Updating Behavior of Inflation Expectations:

Evidence from Japanese Household Panel Data

June 2014

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Abstract

This study provides insights into the expectation-updating behavior of Japanese households regarding 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. The majority of households repeat updates in a staggered way, while by using a system GMM estimator we find that higher attention to the inflation trend induces a part of single-earner households that are being mortgaged to update their expectations upwardly. On the contrary, there are no clear evidences that these households steadily approach to more accurate forecasts by making more updates. This indicates that against theoretical prediction higher attention does not necessarily induce greater accuracy.

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 so frequently 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 four 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 both upwardly and downwardly; this finding is consistent with theoretical expectations that indicate that past volatility leads to higher attentiveness toward inflation development. Third, I have mixed results with regard to whether higher volatility leads to more accurate expectations. There is also evidence that persistence in forecast errors is quite limited, while each update does not necessarily improve accuracy (i.e., updating in a staggered fashion). At the same time, if I limit the samples to the households with attributes including being mortgaged or single worker with multiple family members, they simply tend to raise their expectations when their attention level is high. Such households are expected to have a motivation to be attentive to the inflation trend given their financial issues close to the top of their agenda, while even among these households there are no clear evidence that indicates that higher attention is linked to more accurate expectations. Finally, towards the end of the survey, a learning effect exists and comes to connect attentiveness to more accurate forecasts, after experiencing several survey waves.

1.1 Literature review

[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.

The empirical analysis undertaken in this study has a basis in two major theoretical models. The first is the sticky-information model introduced by Mankiw and Reis (2002). The essence of this 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 many, including 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.

Andrade and Le Bihan (2013) proposed a model of inattention that incorporated both sticky and noisy information, and fitted a micro-level data of professionals’ forecasts to find that the model fails to quantitatively fit the data in a general sense.

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 other 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.

This study is structured as follows; in section 2, I briefly discuss theoretical models based on the previous literature and derive hypotheses that can be tested empirically. In section 3, I provide the overview of the dataset, followed by several descriptive features of the Japanese households' inflation expectations. In section 4, I introduce the estimation models and major estimation results. Section 5 checks the robustness of the arguments of the previous section. Section 6 then discusses some of the issues related to the estimation methods employed in sections 4 and 5. Section 7 is a supplementary section that focuses on the impact of "news" on the formation of expectations. Section 8 concludes.

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*. 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:

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

$v_{t+h,t}$: 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:

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

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. In order to deal with this, 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

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

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.

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

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

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

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:

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

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

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

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

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

[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.

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]

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

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.

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

[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.

(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.

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)[7] 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 October 2013. 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?"[8]; 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%[9]; or (d) unknown. I take the mid-value of the selected response and consider it the household's inflation expectation.

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[7] From April 2014 and onward, each survey contains data on 8,400 households (single, 2,688; nonsingle, 5,712).

[8] 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). In addition, the survey questionnaire contains an instruction such that "Please reply by assuming how the future prices of the goods you frequently purchase will be in a year's time relative to the current ones, based on the information you collect from your daily shopping as well as from media including newspapers and TV."

[9] 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%." To maintain the consistency of the data, I treat the samples of "increase/decrease of more than 10%" as "increase/decrease of more than 5%" after April 2009.

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 of all items, CPI by age group, CPI by income group, and CPI by region. Data on CPI by five income categories[10] are published on a monthly basis; CPI by region are actually CPI by 47 prefectures and published on a monthly basis as well; CPI by age is 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."[11] 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, CPI by income, or CPI by region, given the fact that the distribution of household inflation asymptotically follows the normal distribution. I estimate a volatility measure of the recent inflation rate by calculating a squared sum of the monthly changes of the CPI, CPI by age, CPI by income, and CPI by region. In addition, I employ the cross-sectional variance of the responded inflation expectations for each survey as an alternative measure of the volatility.

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

[10] 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.

[11] 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.

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[12]. 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 (henceforth, FE) 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). I note that neither FEs nor AFEs are available for the observations of February 2013 and onwards, as the realized inflation rate is only available up to January 2014[13].

3.2 Main features of inflation expectations

In this subsection, I provide an overview of the average level of forecast errors[14] and other statistics that would be 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[15]. Throughout the 15-month survey period, households updated their expectations an average of 3.7 times; this corresponds to around 32.4% of all responses that each household provided[16].

Figure 3-1 shows the trend in average AFE, by survey month. In this subsection, the forecast error is derived from the CPI[17]. First, the average AFE always ranges between 2.2% and 2.5% points, indicating that household expectations always differ from the CPI[18]. On average, the figure does not show a clear trend throughout the 15-month survey period: the average AFE has its peak around the 12th -13th months and declines in the final two 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

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[12] 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.

[13] As of March 2014.

[14] There are 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 manner.

[15] The summary statistics of the other variables including AFEs employed in the estimation are provided in the Appendix (Table A-1).

[16] Note that this result is derived from a dataset containing households that dropped out before the end of the usual survey period.

[17] Parallel analysis based on the CPI by age or by income basically shows similar results.

[18] Ueno and Namba (2014) discuss the possible origins of these positive errors in detail.

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. They do have a small kink in the 13th month and take a slightly gentler slope in the subsequent months. The median number of expectation updates throughout the survey period is three; this indicates that there are many respondents who never update their expectations or, if ever, only once, or twice. Thus, I divide the sample into two subsamples: those who frequently updated their expectations (i.e., more than three times; the "more frequent group") and those who rarely updated their expectations (i.e., up to three times; the "less frequent group"). Figure 3-3 shows that the majority of households update their expectations around the beginning of the survey period, but in the less frequent group the ratio drops and remains stable after the 4th 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 lower in the less frequent group than in the more frequent group up to the 5th month, then it becomes higher up to the end of the survey. The gap between the two groups becomes the largest at around the 12th month. In addition, the average AFE for both groups tends to increase up to the 12th month, but such increasing trend is more obvious in the less frequent group; this implies the possibility 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 11th month within the less frequent group, while the variance does not change so much 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	3.714	3.249	0.558	3.0
Number of updates/Survey length	0.324	0.240	0.061	0.3

Note: Sample period is 2006.4-2013.10. "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).

Figure 3-1 Average level of AFE

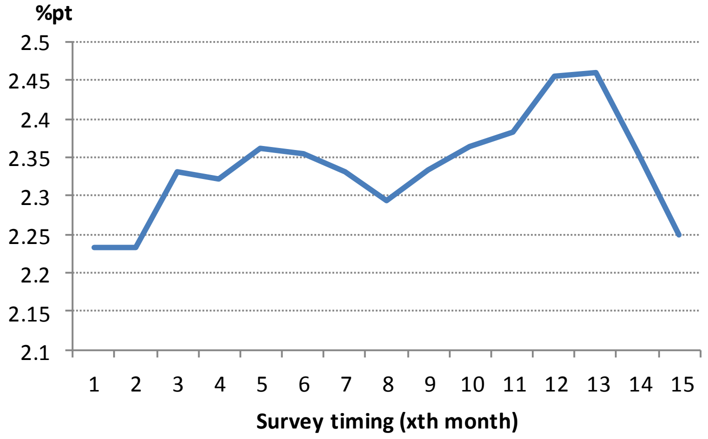


Figure 3-2 Average cumulative errors

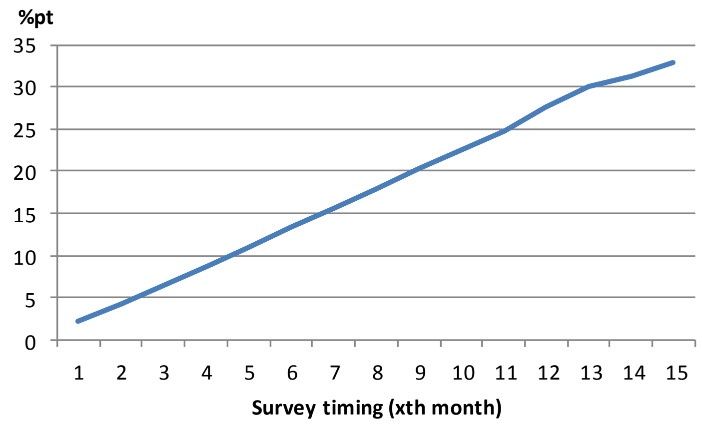


Figure 3-3 Proportion of households that updated their expectation, by survey month

