Table A-1 Summary statistics (2)

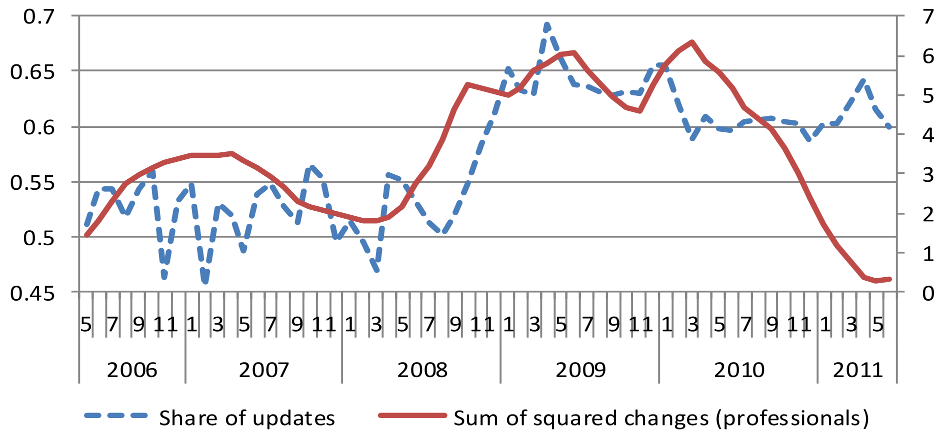
Variable		Mean	SD	Min	Max	N
Frequency measure	cum_change	3.17	2.79	0.00	14.00	323,558
	ratio_change	0.23	0.20	0.00	0.93	323,558
Volatility measure	$\sigma^2(\pi_t)$	14.78	13.12	0.60	38.08	318,905
	$\sigma^2(\pi^{e,\ professional}{}_t)$	3.54	1.63	0.28	6.32	318,905
	$\sigma^2(\pi^{e,\ household}{}_t)$	0.79	0.24	0.22	1.13	250,702
	$Gap(\pi^{e,\ professional}{}_t)$	0.74	0.30	0.30	1.35	325,418

Note: "cum_change" stands for the number of updates up to the previous survey month, and "ratio_change" is "cum_change" divided by the number of surveys up to the previous month. $\sigma^2(\pi_t)$ is the sum of the squared changes of realized inflation over the previous 12 months. $\sigma^2(\pi^{e,\ professional}{}_t)$ corresponds to the sum of squared changes in inflation expectations of professional forecasters over the previous 12 months. $\sigma^2(\pi^{e,\ household}{}_t)$ is the sum of the squared changes in mean inflation expectations of the "Consumer Confidence Survey" over the previous 12 months. $Gap(\pi^{e,\ professional}{}_t)$

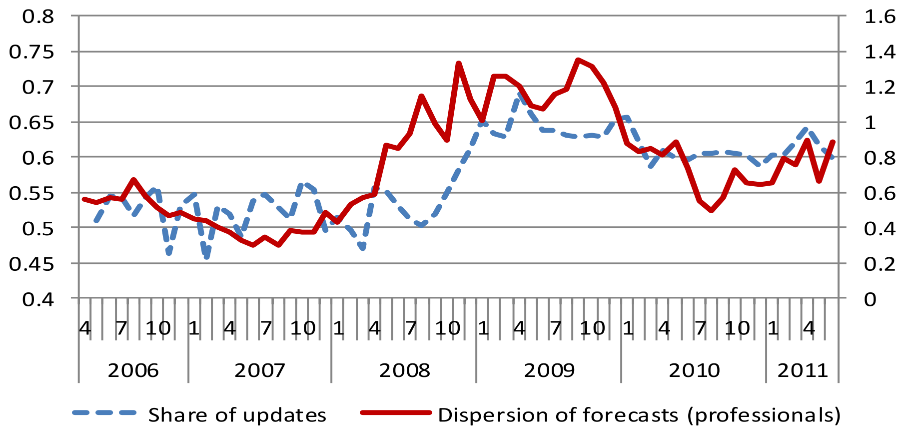
is the difference between the average one-year-ahead expectations of the top eight institutions and those of the bottom eight institutions.

