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The Formation of Inflation Expectations: Micro-data Evidence from Japan*

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Abstract

We propose a novel approach for measuring inflation expectations, which can alleviate the rounding number problem. Further, we examine how consumers form inflation expectations. We find that consumers heterogeneously update their information sets on prices; 46% of the consumers collect information about the consumer price index at least once a quarter, while the remaining consumers less frequently or never obtain this information. We also find that forecast revisions are sensitive to a change in food prices. More than half of consumers are attentive only to a change in food prices and may form their inflation expectations using food price changes as a signal of fluctuations in the overall inflation rates. The existence of consumers who are inattentive to aggregate inflation casts doubt on the transmission of monetary policy through the management of expectations.

JEL Classification: C53; D84; E31

Keywords: disagreement; expectations; forecast bias; forecast revision; inflation; rational inattention; rounding; sticky information

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1 Introduction

Under the effective lower bound of short-term nominal interest rates, how economic agents form their inflation expectations has been receiving increasing attention. Despite its importance in macroeconomic theory, the formation of expectations has not been fully uncovered. Bernanke (2007) highlights the lack of a precise understanding of the state of inflation expectations and how it should be measured. Kuroda (2017) admits that “we have learned a lot about inflation expectations in the past few years, but there still remain many research questions on this issue yet to be addressed.”

This study aims to answer how consumers form inflation expectations. We focus on how and how often consumers process information about prices and how consumers form their shorter- and longer-term inflation forecasts. To this end, we conduct an online survey of consumers every quarter to collect their shorter- and longer-term forecasts on inflation rates and understand how they process information about prices. We also combine the survey with the data on the actual expenditure of each respondent and examine the effects of purchasing behavior on their expectations. By asking respondents to forecast the aggregate price level, and not percent change in inflation rates, we find that our survey can alleviate the “rounding number” problem, as documented in Kahneman and Tversky (2000), Manski and Molinari (2010), and Binder (2017).

There are three findings. First, disagreements on inflation forecasts among consumers are larger for the shorter-term horizons than those for the longer-term horizons. Consumers’ inflation forecasts for the shorter-term horizons are widely dispersed, while those for the 10-year horizon are anchored at 1%, which is much below Bank of Japan’s inflation target level of 2%. Moreover, cross-sectional disagreements are predicted by socioeconomic factors of respondents, which decline after respondents update their information sets on price levels.

Second, consumers heterogeneously update their information sets on prices. Only 40% of the consumers collect information about the nationwide price levels at least once a quarter, while the remaining consumers less frequently or never procure this information. Half of the respondents update their information sets on the overall prices, implying that typical consumers disregard the consumer price index (CPI). The existence of numerous consumers that are inattentive to the nationwide price levels casts doubt on the transmission mechanism of the monetary policy through the management of expectations.

Third, we find that consumers' forecasts are sensitive to a change in food prices. Revisions of inflation forecasts react significantly and positively to changes in food prices. We also find that forecast revisions over longer horizons are sensitive to changes in food prices. While Binder (2018) and Coibion and Gorodnichenko (2015) report a high sensitivity to changes in oil prices in the United States, Japanese consumers revise their forecasts in response to a change in food prices and not energy prices. Moreover, the sensitivity of forecast revisions depends on the purchase volume of each respondent—a respondent who purchases a higher amount of food items in retail stores is more sensitive to a change in food prices. The evidence implies that a change in food prices matters in the formation of inflation expectations and that daily shopping may help Japanese consumers to predict the upcoming fluctuations in overall inflation rates.

Our study is related to three strands of the literature. First, our study is related to those exploring the determinants of consumers' inflation expectations. A large body of the literature examines how consumers form their inflation expectations; this literature reports that socioeconomic factors, such as income, age, or gender, play a significant role in shaping these expectations.[1] Beyond the well-known factors, Ehrmann et al. (2017) and Pfajfar and Santoro (2013) find that inflation expectations are related to respondents' financial situation, purchasing attitude, and macroeconomic perspectives and to news on inflation. Diamond et al. (2020) find a positive correlation between consumers' inflation expectations and age. Coibion and Gorodnichenko (2015) find that inflation forecasts of consumers react positively to changes in oil prices in the United States. Our findings contribute to the existing literature by presenting other determinants of consumers' inflation expectations.