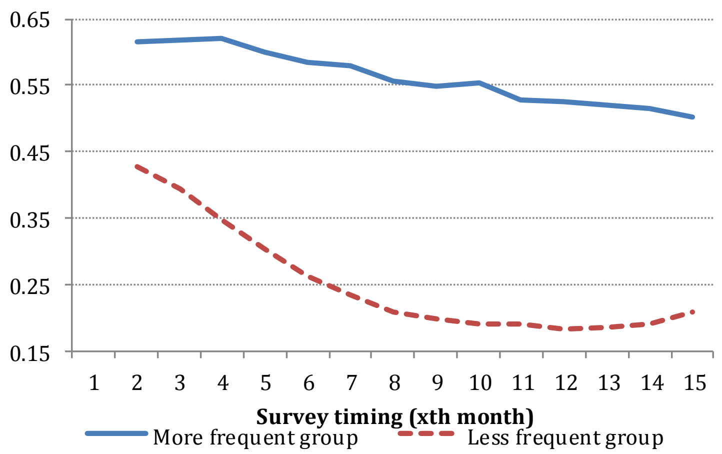


Figure 3-4 Average AFE, by survey month

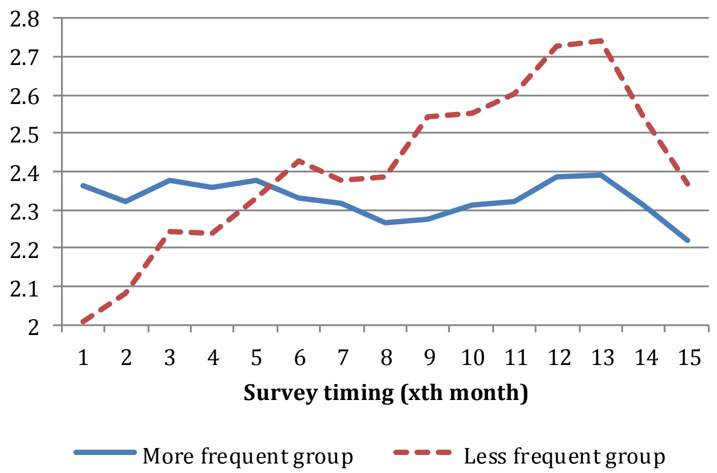
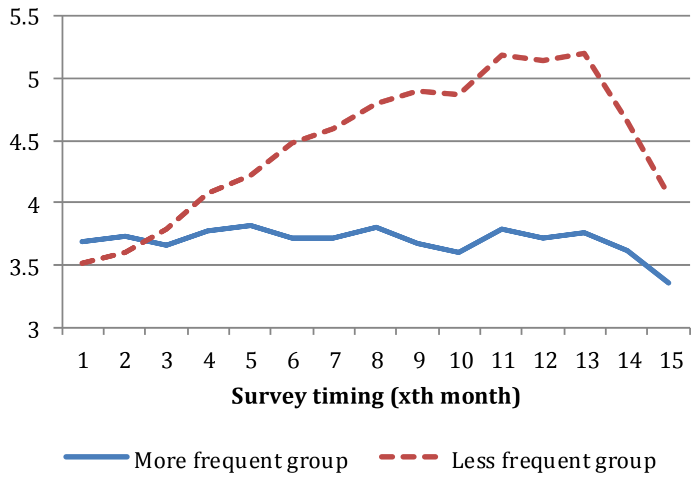


Figure 3-5 Variance of AFE, by survey month



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)	max. # of updates	Share of frequent updaters
Average household	45,053	59.5	487.7	1.72	-1.65	2.33	4.43	76.4%
1. Single, non-employed	7,372	71.5	312.6	1.78	-1.76	2.40	4.12	72.8%
2. Couple, non-employed	6,686	72.9	364.0	1.81	-1.70	2.35	4.45	75.2%
3. Single, employed or self-employed	7,337	46.6	398.9	1.52	-1.50	2.29	4.22	76.6%
4. Couple (no kids, single worker), employed or self-employed	2,604	59.5	509.8	1.72	-1.59	2.30	4.51	76.5%
5. Couple (no kids, two workers), employed or self-employed	2,759	57.8	553.0	1.66	-1.52	2.26	4.60	76.8%
6. Couple + someone (single worker), employed or self-employed	5,356	44.9	589.7	1.71	-1.65	2.29	4.40	77.7%
7. Couple + someone (two workers), employed or self-employed	6,413	50.4	640.7	1.72	-1.63	2.31	4.64	78.8%
8. Couple + someone (more than two workers), employed or self-employed	3,893	58.7	746.1	1.69	-1.61	2.32	4.67	78.2%
9. Others	2,633	61.0	489.1	1.68	-1.67	2.37	4.55	77.0%

Note: N is the number of households within each category. “max. # of updates” is the total number of changes as of the last wave of the survey. “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.

3.2.2 Descriptive macro-level evidence of inflation expectations

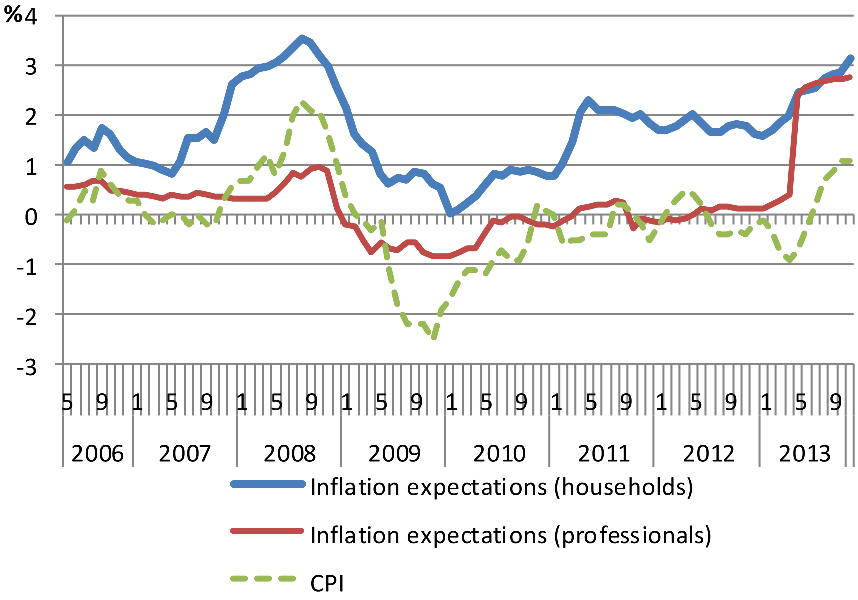
I now briefly overview the time-series trend of inflation expectations by households as well as that by professional forecasters. During the observation period, the Japan’s economy experienced two recession periods (March 2008- March 2009 and May 2012-

fall 2012[19]). In terms of the economic policy management, there was a major change in monetary policy as a part of the "Abenomics" (from December 2012). Further, the government made a decision on the increase in the consumption tax rate (from 5% to 8%) from April 2014. In addition, Japan experienced the Great East Japan Earthquake (March 2011) and its aftermath. All these events could have affected the households' inflation expectations, together with the current trend of the CPI.

Figure 3-6 shows the trend of inflation expectations among households, the trend of inflation expectations among professional forecasters, and the trend of the CPI. Although the households are asked to respond their inflation expectations in the upcoming year, their expectations are obviously highly correlated with the current trend of the CPI. In addition, the level of the expectations are always greater than the level of the current CPI. With regard to the future increase of the consumption tax rate, professionals' forecasts reflect its impact in a precise manner from April 2013 (i.e. one year in advance of the increase), whereas households' expectations do not have such a jump; they rather continued to increase gradually from the beginning of 2013 in accordance with the current trend of the CPI, just after the start of the "Abenomics" policies. It indicates the possibility that most households are short-sighted and do not take account of the future increase in the consumption tax rate well in advance. Another possibility is that prices gradually started to rise from 2013 in anticipation of the increase in consumption tax rate, so that households responded to such changes in an adaptive manner.

[19] Business cycle dates are decided by the Cabinet Office of the Japanese Government. The ending point of the second recession has not yet been decided as of March 2014.

Figure 3-6 Inflation expectations among households and professionals



Note: The expectations are the average of all samples observed for each period.

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 (section 2), as follows:

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

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[20] as instruments. Since gasoline prices have significant effects on CPI inflation[21], 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 Test of information rigidity (1)

	(1)	(2)	(3)	(4)
Forecast revision $(E_t(\pi_{t+12})-E_{t-1}(\pi_{t+11}))$	2.239	2.269 ***	2.584 ***	2.243 ***
	(3.058)	(0.474)	(0.470)	(0.132)
Constant	-1.700 ***	-1.711 ***	-1.726 ***	-1.718 ***
	(0.184)	(0.030)	(0.030)	(0.011)
N	81	3,807	3,807	330,299
First stage F-statistics	7.16	152.86	156.15	132.72
Wald χ^2	0.39	7.34	62.49	530.90
Prob > χ^2	0.531	0.000	0.000	0.000
Hansen's J $\chi2(5)$	-	-	26.01	106.70
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)[22]. 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

[20] 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.

[21] 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.

[22] 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 average AFEs surged.

instrumented not only with gasoline price shocks but also with the average demographic 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)).

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 $\hat{\beta} \approx 2.24$ of model (4) implies that δ in formulation (3) is around 0.692; thus, households update their information, on average, once every 3.24 months[23].

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)[24]—and apply the same estimation formulation (10), as before.

[23] 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.

[24] I divide the sample at the threshold of the 6^{th} 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 $(E_t(\pi_{t+12})\text{-}E_{t-1}(\pi_{t+11}))$	1.843 ***	1.174 ***	3.096 ***	3.144 ***
	(0.445)	(0.133)	(0.653)	(0.257)
Constant	-1.650 ***	-1.712 ***	-1.793 ***	-1.734 ***
	(0.034)	(0.012)	(0.037)	(0.019)
N	3,730	141,832	3,485	163,108
First stage F-statistics	14.96	61.56	20.82	56.81
Wald $\chi^2(4)$	59.92	246.25	83.41	227.25
Prob > $\chi^2(4)$	0.000	0.000	0.000	0.000
Hansen's J $\chi2(5)$	6.25	115.87	9.30	27.11
Prob > $\chi^2(5)$	0.100	0.000	0.026	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., 3.14 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. In a subsequent section, I further investigate the possible impact of volatility in inflation expectations on forecast updates as well as forecast errors.

4.2 Updates to inflation expectations

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:

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

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:

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

where α is a constant, π_{t-1} is the realized inflation rate last observed, X_{it} is a vector of sociodemographic characteristics of the *i*th household[25], and σ_{t-1} is the volatility of realized inflation as observed by households before the decision of updating their epectations.