Figure A-1

Expectation updating and volatility measure (2)



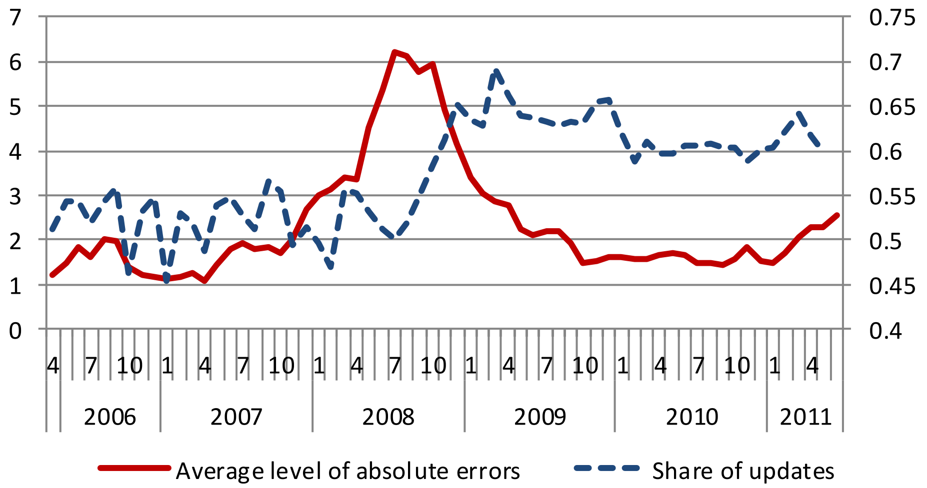
Expectation updating and volatility measure (3)



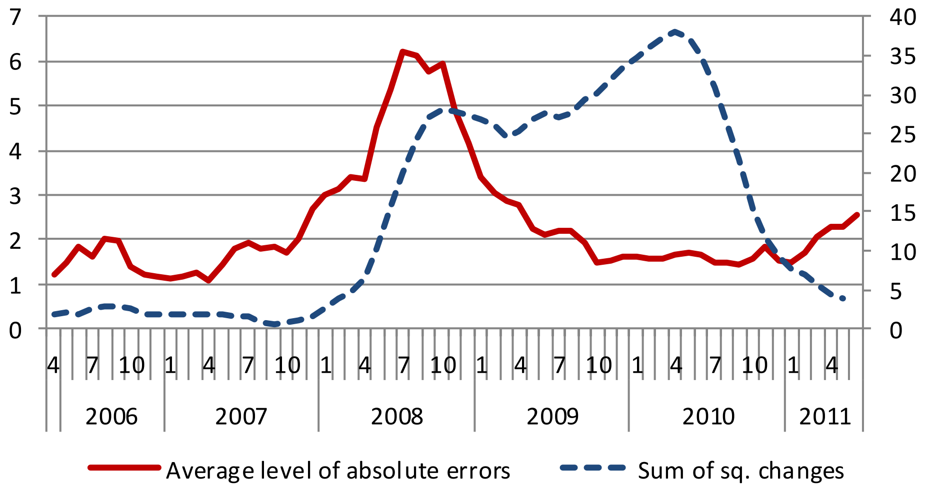
Note: The share of updates is plotted on the left-hand axis, and volatility measures are on the right-hand side. Share of updates is adjusted for FY2006–FY2008, because of the obvious impact of using two different survey methods. Details of the volatility measures are provided in the text. The correlation for the upper panel is 0.452 (*p*-value 0.000), while that for the lower panel is 0.696 (*p*-value 0.000).

Figure A-2

Expectation updating and average AFEs



Average AFEs and volatility measure



Note: The average level of AFEs is plotted on the left-hand axis, and the share of updates/sum of squared changes is on the right-hand side. The share of updates is adjusted for FY2006–FY2008, because of the obvious impact of using two different survey methods.