Second, our approach is related to previous studies indicating that economic agents do

[1] See, for example, Cavallo et al. (2017), Coibion et al. (2018a), and Easaw et al. (2013). Concerning firms' expectation formation, see Coibion et al. (2018b) and Coibion et al. (2020). Coibion et al. (2018a) provide a comprehensive survey about the formation of inflation expectations.

not always update their information sets. While standard economic theories assume full-information rational expectations (FIRE), Mankiw and Reis (2002) and Carroll (2003) maintain the *sticky* information hypothesis that information disseminates slowly. Dupor et al. (2010) develop a model that integrates sticky prices and information and show that both rigidities are present in the U.S. data. Coibion and Gorodnichenko (2012) and Andrade and Le Bihan (2013) find information rigidities even among the board of governors of the Federal Reserve as well as professional forecasters. Patton and Timmermann (2010), Capistrán and Timmermann (2009), Andrade et al. (2016), and Falck et al. (2021) also examine disagreement in inflation expectations. Hori and Kawagoe (2013) report that the *sticky* information hypothesis is supported for Japanese consumers. Our unique survey data allows us to investigate whether FIRE holds, by directly asking respondents how often they collect price information. Our survey shows that half of the respondents never update their information sets. The existence of inattentive consumers entails a larger disagreement on inflation forecasts among households than predicted by the existing theory. It also suggests that the literature should incorporate rational inattention models as well as the sticky information model.

Third, our study is related to the literature analyzing longer-term inflation forecasts of consumers. The literature examining the formation of consumers' expectations uses data on inflation forecasts by consumers over the shorter-term horizons owing to data limitations. The past empirical studies usually utilize 1-year-ahead forecasts with few exceptions.[2] However, since our survey collects forecasts of inflation rates over the 1-, 3-, and 10-year horizons, we can investigate the formation of inflation expectations over both the shorter-term and longer-term horizons. Our survey allows us to examine the term structure of inflation expectations and check whether an inflation target contributes toward anchoring consumers' expectations over the longer-term horizons.

The structure of this paper is as follows. Section 2 summarizes the survey and the descriptions of the inflation forecasts by Japanese consumers. Section 3 shows how con-

[2] While Andrade et al. (2016) show that forecasters disagree at all horizons, including the long run, they use forecasts submitted by professionals. While Chan et al. (2018) also examine the link between trend inflation and the long-run forecasts, their approach depends on professionals' forecasts.

sumers revise expectations. Section 4 summarizes the findings and concludes.

2 Survey and inflation expectations

2.1 Questionnaire

This section summarizes the survey data on consumers' inflation expectations and shows basic statistics. We conduct a quarterly online survey of Japanese consumers from 2015Q4 to collect inflation expectations over the short- and long-term horizons. Every quarter, approximately 30,000 consumers provide an outlook on price changes in Japan.[3] Respondents are asked the following questions:[4]

(1) Frequency of updating information on inflation rates.
   (a) "How often do you collect information on the overall price levels?"
   (b) "How often do you collect information on the prices of goods and services you frequently purchase?"

(2) Outlook of price levels over shorter- and longer-term horizons.
   - "What do you think will be the levels of CPI over the next one-, three-, and ten-year horizons, given that the current level of CPI is 10,000? Provide price-level figures over each horizon, excluding the impact of consumption tax hike on the price levels."

Regarding Questions (1)-(a) and (1)-(b), respondents choose the most appropriate one from the following choices. These questions can directly reveal the manner of consumers' information collection. Our focus is on how they update their information sets; we also aim to determine whether there exist any differences in the frequency of updating their information sets among the aggregate price levels and prices of daily commodity.

[3]We ask approximately 50,000 online observers, who are registered with INTAGE Inc., to present inflation forecasts as well as an outlook on the financial variables. The response rate of the online survey is approximately 60%. Thus, the sample size is approximately 30,000 every quarter.

[4]Tables 1 and 2 show the basic statistics of inflation forecasts by consumers.