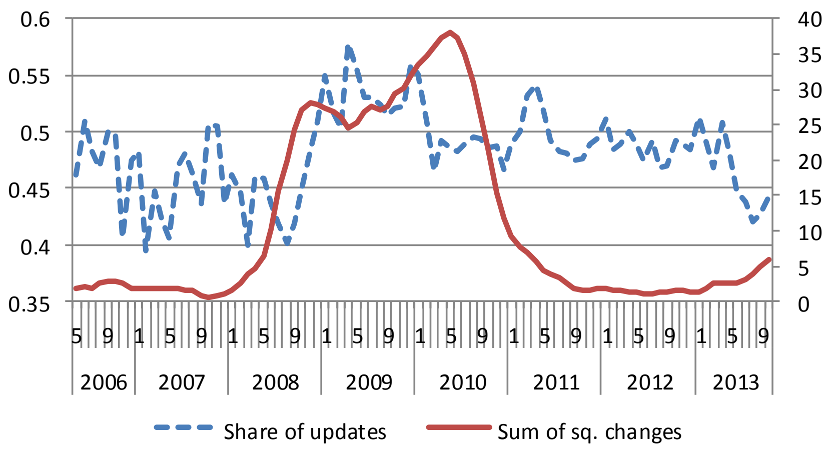
As a measure of such volatility, I follow Drager and Lamla (2013) and use the sum of squared changes of inflation for the preceding one year (i.e., from *t* – 12 to *t* – 1). For this volatility measure, I use either the actual inflation rate, the average forecast inflation rate made by professional forecasters. I also use the variance of the observed average inflation expectations among households for each survey. Further, I use the gap in professional forecasts in inflation in one year's time—between those institutions with

[25] I use a variety of variables: age of household head, household income, number of family members, and survey months. All the variables except for survey months are time-invariant.

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 limiting the sample. In concrete, lagged AFEs are instrumented with the lagged error of the professionals' forecasts that have already been realized[26].

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 for the period from April 2006 to June 2011 (0.667, p-value 0.000), whereas no clear correlation is observed after mid-2011[27].

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.

[26] 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.

[27] Appendix Figure A-1 shows the correlation between the other volatility measures and the share of updates. The correlation with the volatility of professional forecasts seems to be similar with that of Figure 4-1.

Table 4-3 summarizes the estimation results for the probability of updating inflation expectations. The models contain various measures of inflation volatility[28], 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.

In general, the estimation results support (H1). Models (1)- (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 (2) includes the interaction term between "consumption-tax dummy[29]" and volatility measures. With regard to professional forecasts, its volatility measure increased quite rapidly from April 2013, taking account of the scheduled increase in the tax rate in April 2014. Households updating behavior does not catch up such a drastic increase in the professional's forecasts. 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 0.003 (model (5)), while that of the one-month lagged forecast error is 0.024—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 correlated with the recent inflation rate: when the inflation rate increases, households tend to stay with their current expectation levels.

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

[29] The dummies take the value of one from April 2013 and onwards, and the value of zero before April 2013. The rate of consumption tax was supposed to be raised from five to eight percent in April 2014 (as of March 2014).

Table 4-3 Probability of updating inflation expectations

	(1)	(2)	(3)	(4)	(5)	(6)
π_{t-1}	-0.0500 ***	-0.0478 ***	-0.0443 ***	-0.0527 ***	-0.0591 ***	-0.0954 ***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)
$\sigma^2(\pi_{t-1})$	0.00176 ***					
	(0.000)					
$\sigma^2(\pi^{e,\ professional}{}_{t-1})$		0.00145 ***				
		(0.000)				
$\sigma^2(\pi^{e,\ professional}{}_{t-1})$* consumption tax dummy		-0.0290 ***				
		(0.003)				
$\sigma^2(\pi^{e,\ household}{}_{t-1})$			0.0873 ***			
			(0.003)			
$Gap(\pi^{e,\ professional}{}_{t-1})$				0.0763 ***		
				(0.011)		
Forcast error (lagged)					0.0073 **	0.0619 ***
					(0.004)	(0.011)
N	370,535	370,535	370,535	370,535	27,530	322,661
Demographic controls	yes	yes	yes	yes	yes	yes
Wald	2062.15	2165.67	2651.97	2044.01	76.50	1299.05
chi2>0	0.000	0.000	0.000	0.000	0.000	0.000

Models (1)–(5): panel probit estimation (random effects model). Model (6): iv probit estimation. Note: For model (6), clustered standard errors are reported in parentheses[30]. ***, **, 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 changes of inflation expectations of professional forecasters over the previous 12 months. Consumption tax dummy is defined in footnote 29. $\sigma^2(\pi^{e,\ household}{}_{t-1})$ is the variance of inflation expectations of the "Consumer Confidence Survey" for each survey. $Gap(\pi^{e,\ professional}{}_{t-1})$ 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 4-4 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.

[30] 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.

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

[Panel A]

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}	-0.0214 ***	-0.0215 ***	-0.0229 ***	-0.0246 ***	-0.0295 ***	-0.0241 ***	-0.0296 ***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)
$\sigma^2(\pi_{t-1})$	0.00355 ***	0.00197 ***	0.0013 ***	0.0010 ***	0.0004	0.0004	0.0008 **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	164,373	77,479	69,161	58,007	34,796	20,663	13,972
Demographic controls	yes	yes	yes	yes	yes	yes	yes
Wald	6363.21	2824.80	2645.99	2088.53	1341.96	797.37	574.79
chi2>0	0.000	0.000	0.000	0.000	0.000	0.000	0.000

[Panel B]

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}	-0.0001	0.0022	-0.0005	0.0009	0.0033	0.0027	0.0032
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
$\sigma^2(\pi_{t-1})$	-0.00051 ***	0.00028 **	0.00086 ***	0.00091 ***	0.00093 ***	0.00095 ***	0.00086 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	164,373	77,479	69,161	58,007	34,796	20,663	13,972
Demographic controls	yes	yes	yes	yes	yes	yes	yes
Wald	195.6	99.39	110.02	97.89	68.38	29.57	27.36
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 except for the lowest income group; The signs are positive and mostly significant in the case of upward revision for most income groups. Therefore, the previous conjecture that volatility leads to a higher attention level and more updates seems to hold in the case of both upward and downward revisions. The only exception is the lowest income group; great volatility leads only to upward revision. In this income group, the propensity of consumption is likely to be relatively high with lower wealth level, thus they can be more cautious towards the possibility of upcoming rise in inflation rate by observing volatile trend of recent inflation. 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 inflation rates increased, households tend not to update their expectations upward), while the coefficients of the rate are not significant in the case of downward revision.

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 forecast errors. 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[31]. I thus expect that, conditional on previous updates, the coefficient of update frequency up to the current survey point should have a negative sign with respect to the AFEs[32]. 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 of the AFEs.

[31] Andrade and Le Bihan (2013) employ the frequency of forecast updating as a measure for the degree of attention.
[32] 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 4-5 AFEs and household attentiveness (1)

	(1)	(2)	(3)	(4)	(5)	(6)
Number of previous updates	-0.0494 ***					
	(0.005)					
Frequency of previous updates		-0.4271 ***				
		(0.044)				
$\sigma^2(\pi_{t-1})$			0.02329 ***			
			(0.000)			
$\sigma^2(\pi^{e,\ professional}_{t-1})$				0.0489 ***		
				(0.005)		
$\sigma^2(\pi^{e,\ household}_{t-1})$					0.3416 ***	
					(0.006)	
$Gap(\pi^{e,\ professional}_{t-1})$						1.8817 ***
						(0.019)
N	168,741	168,741	168,969	168,969	168,969	168,969
Lagged inflation rate	yes	yes	yes	yes	yes	yes
F/Wald	2288.81	2275.76	11848.28	9723.39	12963.27	20682.81
Prob>F/Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000

Note: Explained variable = AFEs. A fixed-effects model is selected for (1)–(2). (3)-(6) are estimated with a random-effects model. 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" 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 variance of inflation expectations of the "Consumer Confidence Survey" for each survey. $Gap(\pi^{e,\ professional}_{t-1})$ 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 4-5 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. 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 all positive against the expectation from the theory. 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 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 4-6 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 4-6 AFEs and household attentiveness (2)

Last period's performance	Overestimation (1)	(2)	Underestimation (3)	(4)
$\sigma^2(\pi_{t-1})$	0.0234 ***		0.0172 ***	
	(0.001)		(0.001)	
$\sigma^2(\pi^{e,\ professional}_{t-1})$		0.0663 ***		0.0048
		(0.003)		(0.005)
N	112,045	112,045	52,946	52,946
Lagged inflation rate	yes	yes	yes	yes
Wald chi_sq(3)	10856.28	9204.45	879.31	732.53
Prob>chi_sq	0.000	0.000	0.000	0.000

Note: Explained variable = AFEs. A random-effects model. Conditional on updates.

4.2.3 Dynamic panel analysis

The null hypothesis of no information rigidity is rejected in subsection 4.1, so that there can be persistence or inertia[33] 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:

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

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

where AFE_{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 is proxied[34] by the frequency of updating up to the point of current survey, following the idea of Andrade and Le Bihan (2013)), X_{jt} is individual household characteristics, μ_j is individual-specific characteristics, δ_t is an aggregate shock that affects all households in the same way, 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[35], AFE_{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 be serially correlated or 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[36]. Table 4-7 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.