Table A-2 AFEs and household attentiveness (based on CPI by age)

	(1)		(2)		(3)		(4)		(5)		(6)	
Number of previous updates	-0.0447	***										
	(0.011)											
Frequency of previous updates			0.0328									
			(0.138)									
$\sigma^2(\pi_{t-1})$					-0.00142							
					(0.003)							
$\sigma^2(\pi^{e,\ professional}_{t-1})$							-0.1565	***				
							(0.009)					
$\sigma^2(\pi^{e,\ household}_{t-1})$									1.5048	***		
									(0.050)			
$Gap(\pi^{e,\ professional}_{t-1})$											1.0890	***
											(0.053)	
N	64,447		64,447		56,046		64,746		51,003		64,746	
Lagged inflation rate	yes		yes		yes		yes		yes		yes	
Demographic controls	yes		yes		yes		yes		yes		yes	
F	250.45		249.69		252.51		291.97		375.13		330.86	
Prob>F	0.000		0.000		0.000		0.000		0.000		0.000	

Note: A fixed-effects model is selected for (1)–(6). Conditional on updates. Clustered standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. “Frequency of previous updates” is the ratio of update to survey length up to the survey point. $\sigma^2(\pi_{t-1})$ is the sum of the squared changes in realized inflation by age over the previous 12 months. $\sigma^2(\pi^{e,\ professional}_{t-1})$ corresponds to the sum of squared changes in the inflation expectations of professional forecasters over the previous 12 months. $\sigma^2(\pi^{e,\ household}_{t-1})$ is the sum of the squared changes in mean inflation expectations of the “Consumer Confidence Survey” over the previous 12 months. $Gap(\pi^{e,\ professional}_{t-1})$ is the difference between the average one-year-ahead expectations of the top eight institutions and those of the bottom eight institutions.

Table A-3 Absolute AFEs and household attentiveness (based on CPI by income)

	(1)		(2)		(3)		(4)		(5)		(6)	
Number of previous updates	-0.0855	***										
	(0.008)											
Frequency of previous updates			-0.2454	***								
			(0.092)									
$\sigma^2(\pi_{t-1})$					-0.02884	***						
					(0.001)							
$\sigma^2(\pi^{e,\ professional}_{t-1})$							-0.2015	***				
							(0.010)					
$\sigma^2(\pi^{e,\ household}_{t-1})$									1.1710	***		
									(0.060)			
$Gap(\pi^{e,\ professional}_{t-1})$											1.3305	***
											(0.045)	
N	123,423		123,423		124,084		64,746		51,003		124,084	
Lagged inflation rate	yes		yes		yes		yes		yes		yes	
Demographic controls	yes		yes		yes		yes		yes		yes	
F	63.17		46.53		178.47		74.67		87.52		194.94	
Prob>F	0.000		0.000		0.000		0.000		0.000		0.000	

Note: A fixed-effects model is selected for (1)–(6). Conditional on updates. The other notes are the same as those for Table A-2.

Table A-4 Changes in AFEs and household attentiveness

	(1)		(2)	
(A)				
Frequency of previous updates	-2.500	***		
$\sigma^2(\pi_{t-1})$			-0.0204	***
Cross-terms with (A) and survey-point dummies				
First month	-		-	
Second month	-		-0.0002	
Third month	1.824	***	0.002	*
Fourth month	2.012	***	0.001	
Fifth month	2.005	***	0.003	**
Sixth month	2.205	***	-0.001	
Seventh month	2.550	***	0.002	*
Eighth month	2.275	***	-0.0001	
Ninth month	2.516	***	-0.001	
Tenth month	2.578	***	-0.001	
Eleventh month	2.528	***	0.001	
Twelfth month	2.611	***	-0.002	**
Thirteenth month	2.641	***	-0.002	***
Fourteenth month	2.644	***	0.001	
Fifteenth month	2.757	***	-	
N	224,459		249,633	
Lagged inflation rate	yes		yes	
Demographic controls	yes		yes	
F	22.78		146.84	
Prob>F	0.000		0.000	

Note: The other notes are the same as those for Table 4-9.

Table A-5 Absolute forecast errors and household attentiveness by direction of updates

(based on CPI of all items)

Direction of updates	Upwards		Downwards	
	(1)	(2)	(3)	(4)
$\sigma^2(\pi_{t-1})$	0.0069 ***		0.0031 **	
	(0.001)		(0.001)	
$\sigma^2(\pi^{e,\ professional}_{t-1})$		-0.105 ***		-0.026 ***
		(0.007)		(0.008)
N	75,493	75,493	59,187	59,187
Lagged inflation rate	yes	yes	yes	yes
Demographic controls	yes	yes	yes	yes
F	1012.34	1033.59	284.27	285.58
Prob>F	0.000	0.000	0.000	0.000

Note: A fixed-effects model is selected for (1)–(4). Conditional on updates.