Options	
(1)	Almost every day
(2)	Four or five times a week
(3)	Twice or thrice a week
(4)	Once a week
(5)	One or more times a week
(6)	Twice or thrice a month
(7)	Once a month
(8)	Once every two to three months
(9)	Once in six months
(10)	Once a year
(11)	Less than once a year
(12)	Do not collect

Question (2) asks respondents to report their forecasts numerically for the next 1, 3, and 10 years, on an average. This question can directly measure consumers' inflation expectations over both the shorter- and longer-term horizons. The questionnaire is also beneficial in measuring consumers' inflation expectations owing to the following three reasons.

Term structure of inflation expectations

First, the qualitative nature of the questionnaire on inflation expectations allows us to compute "forward" as well as "spot" rates with precision. Suppose that responses on the forecasts on the aggregate price levels over the next 1, 3, and 10 years are 10,080, 10,080, and 11,000, respectively. The forecasts on annualized inflation rates are calculated as shown below. The respondents' forecasts on inflation rates over the next 1-, 3-, and 10

Years Later	1-year	3-year	10-year
Forecast on price levels	10,080	10,600	11,000

$\downarrow$

Annualized inflation rates	"Spot" inflation rates			"Forward" inflation rates	
Years later	1-year	3-year	10-year	1 to 3-year	3 to 10-year
Inflation expectations: π^e	0.80%	1.96%	0.96%	2.55%	0.53%

years (or the next 4, 12, and 40 quarters) are computed as 0.80%, 1.96%, and 0.96%, respectively. We call them "spot" rates and denote $E_t^i[\pi_{t,t+q}]$ as consumer i's inflation forecasts over the next q-quarter. We can also compute "forward" rates—an annualized forward rate for years n through $n+k$ is calculated from the forecasts of price levels over the next n and $n+k$ year. When responses for the price level forecasts over the next 1, 3, and 10 years (or the next 4, 12, and 40 quarters) are 10,080, 10,600, and 11,000, the forward rates $E_t^i[\pi_{t+4,t+12}]$ and $E_t^i[\pi_{t+12,t+40}]$ are 2.55% and 0.53%, respectively.

Avoiding response bias

Second, asking respondents to provide figures for the price levels can avoid response bias. As Dillman et al. (2014) discuss, many respondents use the response scale as a guide to help them formulate answer. For example, when asked inflation forecasts by a multiple choice question, respondents might assume that the range represents the low and high scales.[5] Another assumption is that the middle option represents the *average* forecast. Suppose that the range is set from -10% to $+10\%$ and the midpoint as 0%. In this case, respondents might conclude that inflation rates vary from -10% to $+10\%$ and the average forecast is around 0%. In such a situation, the scale range and midpoint of a multiple-choice question will influence the answer. The range and midpoint tend to inform respondents when they are unfamiliar with the distribution of inflation rates; this leads to biased responses. Thus, by asking respondents to provide the price level, our survey can mitigate the bias resulting from providing scales that approximate the actual distribution of inflation rates in the population.[6]

Rounding number problem

[5] Another example is shown in Smyth et al. (2007).

[6] As for Questions (1)-(a) and (1)-(b), one might think the scale range and midpoint of a multiple-choice question will influence the answer when respondents estimate the updating frequency of their information sets. However, we believe that the question about the frequency of information updating may be more straightforward for respondents to answer compared to the question about the aggregate price levels over the next few years; Questions (1)-(a) and (1)-(b) to estimate the updating frequency are the questions about themselves. The scale range might also bias responses if it affects how respondents define a vague concept such as experiencing anger (Dillman et al., 2014). As Questions (1)-(a) and (1)-(b), which enquire about the updating frequency of consumers' information, are straightforward without vague concepts, we believe that they are less subject to bias from a multiple-choice question.

Third, asking respondents to provide the figures of the aggregate price levels can mitigate the "round number" problem. The psychological literature on survey and questionnaire response behavior posits the premise that answering a survey question is a process consisting of several distinct steps (Ruud et al., 2014). These include (i) understanding the question, (ii) recalling information from memory, and (iii) formulating the response itself (Tourangeau et al., 2000). Regarding rounding, the literature on psychology documents that the use of round values can reflect uncertainty in the representation of the estimated quantity and (or) uncertainty in mapping that quantity onto a numeric response (Tourangeau et al., 2000), while the literature on cognition and communication documents that people use round numbers to convey uncertainty (Binder, 2017).[7] In a consumer survey on inflation forecasts, fixing the rounding number problem will require reducing the degree of uncertainty in providing inflation expectations.