Table 4-7 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_{jt-1}	-0.335 ***	-0.357 ***	-0.368 ***	-0.316 ***	-0.344 ***	-0.319 ***	-0.305 ***	-0.209 ***
	(0.022)	(0.01)	(0.019)	(0.021)	(0.022)	(0.025)	(0.033)	(0.045)
FU_{jt-1}	0.140	-1.322 *	0.922	1.678	-0.340	-0.654	2.167	-1.483
	(1.371)	(0.791)	(1.470)	(1.482)	(1.720)	(1.933)	(2.121)	(2.307)
N	136,482	46,289	24,906	22,306	19,572	11,797	7,085	4,824
Hansen test of over-identification (p-value)	0.341	0.000	0.111	0.624	0.582	0.002	0.775	0.101
Test for first-order serial correlation (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Test for second-order serial correlation (p-value)	0.151	0.102	0.222	0.331	0.875	0.002	0.575	0.320

Note: Conditional on updates. AFE_{jt-1} stands for the absolute forecast error of household j of the previous period. FU_{jt-1} stands for the frequency of updating of household j at the previous period. Instruments used in level equations: ΔAFE_{jt-1}, ΔCPI_{t-1}, $\Delta\sigma^2(\pi_{t-1})$, ΔFU_{jt-1}, and Δgasoline_price_innovation$_{t-1}$; instruments used in first-difference equations: $AFE_{jt-2, t-3, t-4, t-5}$, $CPI_{t-2, t-3, t-4}$, $\sigma^2(\pi_{t-1})_{t-2, t-3, t-4}$, $FU_{jt-2, t-3, t-4}$, gasoline_price_innovation$_{t-1, t-2, t-3, t-4}$, and time dummies.

34 I employ a volatility measure of inflation up to the previous period as well as an alternative measure, although in this case the explanatory variables are not heterogeneous at an individual household level.

35 I also assume lagged errors (dated t-2 or earlier) are not correlated with ε_{jt}, as households do not recognize their actual value of lagged errors up to the end of the survey period.

36 I used a Stata code provided as xtabond2 (Roodman 2009a).

“Gasoline_price_innovation” is estimated innovation in gasoline prices (see footnote 20). Collapsed GMM[37].

[Panel B: Explained = FEs]

	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_{jt-1}	-0.256 ***	-0.280 ***	-0.278 ***	-0.255 ***	-0.289 ***	-0.229 ***	-0.240 ***	-0.186 ***
	(0.01)	(0.015)	(0.019)	(0.021)	(0.023)	(0.032)	(0.039)	(0.042)
FU_{jt-1}	0.696	2.454	1.832	-3.662	-5.399	-2.684	-1.514	1.892
	(1.706)	(1.965)	(1.950)	(3.732)	(4.416)	(4.205)	(4.442)	(7.127)
N	136,482	46,289	24,906	22,306	19,275	11,797	7,085	4,824
Hansen test of over-identification (p-value)	0.000	0.000	0.000	0.019	0.518	0.023	0.384	0.127
Test for first-order serial correlation (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Test for second-order serial correlation (p-value)	0.246	0.695	0.191	0.528	0.926	0.013	0.189	0.444

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.

In case of either AFEs or FEs, I do not derive clear impacts of the attention level on the (absolute) forecast errors. Interestingly, the estimated coefficients of lagged AFEs or of lagged FEs are all negative, ranging between –0.2 and –0.4. This indicates that the suggested persistence in (absolute) forecast errors is quite limited and even significant. The implication here is that higher volatility indeed leads to more frequent updates in both directions, whereas I do not have any evidence that higher volatility improves forecast accuracy.

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 the average AFEs drop from the 13th month of the survey period (Figure 3-3), I expect the response of the AFE to the update frequency or to inflation volatility to be more distinct at the end of the survey period than around the beginning or in the middle. Thus, I add the interaction terms between update frequency (or inflation volatility) and the dummies that relate to survey timing.

[37] 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.

Table 4-8 AFEs and household attentiveness (3)

	(1)		(2)	
(A)				
Number of previous updates	-			
$\sigma^2(\pi_{t-1})$			-0.019	***
Interaction-terms with (A) and survey-point dummies				
First month	-		-	
Second month	-0.110	***	0.036	***
Third month	-0.051	**	0.033	***
Fourth month	-0.090	***	0.028	***
Fifth month	-0.046	***	0.028	***
Sixth month	-0.082	***	0.021	***
Seventh month	-0.064	***	0.021	***
Eighth month	-0.070	***	0.016	***
Ninth month	-0.065	***	0.013	***
Tenth month	-0.055	***	0.010	***
Eleventh month	-0.046	***	0.010	***
Twelfth month	-0.041	***	0.007	***
Thirteenth month	-0.044	***	0.004	***
Fourteenth month	-0.039	***	0.003	***
Fifteenth month	-0.045	***	-	
N	168,741		168,741	
Lagged inflation rate	yes		yes	
Lagged forecast error	-		-	
F	432.06		455.97	
Prob>F	0.000		0.000	

Note: Explained variable=AFEs. Conditional on updates. The other notes are the same as those in Table 4-5.

Table 4-8 summarizes the estimation results with the interaction terms, conditional on a change. The results of models (1) and (2) clearly indicate that the responses vary with survey timing, and that the absolute level of responses to the past updating frequency tend to be greater at the beginning of the survey, but approaches a small value towards the end of the survey period. Thus, after that time, additional updates no longer contribute overly much to a reduction in AFEs. Regarding marginal responses to inflation volatility, the results of model (2) imply that around the beginning of the period, they are positive, but they gradually diminish toward the end of the survey period and ultimately turn negative. Based on the idea of the theoretical model, 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. Conditional on updates, I undertake individual-level panel estimation to examine whether changes in individual-level errors are reduced by making repeated updates. The results are found in Table 4-9.

Table 4-9 Changes in AFEs and household attentiveness (1)

	(1)	(2)	(3)	(4)	(5)	(6)
Number of previous updates	-0.0074					
	(0.006)					
Frequency of previous		-0.1910 ***				
		(0.055)				
$\sigma^2(\pi_{t-1})$			-0.0125 ***			
			(0.000)			
$\sigma^2(\pi^{e,\ professional}_{t-1})$				-0.0717 ***		
				(0.002)		
$\sigma^2(\pi^{e,\ household}_{t-1})$					-0.1250 ***	
					(0.004)	
$Gap(\pi^{e,\ professional}_{t-1})$						-0.4930 ***
						(0.013)
N	160,517	160,517	160,517	160,517	160,517	160,517
Lagged inflation rate	yes	yes	yes	yes	yes	yes
F/Wald chi_sq(3)	84.93	88.70	2315.1	1952.10	1118.8	1598.3
Prob>F/Prob>chi_sq	0.000	0.000	0.000	0.000	0.000	0.000

Note: Explained variable=changes in AFEs from previous period. A fixed-effects model is selected for (1)–(2). (3)-(6) are estimated by a random-effects model. 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 4-5.

The implications derived from the contents of Table 4-9 can be summarized as follows. First, if previous updates have been frequent, this seems to affect changes in AFEs significantly; this can be an evidence of convergence in errors through repeated updates. This finding aligns 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. In addition, the second implication is consistent with H3: more volatile inflation is correlated with a limited extent of future changes in AFEs possibly because of a higher attention level. However, in examining the results in Tables 4-3, 4-5 and 4-9 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 (i.e. no convergence).
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-3). The results are rather unclear; there seems to be no clear trend in the coefficients as the survey proceeds.

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 4-10 Changes in inflation expectations and household attentiveness with updated expectations (1)

	(1)	(2)	(3)	(4)	(5)	(6)
Number of previous updates	-0.0298 ***					
	(0.006)					
Frequency of previous updates		0.0398				
		(0.045)				
$\sigma^2(\pi_{t-1})$			0.0019 ***			
			(0.000)			
$\sigma^2(\pi^{e,\ professional}_{t-1})$				0.0005		
				(0.001)		
$\sigma^2(\pi^{e,\ household}_{t-1})$					0.2073 ***	
					(0.006)	
$Gap(\pi^{e,\ professional}_{t-1})$						0.4066 ***
						(0.020)
N	178,851	178,851	178,851	178,851	178,851	178,851
F/Wald chi_sq(3)	120.16	118.92	393.42	386.13	1486.3	817.12
Prob>F/Prob>chi_sq	0.000	0.000	0.000	0.000	0.000	0.000

Note: A fixed-effects model is selected for (1)–(2). Conditional on updates. The other notes are the same as those for Table 4-5.

Table 4-10 summarizes the estimation results with updated expectations. From model (1), 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. However, I do not obtain consistent results from model (2). Results with volatility measures all indicate that a more volatile inflation rate, and thus a higher attention level, leads to greater changes in expectations.

Regarding possible parameter heterogeneity by survey timing, Table 4-11 contains estimation results with regard to inflation volatility upon updates in expectations[38].

[38] 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 4-11.

Table 4-11 Changes in inflation expectations and household attentiveness with updated expectations (2)

	(1)		(2)	
(A)				
$\sigma^2(\pi_{t-1})$	-0.010	***		
$\sigma^2(\pi^{e,\ professional}_{t-1})$			-0.002	**
Interaction-terms with (A) and survey-point dummies				
First month	-		-	
Second month	0.019	***	0.060	***
Third month	0.015	***	0.039	***
Fourth month	0.012	***	0.028	***
Fifth month	0.010	***	0.019	***
Sixth month	0.008	***	0.011	***
Seventh month	0.007	***	0.009	***
Eighth month	0.007	***	0.003	
Ninth month	0.006	***	-0.003	
Tenth month	0.004	***	-0.007	***
Eleventh month	0.004	***	-0.007	***
Twelfth month	0.004	***	-0.005	*
Thirteenth month	0.001		-0.010	***
Fourteenth month	0.001		-0.009	***
Fifteenth month	-		-0.006	**
N	178,851		178,851	
Lagged inflation rate	yes		yes	
F	24.81		19.05	
Prob>F	0.000		0.000	

Note: Conditional on updates; other notes are the same as those for Table 4-5.