Table A-6 Determinant of inflation expectations by income

[Explained = Inflation expectations]

	All households	By income						
		3million-	3-4million	4-5.5million	5.5-7.5million	7.5-9.5million	9.5-12million	12million-
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inflation Expectation$_{t-1}$	-0.213 ***	-0.243 ***	-0.190 ***	-0.212 ***	-0.273 ***	-0.166 ***	-0.146 ***	-0.146 **
	(0.012)	(0.024)	(0.024)	(0.029)	(0.028)	(0.032)	(0.050)	(0.059)
$\sigma^2(\pi_{t-1})$	0.169 ***	0.082	0.118 **	0.161 **	0.081	0.250 ***	0.147	0.221
	(0.060)	(0.084)	(0.056)	(0.063)	(0.064)	(0.082)	(0.103)	(0.153)
N	60,124	19,864	10,521	9,216	8,005	5,052	2,968	2,174
Hansen test of over-identification (p-value)	0.002	0.215	0.231	0.737	0.048	0.495	0.530	0.255
Test for first-oreder serial correlation (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Test for second-oreder serial correlation (p-value)	0.317	0.972	0.130	0.234	0.527	0.180	0.713	0.272

Note: Conditional on updates; other notes are the same as those for Table 4-8 (Panel A), except that the instruments here use lagged or differenced values of the inflation expectation itself.

Table A-7 Determinants of AFEs in inflation expectations
(CPI by income)

Explained = AFEs

	All households		By income									
			3million -		3-5.5 million		5.5-7.5 million		7.5-9.5 million		9.5-million	
	(1)		(2)		(3)		(4)		(5)		(6)	
AFE_{t-1}	-0.277	***	-0.301	***	-0.278	***	-0.311	***	-0.231	***	-0.232	***
	(0.010)		(0.018)		(0.016)		(0.027)		(0.037)		(0.033)	
$\sigma^2(\pi_{t-1})$	0.166		0.055		-0.251	**	-0.108		0.018		-0.045	
	(0.151)		(0.054)		(0.115)		(0.194)		(0.237)		(0.103)	
N	61,384		20,230		20,585		8,151		5,147		5,341	
Hansen test of over-identification (p-value)	0.000		0.030		0.290		0.108		0.048		0.238	
Test for first-oreder serial correlation (p-value)	0.000		0.000		0.000		0.000		0.000		0.000	
Test for second-oreder serial correlation (p-value)	0.957		0.665		0.505		0.101		0.286		0.385	

Note: Conditional on updates. AFE_{t-1} stands for absolute forecast error of the previous period. The other notes are the same as those for Table 4-8 (Panel A).

Figure A-3 CPI general by income quintiles
(year-to-year growth rate)