In order to alleviate the rounding number problem, we benefit from a novel approach for measuring inflation expectations. First, the rounding number problem is related to the financial literacy of subjects. Lusardi and Mitchell (2008) report that when asked about inflation, 12.8 percent of subjects responded with "don't know," while 14.5 percent gave a wrong answer. This suggests that approximately 27% of subjects may be unfamiliar with or lack a sound understanding of inflation rates. The lack of financial literacy induces them to face a high degree of uncertainty when asked to share their inflation expectations, which produces the rounding number problem. The lack of financial literacy also entails interrupting the response process, which includes understanding the question (Tourangeau et al., 2000). To reduce uncertainty about the unfamiliar, our approach measures inflation expectations without referring to "inflation." Since not using the word "inflation" contributes to reducing uncertainty, our method of measuring inflation expectations by the figures of the price levels can alleviate the rounding number problem.

Second, our approach for measuring inflation expectations is based on evidence that consumers use price memories to form inflation expectations. When subject answer a

[7] Uncertainty causes the rounding of numbers (Kahneman and Tversky, 2000; Ruud et al., 2014) and round responses are associated with imprecise estimates when subjects are asked to report quantitative estimates (Baird et al., 1970; Rowland, 1990).

survey question, they recall information from memory in a response process (Tourangeau et al., 2000). Bruine de Bruin et al. (2010) show that when asked about the inflation rate, most subjects report that they try to recall the prices of specific products. Cavallo et al. (2017) also show that consumers use their own memories of the prices of specific products to form inflation expectations.[8] This suggests that consumers are likely to form inflation expectations based on the price levels of specific products they purchase. Our method of measuring inflation expectations based on the figures of the price levels rather than their percentage change is directly related to the manner in which consumers form inflation expectations. Thus, indicating the figures of the price levels is straightforward for subjects and may reduce the uncertainty in providing inflation expectations. The reduced uncertainty helps alleviate the rounding number problem.

Third, the rounding number problem is related to the psychological burden of performing numerical calculations for evaluating the rate of change. Schwartz (1997) and Lipkus et al. (2001) show that performance on simple numeracy problems, including calculation of probability, is poor even among populations with formal education.[9] Dillman et al. (2014) document that, as a general rule, one should avoid asking questions that require respondents to do math. The literature implies that a lack of numeracy interrupts the response process, which includes formulating the response itself (Tourangeau et al., 2000), because uncertainty in mapping an estimated price level to the rate of inflation may increase the psychological burden of providing inflation expectations. Meanwhile, measuring inflation expectations without calculating percentage changes can mitigate subjects' lack of confidence in their numeracy skills and reduce the uncertainty in providing inflation expectations. Thus, it helps to mitigate the rounding number problem.

Binder (2017) reports that approximate half of the forecasts are reported in multiples of five in the case of Surveys of Consumers, University of Michigan, while our surveys

[8] Cavallo et al. (2017) asked individuals about the information they tried to recall and documented that 64.4 percent of subjects reported that they tried to recall the prices of specific products, which was twice the percentage of those trying to recall inflation statistics.

[9] For example, Lipkus et al. (2001) ask subjects to answer the question: In the ACME PUBLISHING SWEEPSTAKES, the chance of winning a car is 1 in 1,000. What percent of tickets to ACME PUBLISHING SWEEPSTAKES win a car? (Answer: 0.1%). Only 29.8% of the respondents gave the correct answer.