The estimation results indicate that around the beginning of the survey, households update their expectations to a great extent in response to greater inflation volatility. As the survey proceeds, however, households tend not to update their expectations with volatile inflation, which is not consistent with (H4).

5. Robustness checks with various measures of CPI and discussion

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 should vary. Because of data limitations, I cannot determine the exact inflation rate for each household, although some information is available on CPI by households' major characteristics (e.g. CPI by income, age, or region). Since I am interested in the possible differences in updating behavior among various income groups, I first substitute the CPI general with CPI of all items by five income categories (CPI by income) and then employ two other CPI measures (i.e. CPI by age and CPI by region) to examine whether the findings with CPI general are robust. With regard to CPI by income, 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 inflation rates. With regard to CPI by age, there are not particular differences in its volatility level from CPI general, while the volatility measure based on CPI by region is much greater than that based on other CPI measures (Table A-1(2)). This actually suggests that households in the dataset may face a wide variety of the volatilities in the inflation rates, although the levels of the inflation rates are not different too much.

Table 5-1 shows the estimation results of the marginal effects of updating inflation expectations based on CPI by income, by income level and by upward and downward revisions; as such, it comprises a parallel analysis of the results in Table 4-4. The results are consistent with the previous ones. The implications here are summarized as follows: (1) higher inflation in the previous period decreases the probability of revising expectations upward but does not have any significant impact on the probability of revising expectations downward, (2) higher volatility is likely to lead to an updating of expectations both downward and upward, except in the lowest-income group. In the lowest-income group, higher volatility leads to an upward updating, whereas it is less likely to lead to a downward updating.

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

[Updating expectations upward]

Income	3million -	3-5.5 million	5.5-7.5 million	7.5-9.5 million	9.5-million
π_{t-1}	-0.0220 ***	-0.0236 ***	-0.0250 ***	-0.0307 ***	-0.0272 ***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
$\sigma^2(\pi_{t-1})$	0.00244 ***	0.00139 ***	0.0008 ***	0.0004 *	0.0005 **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	164,373	146,640	58,007	34,796	34,635
Demographic controls	yes	yes	yes	yes	yes
Wald	6349.41	5557.12	2102.08	1350.57	1374.29
chi2>0	0.000	0.000	0.000	0.000	0.000

[Updating expectations downward]

Income	3million -	3-5.5 million	5.5-7.5 million	7.5-9.5 million	9.5-12 million
π_{t-1}	0.0003	0.0010	0.0013	0.0043 *	0.0024
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
$\sigma^2(\pi_{t-1})$	-0.00025 ***	0.00049 ***	0.0008 ***	0.0008 ***	0.0008 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	164,373	146,640	58,007	34,796	34,635
Demographic controls	yes	yes	yes	yes	yes
Wald	177.72	197.08	105.95	68.50	53.73
chi2>0	0.000	0.000	0.000	0.000	0.000

Note: Panel probit estimation; random effects model. $\sigma^2(\pi_{t-1})$ is estimated based on CPI by income.

I then examine the relationships between inflation volatility and AFEs. First, 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 based on CPI by income, which are consistent with those based on the usual CPI (Table A-2). In the case of downward revision, higher volatility leads to smaller change level of AFEs but mixed results with the level of AFEs. This finding aligns with (H3). In the case of upward revision, the results are mixed with regard to the consistency with (H3), but opposite to (H2). 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 in both directions. However, there are not any clear evidence that households' expectations become more accurate either through upward or through downward revisions.

In addition, the results of a dynamic panel analysis have similar implications. As the estimation results of the dynamic panel analysis by using all samples (conditional on updates) do not pass Hansen overidentification test or difference-in-Hansen test, I try different formulations by dividing samples based on household characteristics which are pre-determined before the survey starts.

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

[Panel A: Explained = AFEs]

Direction of updates	Upwards (1)	(2)	(3)	Downwards (4)	(5)	(6)
$\sigma^2(\pi_{t-1})$	0.0246 ***			0.0143 ***		
	(0.000)			(0.000)		
$\sigma^2(\pi^{e,\ professional}_{t-1})$		0.1043 ***			0.0904 ***	
		(0.003)			(0.003)	
A_{jt-1} (frequency of previous updates)			0.8372 ***			-0.2729 ***
			(0.027)			(0.060)
N	117,312	117,312	114,531	82,727	82,727	82,727
Lagged inflation rate	yes	yes	yes	yes	yes	yes
F/Wald	17656.52	15934.01	3878.52	4980.56	4464.48	774.55
Prob>F/Prob>chi_sq	0.000	0.000	0.000	0.000	0.000	0.000

[Panel B: Explained = Change in AFEs]

Direction of updates	Upwards (1)	(2)	(3)	Downwards (4)	(5)	(6)
$\sigma^2(\pi_{t-1})$	0.0100 ***			-0.0208 ***		
	(0.000)			(0.000)		
$\sigma^2(\pi^{e,\ professional}_{t-1})$		-0.0178 ***			-0.0711 ***	
		(0.004)			(0.004)	
A_{jt-1} (frequency of previous updates)			-0.5082 ***			-0.3965 ***
			(0.073)			(0.078)
N	82,221	82,221	82,221	78,296	78,296	78,296
Lagged inflation rate	yes	yes	yes	yes	yes	yes
F/Wald	5237.16	4481.66	702.44	6401.43	4514.05	767.90
Prob>F/Prob>chi_sq	0.000	0.000	0.000	0.000	0.000	0.000

Note: A fixed-effects model is selected for (3) and (6). Conditional on updates either upwards or downwards. FU_{jt-1} stands for the frequency of updating of household j at the previous period. $\sigma^2(\pi_{t-1})$ is estimated based on CPI by income.

The results of the dynamic panel analysis in the previous section indicate that the attention level does not seem to have any impact on the AFEs with the control of previous AFEs. This seems to be a reasonable result, given the fact that the economy was experiencing a period of "low inflation" through the survey period. During such period, households do not have a motivation to pay sufficient attention to the inflation trend, as the cost of forecast errors are relatively limited compared to the period of "high inflation". However, households with certain characteristics may tend to be more motivated to pay attention to the inflation than the rest of the households; for example, when households take out a mortgage, or when income per household member is low. I thus focus on the expectation-formation behavior of the households that have a mortgage and that have more than three members with only one worker. Although there are not any theoretical backgrounds, I expect that such households are typical examples that tend to be more attentive to the inflation trend and tend to be more likely to update their expectations in response to new information.

Table 5-3 contains the estimation results of households of single income, with children[39], and who are mortgage borrowers, based on CPI general and on alternative CPI measures. The result with CPI general implies that higher attention leads to smaller FEs, indicating that higher attention level up to previous period implies higher level of expectations in a current period. Further, the results with alternative CPI measures all indicate that higher attention implies smaller FEs at the current survey, thus higher expectation levels. On the other hand, the coefficients of the attention level are positive, but not significant with regard to AFEs. Table 5-4 shows the sensitivity test results, in which I employ alternative volatility measures of inflation, as in the estimations in the previous section. The estimation results of Table 5-4 are consistent with those derived in Table 5-3, indicating that higher attention leads to higher expectations, but not to more accurate ones at these households.

Table 5-3 Determinants of AFEs in inflation expectations
(CPI general and alternative CPI measures)

	CPI general		CPI by age		CPI by income		CPI by region	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
AFE_{jt-1}	-0.340 ***		-0.345 ***		-0.355 ***		-0.352 ***	
	(0.033)		(0.033)		(0.034)		(0.033)	
FEj_{t-1}		-0.269 ***		-0.280 ***		-0.263 ***		-0.271 ***
		(0.044)		(0.044)		(0.042)		(0.039)
FU_{jt-1}	0.511	-3.619 ***	0.658	-3.705 ***	0.354	-3.527 ***	0.629	-3.662 ***
	(0.788)	(1.066)	(0.740)	(1.074)	(0.817)	(0.859)	(0.773)	(0.949)
N	6,565	6,565	6,565	6,565	6,565	6,565	6,565	6,565
Hansen test of over-identification (p-value)	0.240	0.197	0.123	0.136	0.150	0.092	0.467	0.205
Test for first-order serial correlation (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Test for second-order serial correlation (p-value)	0.310	0.422	0.189	0.350	0.360	0.565	0.336	0.507

Note: Conditional on updates. Samples are limited to the households with mortgage of type 6 in Table 3-2 (couple with someone, single worker). Other notes are the same as those for Table 4-7.

[39] From the questionnaire, I can only identify the total number of family numbers and the number of family members who are working. I select households with a single worker and more than three members, which could include those consisted of a couple and their parent(s).