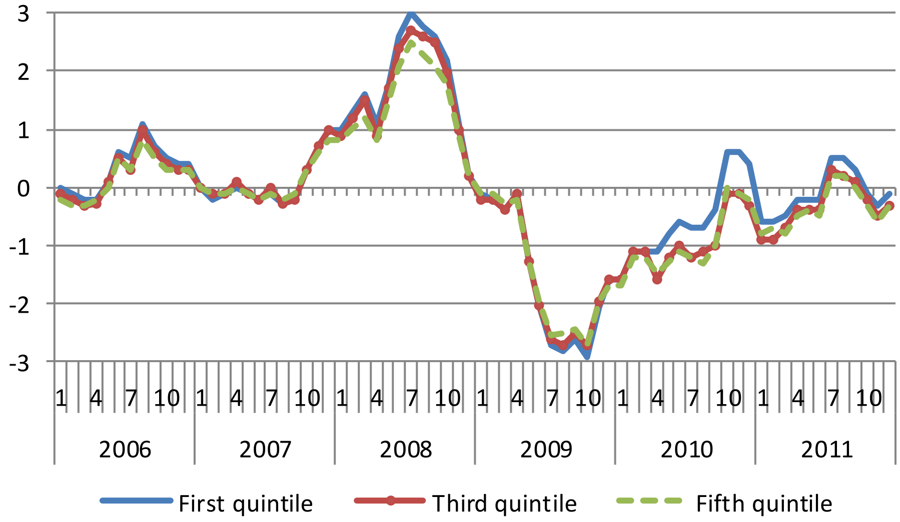
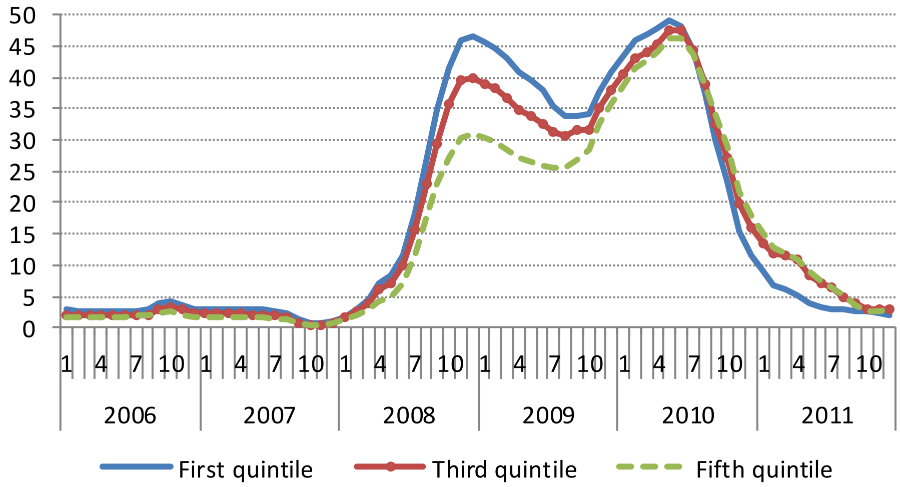


Figure A-4 CPI general by income quintiles
(Squared sum of growth rate)



Note: Data are from the Annual Book of the Consumer Price Index; estimations are made by the author.

Table A-8 Absolute forecast errors and household attentiveness (CCE approach)

	(1)	(2)	(3)
Frequency of previous updates	-0.4454		
	(5.787)		
$\sigma^2(\pi_{t-1})$		-0.0159	
		(0.087)	
$\sigma^2(\pi^{e,\ professional}_{t-1})$			0.23938
			(0.178)
N	136,931	136,931	136,931
Lagged inflation rate	yes	yes	yes
Demographic controls	yes	yes	yes
F	8.44	3.77	3.29
Prob>F	0.296	0.806	0.857

Note: CCE results, Samples are limited to those with 15 observations

Table A-9 Attrition probit for AFEs

	Coef.	Std. Err.	z	P>z
age	0.00	0.00	-6.67	0.000
number	-0.08	0.01	-13.02	0.000
income	0.00	0.00	1.15	0.249
citysize	-0.02	0.02	-1.05	0.294
Lagged AFE	0.10	0.01	13.85	0.000
Differenced AFE	-0.02	0.00	-4.09	0.000
Attrition rate by prefecture	3.18	0.13	24.24	0.000
constant	-2.06	0.07	-31.21	0.000
N	212694			
Wald chi2(18) = 8565.26				
Prob > chi2 = 0.0000				
Log pseudolikelihood = -125273.74 Pseudo R2 = 0.0702				

Note: Standard errors are adjusted for 47 clusters in prefecture.
Coefficients of dummies of survey month are omitted.

Table A-10 Attrition pooled regression

	Coef.	Robust Std. Err.	t	P>t
age	-0.003	0.001	-2.70	0.01
number	0.008	0.011	0.69	0.50
income	0.000	0.000	-3.40	0.00
citysize	0.032	0.023	1.41	0.17
Lagged AFE	0.403	0.009	42.72	0.00
Differenced AFE	-0.333	0.006	-55.02	0.00
Attrition rate by prefecture	1.401	0.519	2.70	0.01
Interaction terms (above variables * attrition dummy)				
cross_age	0.011	0.001	10.94	0.00
cross_income	0.000	0.000	-6.39	0.00
cross_number	0.010	0.011	0.88	0.38
cross_citysize	-0.073	0.023	-3.23	0.00
cross_Lagged_AFE	-0.065	0.009	-6.81	0.00
cross_attrition rate	-0.016	0.430	-0.04	0.97
cross_Differenced AFE	0.029	0.006	4.79	0.00
Attrition dummy	-0.689	0.034	-20.13	0.00
Constant	1.574	0.196	8.03	0.00
N=169261				
Note: Standard errors are adjusted for 47 clusters in prefecture				