shows that 24% of the forecasts are reported as multiples of five. Imaginably, our survey also includes forecasts in multiples of five. However, in our survey, since the measures used to capture inflation expectations are calculated by point predictions of certain price levels, the computed measures are not always a multiple of five. Our survey observes that a significant number of forecasts are reported over the 1-year horizon; 10,100; 10,200; and 10,300. Although these values are actually reported as multiples of five, they are computed into 1.0%, 2.0%, and 3.0%, respectively, as annualized inflation forecasts. While the annualized rates are at one-percent intervals, they are not multiples of five.[10] As a result, our survey can obtain more granular estimates of consumers' inflation expectations than when using multiple choice questions or asking for point predictions as percentage values. Figure 1 shows the kernel density estimate of inflation expectations for the 1-year, 3-year, and 10-year horizons from our survey data. The figure shows the distributions of inflation expectations with fewer clear spikes. While the figure shows that the distribution of inflation expectations over the 1-year horizon has a small nodule at multiples of five, it provides no clear evidence from the distribution over the next 3-year and 10-year horizons.[11] It is pertinent to remember that approximately half of the forecasts are reported in multiples of five in the case of Surveys of Consumers, University of Michigan. However, our method can reduce the round numbers by approximately half. Thus, providing the figures of the price levels rather than responding to multiple-choice questions can alleviate the rounding problem.

2.2 Consumers' inflation expectations

Tables 1 and 2 show "spot" and "forward" inflation forecasts of consumers, respectively.[12] Tables 1 and 2 indicate disagreements among forecasters, especially for shorter-term horizons. Based on the simple average, Table 1 shows that inflation forecasts for the 1-year

[10] In our survey, the forecasts 10,500; 11,000; 11,500; 12,000; and 12,500 are reported in "multiples of five" because they are computed into 5%, 10%, 15%, 20%, and 25%, respectively, as annualized inflation forecasts.

[11] Detmeister et al. (2016) shows the distribution of inflation expectations for the 1-hear horizon using data from the Consumer Survey, University of Michigan. As Binder (2017) suggests, the distribution of inflation expectations shown in Detmeister et al. (2016) clearly spikes at multiples of five.

[12] The (annualized) inflation forecasts exclude all forecasts of inflation above 25 and below -5 percent.

and 3-year horizons are above 2.0%, while 10-year-ahead forecasts are at 1.5%. This suggests that the "term structure" of inflation forecasts is not flat but inverted. The inversion of the term structure of inflation forecasts is also found in "forward" forecasts of inflation rates. Table 2 shows that the average of forecasts for the 1- to 3-year horizons is larger than those for the 3- to 10-year horizons. However, forecasts based on median values are 0.5%, 0.9%, and 1.0% for the 1-year, 3-year, and 10-year horizons, respectively. Basically, median values are all 1.0% or below, and the term structure is a little upward. The front end of the curve is upward-sloping and the back end is almost flat. The difference between the mean and median values for the shorter-term forecasts suggests that the forecasts are dispersed. For example, the difference between the mean and median values for the 1-year horizon is 2.0%, while those for the 10-year horizon is 0.5%. We find this outcome in Table 2; it implies that the disagreements among forecasters for the shorter-term horizons is more than those for the longer-term horizons. In fact, the median of forecasts for the 10-year horizon, which seems to be less influenced by a short-term disturbance, is partially "anchored" at 1.0%. Table 3 shows standard deviations of inflation forecasts and supports the above fact. Standard deviation for the shorter-term horizons is significantly larger than that for the longer-term horizons. This suggests disagreements on inflation forecasts among consumers; forecasts for shorter horizons are widely dispersed, while those for the 10-year horizon are partially anchored much below than 2%, which is the price stability target by the Bank of Japan.

Our measure to capture consumers' inflation expectations is reasonable in sense that respondents' covariates explain the level of forecasts. The average forecasts of female, lowly qualified, and lower-income respondents are higher than those who are male, highly qualified, and higher-income earners. This evidence is found in both spot and forward forecasts of inflation rates in Tables 1 and 2.

In order to formally test whether covariates of respondents can predict inflation expectations, we regress inflation forecasts on their socioeconomic factors. Table 4 shows that the socioeconomic factors can explain inflation forecasts of each respondent over both the shorter- and longer-term horizons. The forecasts of female, lowly qualified, and lower-income respondents are higher than those who are male, highly qualified, and higher-income earners. This is consistent with several studies examining inflation expectations of consumers such as Ehrmann et al. (2017), Jonung (1981), and Souleles (2004).