Table 5-4 Determinants of AFEs in inflation expectations
(with alternative volatility measures)

[Estimation with $\sigma^2(\pi^{e,\ professional}_{t-1})$]

	CPI general (1)	CPI general (2)	CPI by age (1)	CPI by age (2)	CPI by income (1)	CPI by income (2)	CPI by region (1)	CPI by region (2)
AFE_{jt-1}	-0.341 ***		-0.341 ***		-0.355 ***		-0.350 ***	
	(0.033)		(0.037)		(0.034)		(0.034)	
FE_{jt-1}		-0.275 ***		-0.272 ***		-0.263 ***		-0.254 ***
		(0.044)		(0.044)		(0.042)		(0.037)
FU_{jt-1}	0.791	-3.554 ***	0.629	-3.886 ***	0.354	-3.527 ***	0.595	-3.417 ***
	(0.790)	(1.137)	(0.865)	(1.083)	(0.817)	(0.859)	(0.761)	(0.853)
N	6,565	6,565	6,565	6,565	6,565	6,565	6,565	6,565
Hansen test of over-identification (p-value)	0.264	0.328	0.377	0.163	0.150	0.092	0.314	0.056
Test for first-order serial correlation (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Test for second-order serial correlation (p-value)	0.258	0.361	0.237	0.394	0.360	0.565	0.172	0.645

[Estimation with $Gap(\pi^{e,\ professional}_{t-1})$]

	CPI general (1)	CPI general (2)	CPI by age (1)	CPI by age (2)	CPI by income (1)	CPI by income (2)	CPI by region (1)	CPI by region (2)
AFE_{jt-1}	-0.341 ***		-0.336 ***		-0.351 ***		-0.348 ***	
	(0.033)		(0.031)		(0.034)		(0.034)	
FE_{jt-1}		-0.266 ***		-0.272 ***		-0.258 ***		-0.277 ***
		(0.042)		(0.041)		(0.038)		(0.043)
FU_{jt-1}	0.686	-3.426 ***	0.435	-3.323 ***	0.459	-3.194 ***	0.687	-3.421 ***
	(0.746)	(1.021)	(0.684)	(0.956)	(0.766)	(0.845)	(0.761)	(1.031)
N	6,565	6,565	6,565	6,565	6,565	6,565	6,565	6,565
Hansen test of over-identification (p-value)	0.259	0.164	0.154	0.052	0.327	0.022	0.393	0.227
Test for first-order serial correlation (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Test for second-order serial correlation (p-value)	0.287	0.450	0.248	0.394	0.174	0.594	0.358	0.450

Note: Conditional on updates. AFE_{jt-1} stands for the absolute forecast error of the previous period. FU_{jt-1} stands for the frequency of updates by household j at the previous period. $\sigma^2(\pi^{e,\ professional}_{t-1})$ corresponds to the sum of squared changes of inflation expectations of professional forecasters over the previous 12 months. $Gap(\pi^{e,\ professional}_{t-1})$ 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.

In the upper panel, instruments used in level equations: ΔAFE_{jt-1}, ΔCPI_{t-1}, $\Delta\ FU_{jt-1}$, $\Delta\sigma^2(\pi^{e,\ professional})_{t-1}$, Δratio of vacancies to the unemployed$_{t-1}$ and Δgasoline_price_innovation$_{t-1}$; instruments used in first-difference equations: $AFE_{jt-2,\ t-3,\ t-4,\ t-5}$, $CPI_{t-2,\ t-3,\ t-4}$, $\sigma^2(\pi^{e,\ professional})_{t-2,\ t-3,\ t-4}$, $FU_{jt-2,\ t-3,\ t-4,}$, ratio of vacancies to the unemployed$_{t-2,\ t-3,\ t-4}$, gasoline_price_innovation$_{t-1,\ t-2,\ t-3,\ t-4}$, and time dummies. In the lower panel, instruments used in level equations: ΔAFE_{jt-1}, ΔCPI_{t-1}, Δ Gap($\pi^{e, professional}_{t-1}$), Δ FU_{jt-1}, Δratio of vacancies to the unemployed$_{t-1}$ and Δgasoline_price_innovation$_{t-1}$; instruments used in first-difference equations: $AFE_{jt-2, t-3, t-4, t-5}$, $CPI_{t-2, t-3, t-4}$, Gap($\pi^{e, professional}$)$_{t-2, t-3, t-4}$, $FU_{jt-2, t-3, t-4}$, ratio of vacancies to the unemployed$_{t-2, t-3, t-4}$, gasoline_price_innovation$_{t-1, t-2, t-3, t-4}$, and time dummies. "Gasoline_price_innovation" is estimated innovation in gasoline prices (see footnote 20). Collapsed GMM.

Finally, I check the consistency of the above estimation results of a dynamic panel analysis with the usual fixed-effects model by using all samples. I create a dummy variable to indicate the households that have a mortgage and single worker with more than three household members (henceforth, high-attention dummy). The explained variable is a forecast error, and the explanatory variables are various volatility measures, their interaction term with the high-attention dummy, and the other controls I employed in the estimation of Table 4-5. Table 5-5 comprises the results; as expected, the coefficients of the interaction term are negative, but statistically significant only for one of the volatility measures. This indicates the possibility that these households are more responsive to the change in the volatility measures in a negative manner, compared with all the rest of the households[40].

Table 5-5 Determinants of forecast errors in inflation expectations (random-effects model)

	(1)	(2)	(3)	(4)
Volatility measures (x)	$\sigma^2(\pi_{t-1})$	$\sigma^2(\pi^{e, professional}_{t-1})$	$\sigma^2(\pi^{e, household}_{t-1})$	Gap($\pi^{e, professional}_{t-1}$)
x	-0.02887 ***	0.0104 ***	-0.3990 ***	-3.157 ***
	(0.001)	(0.004)	(0.008)	(0.023)
x*(High attention dummy)	-0.00422 **	-0.0036	-0.0057	-0.0427
	(0.002)	(0.012)	(0.009)	(0.043)
N	383,439	383,439	383,439	383,439
Lagged inflation rate	yes	yes	yes	yes
Wald	25430.18	23168.24	22753.58	50167.08
Prob>chi_sq	0.000	0.000	0.000	0.000

Note: Conditional on updates. "High attention dummy"=1 if a household has a mortgage, with single workers and more than 3 members. Otherwise it is 0. Other notes are the same as those of Table 4-5.

To summarize the discussion of this section, analysis based on the CPIs that reflect household characteristics indicates that higher volatility is likely to lead to an updating

[40] A similar implication is derived if I focus on the updating behavior of the households that take a mortgage and whose income per household member is below median level (i.e. higher attention level is linked to higher expectations among such households and relative to the rest of the households).

of expectations both upward and downward, accompanied with higher attention level. In particular, in case of downward revisions, the estimation results clearly indicate that higher volatility (or higher attention level) induces the inflation expectations to converge to accurate ones. Once I control the impact of the AFEs of the previous period, the relationship between attention level and forecast errors turn quite ambiguous. However, if I limit the samples to the households with characteristics that may lead to pay greater attention to the inflation trend than the others because they are pressed to meet mortgage payments under relatively limited income flows, the estimation results imply that higher attention can be linked to higher expectations without approaching to more accurate expectations. Although they are likely to be motivated to be attentive to the inflation trend, the estimation results are not consistent with the hypotheses on the accuracy or convergence of the inflation expectations with higher attention level.

The estimation results based on CPI general and alternative price measures are quite consistent. Clearer results might be derived if I take into account the heterogeneity in inflation level that heterogeneous households face in a more precise manner, although sufficient supporting data are not readily available.

6. Issues related to estimation methods[41]

6.1 Cross-section dependence

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[42,43]. Hoyos and Sarafidis

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[41] All the estimations in this section are based on a different dataset from the one employed up to section 5. Its sample size is smaller (325,418 in total) because of shorter periods, while I consider it contains sufficient observations for the discussion.

[42] 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.

(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 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, however, I consider that individual households are likely to be strongly affected by household-specific price information when forming inflation expectations, rather than unobserved macroeconomic factors[44]. 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 heterogeneity. Some of the estimation results are included in Appendix Table A-4, which does not bear statistical significance[45].

6.2 Attrition[46]

Some of the households dropped out from the survey during the 15-month survey period[47]. If those households who dropped out differ systematically from those who stayed, or if such attrition occurs in a nonrandom manner, any results based on the data

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

44 Cavallo et al. (2014) argues that individual consumers assign sufficient weight to their own memories of price changes in forming inflation expectations, based on the field experiments in the US and Argentina.

45 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.

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

47 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). For the main part of my analysis in previous sections, I include these samples. For this subsection's attrition-related analysis, I do not include those respondents who reappeared after dropping out.

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 include variables which may correlate with attrition. One of them 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[48]. 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). 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).

6.2.1 Randomness test

The estimation results of attrition probits are summarized in Appendix Table A-5. 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-6. 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.

[48] 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.

6.2.2 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-7).

7. Further analysis focused on "News on inflation"

This section 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 4-3). In this section, 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)[49]. Due to data availability, the estimation period was January 2008 to October 2013.

First, Figures 7-1 and 7-2 show trends in realized inflation, the intensity of news coverage (using the terms "price" and increase", and "price" and "decrease" respectively), and the average level of expected inflation rate.

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

[49] 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.

correlation between the index (“decrease”) and the expected inflation rate is not so obvious (–0.322, with news index one period ahead).