Table A-11 Linear regressions for AFEs

	Without Attrition Weights			With Attrition Weights		
	Coef.	Robust Std. Err.	P-value	Coef.	Robust Std. Err.	P-value
$\sigma^2(\pi_{t-1})$	0.034	0.001	0.000	0.034	0.001	0.000
Lagged inflation rate	0.956	0.007	0.000	0.988	0.007	0.000
age	0.002	0.001	0.001	0.002	0.001	0.000
income	0.000	0.000	0.000	0.000	0.000	0.000
number	0.021	0.007	0.002	0.015	0.007	0.035
citysize	-0.020	0.008	0.010	-0.020	0.008	0.016
survey_month	0.010	0.002	0.000	0.011	0.002	0.000
constant	2.090	0.049	0.000	2.094	0.053	0.000
N	193052			155070		
R-sq	0.301			0.323		
Root MSE	1.784			1.778		
Note: Standard errors are adjusted for household-level clusters						

Supplementary note on "news on inflation"

This note looks to supplement discussion on the nexus between news coverage on inflation and household inflation expectations. This analytical thinking is based on that found in the recent analysis of Pfajfar and Santoro (2013), which sought to highlight a disconnect among news on inflation, household updating behavior of expectations, and the accuracy of their expectations.

As explained in section 2, the sticky-information model assumes that households update their inflation expectations from news information, while the news spreads only slowly among households, reaching only a fraction of the households in each period (equation (1)). The analysis in subsection 4.2.1 identifies several factors that could affect household updating behavior (Table 4-4). In this note, I examine on a supplementary basis how the level of news coverage of inflation could affect updating frequency; I do so by estimating a panel probit model of (11) and (12), but while also adding an index of news coverage calculated in a manner similar to Carroll (2003)[44]. The estimation period was January 2008 to October 2013[45].

First, Figures S-1 and S-2 show trends in realized inflation, the intensity of news coverage (using the terms "increase" and "decrease" respectively), and the average level of expected inflation rate.

[44] In other words, by using the Nikkei Telecon database, I compute a monthly index of the intensity of news coverage in major national newspapers, the major common press, the business press, news updates available online, and some TV news programs. I look for articles or news stories that contain the words "prices" and either "increase" or "decrease," but exclude stories on countries other than Japan or on financial markets. I convert the numbers of articles for each month into an index, by dividing them by the maximum number.

[45] Owing to data availability, the estimation period does not coincide with that in the main text.

Figure S-1: News coverage with "price" and "increase"