2.3 How often do consumers update their information sets?

In this subsection, we directly identify the updating frequency of consumers' information on the aggregate price levels and prices of goods and services they frequently purchase. The full information rational expectations hypothesis assumes that every economic entity makes decisions using the updated information set. However, the past studies support the *sticky information* hypothesis, which maintains that economic agents do not always revise their information sets. In fact, they are inattentive; even professional forecasters submit their forecasts based on the old information sets. For example, Carroll (2003) provides micro foundations for the sticky information theory and derives a simple equation suitable for empirical analysis. Dupor et al. (2010) develop a model that integrates sticky prices and information and find that both types of rigidities are present in the U.S. data. Using Japanese data, Hori and Kawagoe (2013) test the sticky information hypothesis for consumer inflation forecasts.[13]

Table 5 shows the fraction of consumers that update their information sets on CPI; Figure 2 depicts the cumulative relative frequency of information, derived from the responses to Questions (1)-(a) and (1)-(b). In Figure 2, the blue and red lines refer to the cumulative probability of renewing information sets on CPI and the prices of goods and services consumers frequently purchase. First, the figure shows that more than half of the consumers hardly collect information on CPI. While less than 50% (46%) of the consumers update their information sets, the rest of them do not collect any information or procure it at least once in six months. However, more than 75% of the consumers pay their attention to the prices of regularly purchased items; more than three-fourths of the consumers collect information on the prices of items they frequently purchase at least once a month. Figure

[13] Abe and Ueno (2015) and Abe and Ueno (2016) examine the mechanism of inflation expectation formation using surveys with randomized experiments.

2 shows that the frequency of updating information on the prices of daily commodities and services is considerably higher than that of the aggregate price levels. These results suggest that typical consumers are attentive to prices of daily goods and services, while they are inattentive to the nationwide price levels.[14] The evidence on the existence of inattentive consumers implies that in addition to the sticky information model, the literature should incorporate rational inattention models.

From the perspective of theoretical view, the fact that not all consumers regularly update their information sets supports the sticky information hypothesis. If the *sticky information* hypothesis holds, then the disagreement among forecasters can be explained by whether consumers collect the price information when submitting their forecasts. As long as macroeconomic shocks are not as large as to drastically change inflation expectations, the disagreement among forecasts becomes small as forecasters update their information sets. However, the theoretical prediction suggests that the disagreement among inattentive consumers remains persistently high. The existence of inattentive consumers may limit the effectiveness of monetary policy; the inflation target policy may fail to anchor inflation expectations at the 2% that the Bank of Japan has set as a desirable inflation rate.

In order to confirm whether the disagreement decreases when consumers update their information sets, we conduct the variance ratio test; the null hypothesis is that the standard deviation of inflation forecasts by respondents who do not update their information sets is larger than those by respondents who update their information sets. Disagreement among forecasters, which can be measured by standard deviation, becomes smaller when all forecasters update their information sets when submitting forecasting variables. Thus, the variances of forecasts based on the updated information sets should be smaller than those based on the old information sets when macroeconomic shocks are not as large as to abruptly change inflation expectations.[15]

[14] We further check if the average frequency of information updating is stable over time. We conduct the ADF test to check if the average frequency of information updating is stationary. The test rejects the null hypothesis that the development of the ratio has a unit root at 5%. The result suggests that the average frequency of information updating is constant over time. The evidence that the updating frequency is constant over time is consistent with the assumption of the sticky information hypothesis.

[15] Here, we assume that there are no macroeconomic shocks that would entail drastic changes in inflation

The top panel in Table 6 shows standard deviations for each forecast horizon. The table shows that the disagreement among forecasters decreases when the information sets are renewed in all cases. This evidence is consistent with the sticky information hypothesis, which predicts disagreement among forecasters when there are two types of forecasters—those who update their information sets and those who do not.