Figure 7-1: News coverage with "price" and "increase"

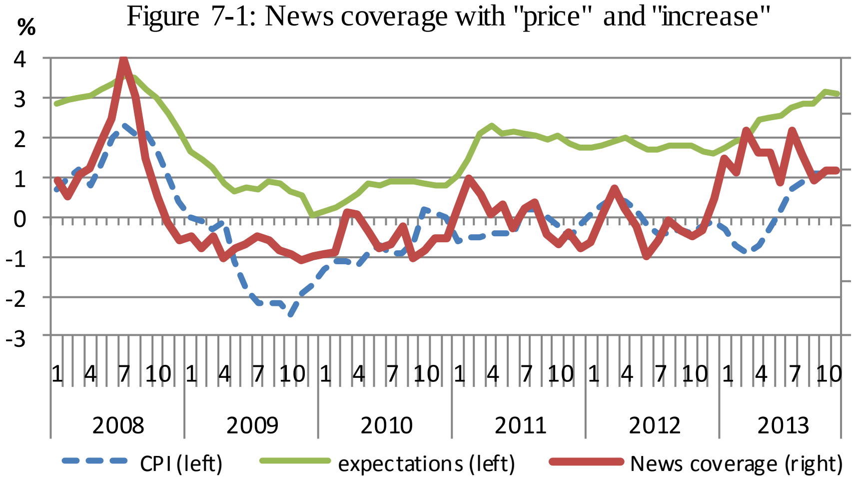

Figure 7-2: News coverage with "price" and "decrease"

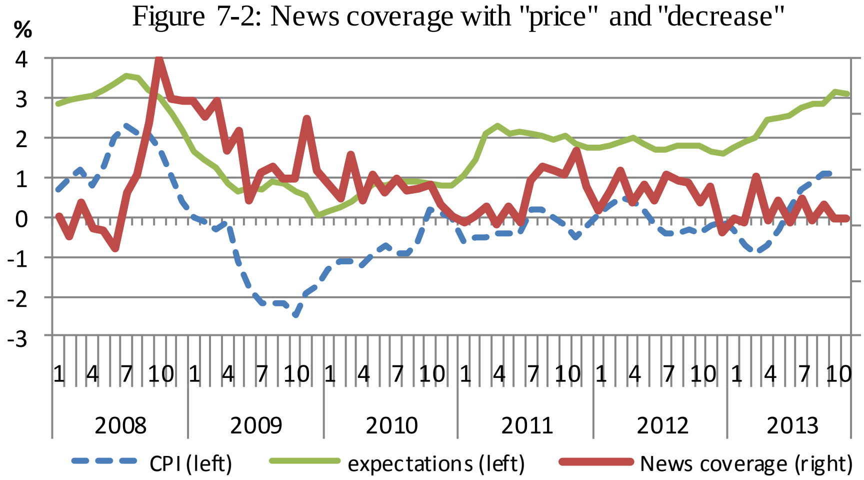

Table 7-1 summarizes the estimation results. These results indicate that with regard to the estimation that specifies the direction of the price change, hearing news about price trends generally increase the probability that households will update their expectations in either direction (i.e., upward 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 7-1 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.

8. 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 3.4 months; this is less rigid than the US case, for example.

Based on this rigidity, I tested several hypotheses with respect to the relationship between inflation expectations and the attention level of the households. It is confirmed that more volatile inflation rates in a recent period will trigger more updates both downwardly and upwardly. 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, this provides evidence that updates do indeed lead to greater accuracy, particularly from the middle of the survey period onward.

On the other hand, the estimation results of a dynamic panel estimation indicate that the majority of households tend to update their expectations in a staggered way. This implies that recent volatility can even be linked to a less accurate expectations. However, if I focus on the households that have a mortgage and with more than three members but single worker, they are more likely to raise their expectations if their attention level is higher. This result is consistent with CPI of all items at a national level as well as with the CPI that reflects the heterogeneity among households. In general, it is expected that such households are better motivated to update their information set than the rest of the households, while the results of a dynamic panel estimation show that their way of updating is not in the direction of improving accuracy; instead, it just induces higher expectations.

In a general sense, when I replace CPI general with the CPIs that partly reflect the variations in households' consumption baskets, the estimation results are quite consistent with previous ones. This might imply that the inflation each household faces varies to a much greater extent than that I tentatively employed as an alternative to CPI general.

Finally, based on the idea of sticky-information model, I tested the impact of the "news on inflation" on the updating behavior. It is indicated that households distinguish between the news on price increase and the news on price decrease, and select the direction of updates in a corresponding manner with the news information. Although the households possibly reflected the perceived news information smoothly, it is interesting to find that the news on the upcoming increase in the consumption tax rate seems to spread and were reflected to the expectations rather moderately among households.

For future study, further elaboration on the measurement of (absolute) forecast errors is important to improve the accuracy of the estimation results. One possible way is to reflect the detailed variation of consumption basket (e.g. by region and by citysize) among households to calculate the inflation level that each household observes. Another is to examine the robustness of the estimation results based on a dynamic panel analysis.

In addition, from policy perspectives, the precise analysis on the timing when the households actually perceived the future increase in the tax rate and reflected it to their expectations might be possible, once sufficient data is available after the introduction of the new consumption tax rate.

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Appendix (Tables and Figures)

Table A-1 Summary statistics (1)

Variable		Mean	SD	Min	Max	N
Based on CPI general	error	-1.65	2.57	-7.9	7.8	383,439
	abs_error	2.33	1.97	0.0	7.9	383,439
	Dabs_error	0.01	1.60	-6.9	6.9	330,299
Based on CPI by income	error	-1.62	2.59	-7.9	8.0	383,439
	abs_error	2.34	1.96	0.0	8.0	383,439
	Dabs_error	0.01	1.60	-7.3	7.3	330,299
Based on CPI by age	error	-1.65	2.47	-7.4	7.1	383,439
	abs_error	2.28	1.91	0.0	7.4	383,439
	Dabs_error	0.01	1.59	-6.6	6.7	330,299
Based on CPI by region	error	-1.61	2.61	-10.3	9.4	383,439
	abs_error	2.35	1.97	0.0	10.3	383,439
	Dabs_error	0.01	1.61	-9.7	10.3	330,299
	Dpricex2	0.03	2.06	-10	10	370,569
	age	59.51	15.67	18	101	472,839
	income	487.73	249.25	300	1200	472,766
	number	2.54	1.49	1	12	472,839
	survey_month	6.94	4.24	1	15	472,839

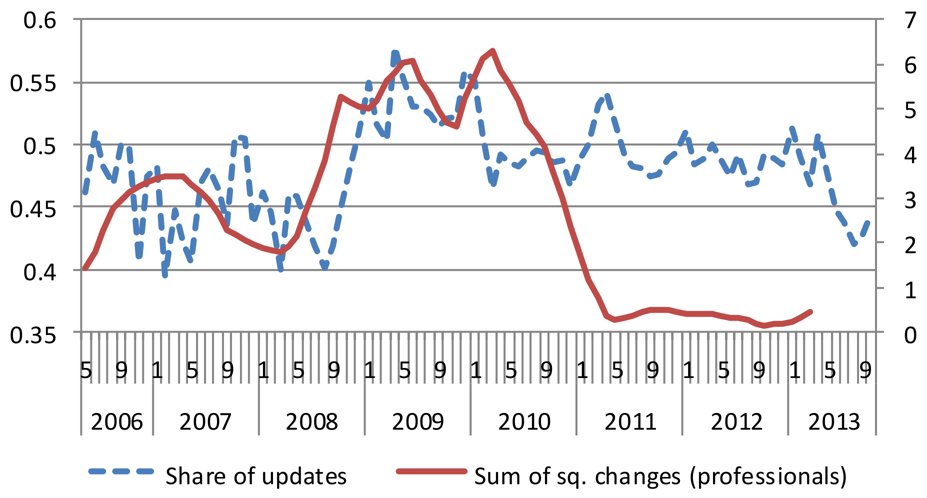
Note: “error” stands for forecast error (realized inflation minus expected inflation). “AFE” stands for the absolute value of “error,” and “Dabs_error” is the change in AFE from the previous month. “Dpricex2” is the change in inflation expectations from the previous month; “number” is the number of household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

Table A-1 Summary statistics (2)

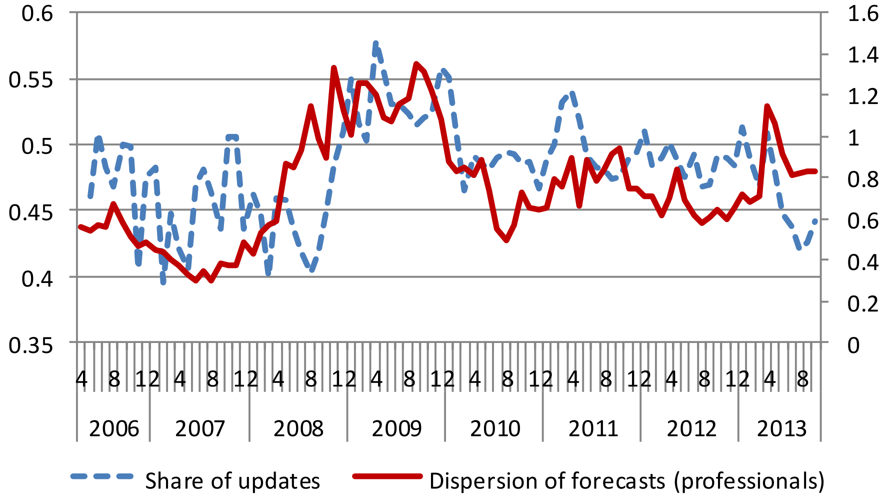
	Variable	Mean	SD	Min	Max	N
Frequency measure	cum_change	4.99	3.11	0.00	14.00	472,839
	ratio_change	0.38	0.21	0.00	0.93	472,839
Volatility measure	$\sigma^2(\pi_{t-1})$ (based on CPI general)	10.64	12.32	0.60	38.08	472,837
	$\sigma^2(\pi_{t-1})$ (based on CPI by income)	10.69	12.29	0.60	38.08	472,839
	$\sigma^2(\pi_{t-1})$ (based on CPI by age)	8.81	9.23	0.36	34.35	472,839
	$\sigma^2(\pi_{t-1})$ (based on CPI by region)	15.35	20.06	0.39	144.33	472,839
	$\sigma^2(\pi^{e,\ professional}_{t-1})$	4.28	6.74	0.16	41.91	472,837
	$\sigma^2(\pi^{e,\ household}_{t-1})$	4.10	0.85	2.36	6.28	472,837
	$Gap(\pi^{e,\ professional}_{t-1})$	0.75	0.26	0.30	1.35	472,837

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. $\sigma^2(\pi_{t-1})$ is the sum of the squared changes of realized inflation over the previous 12 months (based either on CPI general, CPI by income, CPI by age, CPI by region). $\sigma^2(\pi^{e,\ professional}_{t-1})$ corresponds to the sum of squared changes in inflation expectations of professional forecasters over the previous 12 months. $\sigma^2(\pi^{e,\ household}_{t-1})$ is the variance of inflation expectations of the "Consumer Confidence Survey" for each survey. $Gap(\pi^{e,\ professional}_{t-1})$ is the difference between the average one-year-ahead expectations of the top eight institutions and those of the bottom eight institutions.