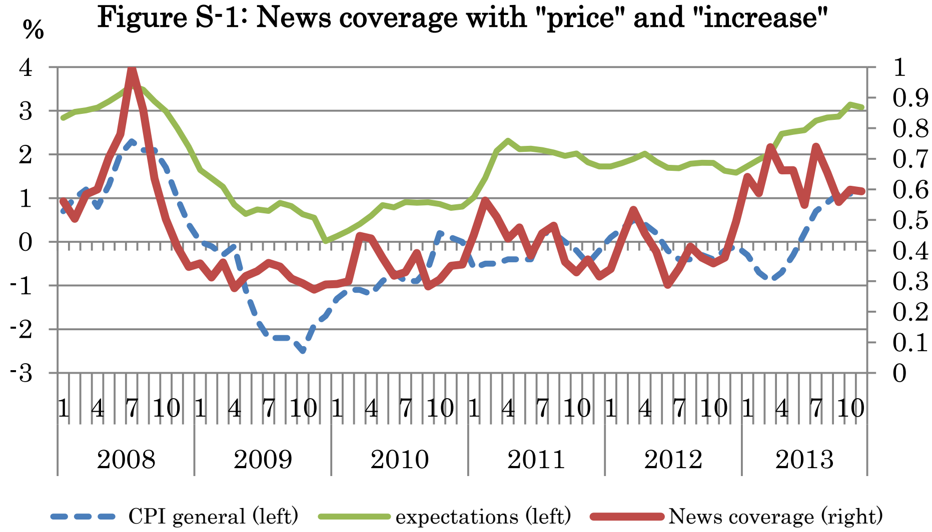
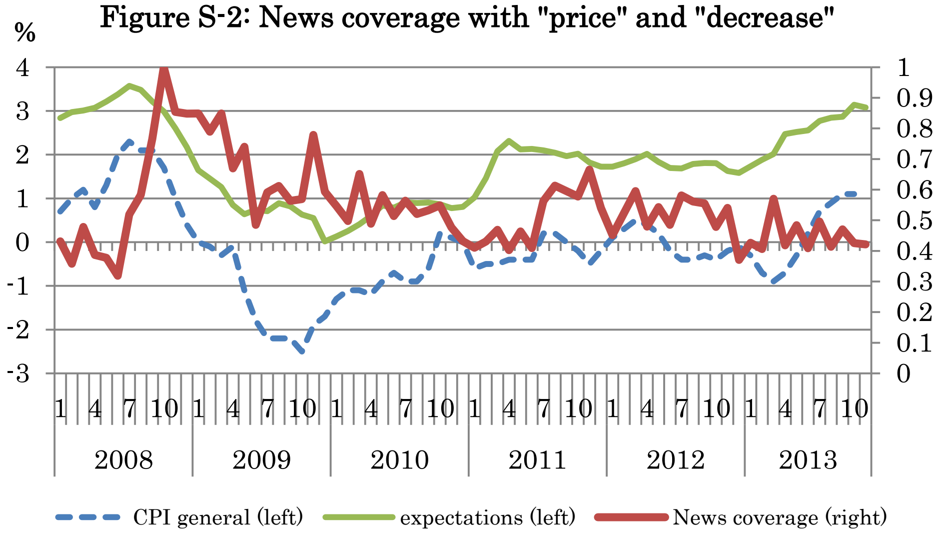


Figure S-2: News coverage with "price" and "decrease"



The correlation between the news coverage index ("increase") and the expected inflation rate is fairly high (0.821, with the news index one period ahead), whereas the correlation between the index ("decrease") and the expected inflation rate is not so obvious (–0.322, with news index one period ahead).

Table S-1 summarizes the estimation results. These results indicate that with regard to the estimation that specifies the direction of the price change, hearing news about price trends generally increase the probability that households will update their expectations in either direction (i.e., upward or downward) (models (1)–(4)). However, this does not necessarily hold in models (5) and (6), wherein current news of price trends tend to negatively affect the probability of updating expectations. This indicates the possibility that households respond only to specific news, clearly distinguishing whether prices are currently increasing or decreasing.

Table S-1 Determinants of expectation updating by households

	(1)		(2)		(3)		(4)		(5)		(6)	
Explained variable	Updating upwards				Updating downwards				Updating in both directions			
π_{t-1}	-0.0080	***	-0.0185	***	-0.0035	***	-0.0035	***	-0.0118	***	-0.0156	***
	(0.001)		(0.001)		(0.001)		(0.001)		(0.002)		(0.001)	
$NEWS_t$	0.0831	***	0.0248	**	0.0087				-0.1789	***		
	(0.016)		(0.010)		(0.009)				(0.017)			
$NEWS_{t-1}$	-0.0281	*			0.1374	***	0.1553	***	-0.0496	***	-0.0591	***
	(0.023)				(0.010)		(0.005)		(0.019)		(0.015)	
$NEWS_{t-2}$	-0.1334	***			0.0160	*			0.1270	***		
	(0.018)				(0.009)				(0.017)			
N	200,334		205,351		200,334		205,351		200,334		205,351	
Sociodemographic controls	yes		yes		yes		yes		yes		yes	
Wald	11664.52		11376.58		2461.7		2464.54		6621.65		6375.82	
chi2>0	0.000		0.000		0.000		0.000		0.000		0.000	

Note: This table reports the marginal partial effects of the panel probit estimation. The explained variables are "whether households update their expectations upward" (models (1) and (2)), "whether households update their expectations downward" (models (3) and (4)), and "whether households update their expectations" (models (5) and (6)). The explanatory variables include the (lagged) level of news coverage (with the terms "price" and "increase" (models (1) and (2)), "price" and "decrease" (models (3) and (4)), or "price" and "increase" or "decrease" (models (5) and (6))), the most recently realized inflation rate, and the sociodemographic attributes of the respondents (age, income, household size, survey timing). Clustered standard errors at a household level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.