Figure A-1 Expectation updating and volatility measure (2)



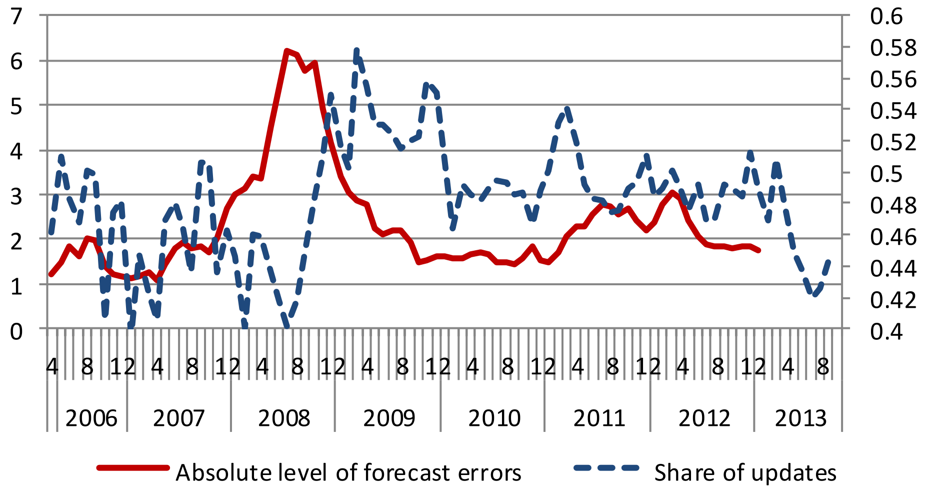
Expectation updating and volatility measure (3)



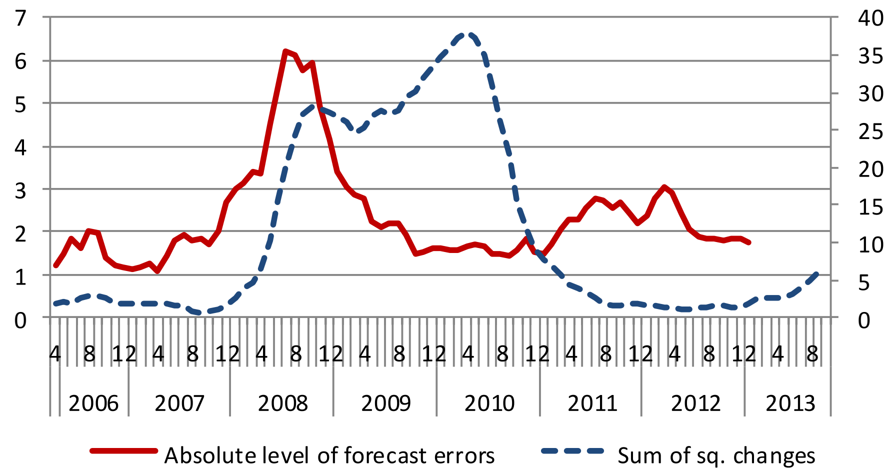
Note: The share of updates is plotted on the left-hand axis, and volatility measures are on the right-hand side. Share of updates is adjusted for FY2006–FY2008, because of the obvious impact of using two different survey methods. The measure of "sum of squared changes among professional forecasters" in the upper panel is plotted only up to March 2013, as the level surged from April 2013 because of the expected increase in the consumption tax rate. Details of the volatility measures are provided in the text.

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 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)	(5)	(6)
$\sigma^2(\pi_{t-1})$	0.035 ***			0.0206 ***		
	(0.001)			(0.001)		
$\sigma^2(\pi^{e,\ professional}_{t-1})$		0.099 ***			0.083 ***	
		(0.003)			(0.003)	
FU_{t-1}			0.840 ***			-0.270 ***
			(0.027)			(0.060)
N	117,312	117,312	114,531	82,727	82,727	82,727
Lagged inflation rate	yes	yes	yes	yes	yes	yes
F/Wald chi_sq	18554.5	15268.98	3865.03	4951.41	4091.77	718.56
Prob>F/Prob>chi_sq	0.000	0.000	0.000	0.000	0.000	0.000

Note: A fixed-effects model is selected for (3) and (6). Conditional on updates.

Table A-3 Changes in AFEs and household attentiveness

	(1)		(2)	
(A)				
Frequency of previous updates	-			
$\sigma^2(\pi_{t-1})$			-0.0213	***
Interaction-terms with (A) and survey-point dummies				
First month	-		-	
Second month	-0.255	***	-0.008	***
Third month	-0.117		-0.005	**
Fourth month	-0.292	***	-0.007	***
Fifth month	-0.063		-0.001	
Sixth month	-0.339	***	-0.009	***
Seventh month	-0.215	***	-0.001	
Eighth month	-0.280	***	-0.003	
Ninth month	-0.202	***	-0.004	**
Tenth month	-0.080		-0.004	**
Eleventh month	-0.119	*	-0.002	
Twelfth month	-0.125	*	-0.003	
Thirteenth month	-0.163	**	-0.006	***
Fourteenth month	0.016		0.001	
Fifteenth month	-0.045		-	
N	160,517		160,517	
Lagged inflation rate	yes		yes	
F	23.84		90.65	
Prob>F	0.000		0.000	

Note: Conditional on updates; other notes are the same as those for Table 4-5.

Table A-4 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

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

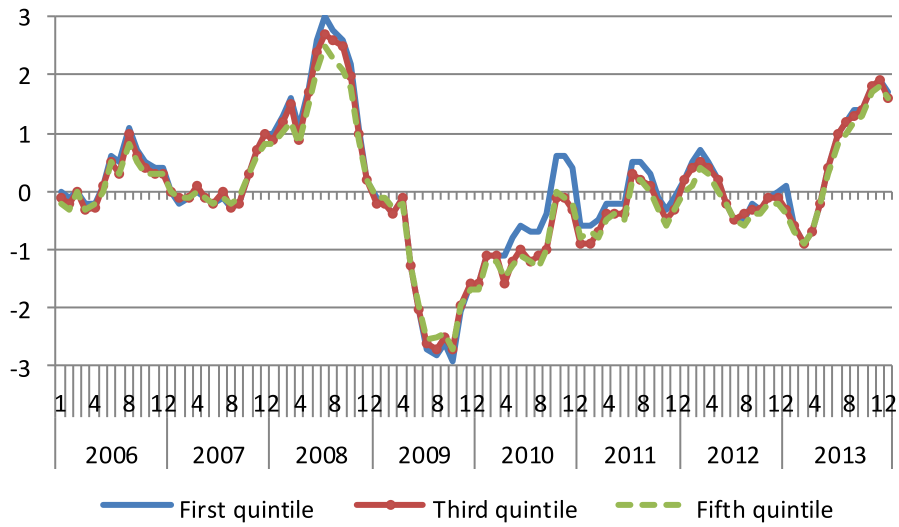
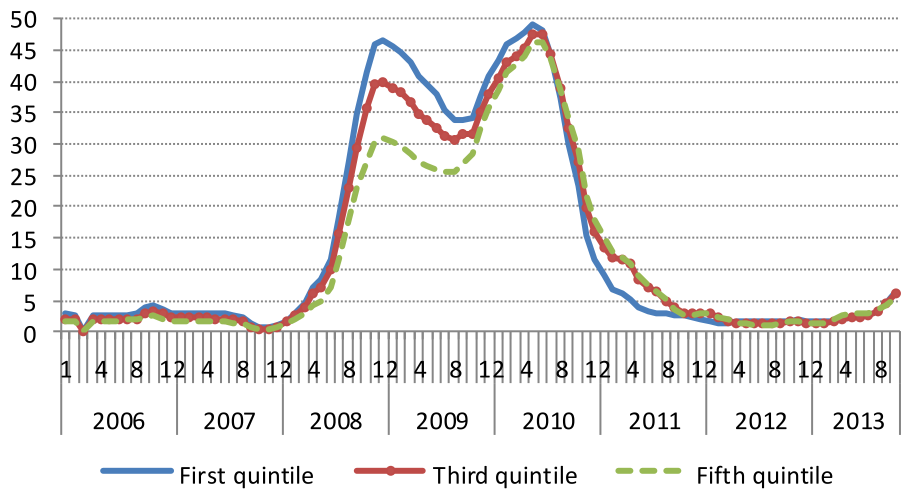


Figure A-4 CPI general by income quintiles
(Squared sum of growth rate)



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

Table A-5 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-6 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-7 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