Our findings imply a discrepancy between the frequencies with which information on CPI and daily goods and services is updated. Table 5 and Figure 2 show that less than half of the consumers update information on the level of CPI more than once a year. However, consumers update their information sets on daily goods and services more frequently than those on CPI. In fact, more than three-fourths of the consumers update their information sets at least one month. The evidence implies that consumers collect information about prices of daily goods and services more frequently than the *sticky* information hypothesis' prediction, while information about an aggregate price level diffuses more slowly than FIRE's prediction. The discrepancy between the frequencies with which information on CPI and daily goods and services is updated may require reconsidering the assumption of information rigidity. Particularly, the existence of numerous consumers that are inattentive to the nationwide price levels casts doubt on the transmission mechanism of the monetary policy through the management of expectations. Our finding suggests that the literature should incorporate rational inattention models as well as the sticky information model.

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expectations over the sample period.

3 Do consumers' forecasts respond to a change in the oil price?

3.1 Sensitivity of forecast revisions to changes in price of oil and food items

The previous section shows that typical consumers are inattentive to the consumer price index. Then, another question arises; how do consumers collect information about overall inflation rates. Coibion and Gorodnichenko (2015) discuss that consumer inflation forecasts in the United States respond to the price of oil closely and show the high sensitivity of consumers' inflation forecasts to oil prices relative to that of professional forecasts. Coibion and Gorodnichenko (2015) indicate that this is because consumers emphasize the prices they observe frequently. The literature implies that inattentive consumers use a change in commodity prices which they frequently observe as a signal of fluctuations in overall inflation rates.

While consumers in the United States emphasize the price of oil, Japanese consumers may be more attentive to food prices than other countries. Figure 3 shows the share of consumer's spending in the G7 countries. The figure shows that the share varies among the seven countries. Concerning food-related spending, the rate of food and non-alcoholic beverages to total expenditure in Japan is 15.4%, which is more than double of that of the United States. Since Japanese consumers have more opportunities to observe the change in food prices more frequently than those in other countries, their inflation expectations may be sensitive to the change in food price rather than the oil price.

In order to examine which of the prices exert a higher influence on the inflation forecasts of Japanese consumers, we estimate the following equation;

$$E_t^i[\pi_{t\to t+k}] - E_{t-2}^i[\pi_{t-2\to t+k-2}] = c_i + \beta_1 \times \pi_{p,t-2\to t}^{Oil} + \varepsilon_t^i, \tag{1}$$

where $E_t^i[\pi_{t\to t+k}]$ and $\pi_{p,t-2\to t}^{Oil}$ are denoted as inflation forecasts by individual i over the next k quarters at time t and a percent change in energy price in the previous two quarters in prefecture p where individual i resides, respectively.[16] For example, when $k = 12$, $E_t[\pi_{t\to t+12}]$ is the inflation forecast over the next 12 quarters (*i.e.* over the next 3 years) at time t. We also estimate the sensitivity of inflation forecasts to the food price rather than the oil price:

$$E_t^i[\pi_{t\to t+k}] - E_{t-2}^i[\pi_{t-2\to t+k-2}] = c_i + \beta_2 \times \pi_{p,t-2\to t}^{Food} + \varepsilon_t^i, \tag{2}$$

where $\pi_{p,t-2\to t}^{Food}$ is a percent change in food price in the previous two quarters in prefecture p where individual i resides. In the both equations, the coefficient β captures the sensitivity of inflation forecasts to price changes.

The top and middle panels in Table 7 summarize the estimation results of Equations (1) and (2). The table shows that consumers update their forecasts in response to the changes in food prices rather than the changes in energy prices. The top panel in Table 7 shows that an energy price change hardly influences forecast revisions of consumers. However, the middle panel in Table 7 shows that a food price change has a significant impact on forecast revisions—an increase in food prices induces an upward revision of forecasts. The impacts of a food price change on forecast revisions are larger when the forecast horizons are shorter—a one percent change in food prices induces an upward revision by approximately 0.18% when forecasts over the 1-year horizon are used. However, even the longer-term forecasts are revised in response to a food price change—β_2 is 0.05 when forecasts over the 3- to 10-year horizons are used. This result is robust when we use a percent change in the "core" CPI. The bottom panel in Table 7 shows, in the four out of five cases, a change in the food price index without fresh food positively impacts forecast

[16]Following Coibion and Gorodnichenko (2015), we use the biannual changes in food (or oil) prices rather than annual changes like $\pi_{t-4,t}^{Food}$. Coibion and Gorodnichenko (2015) also use the biannual changes in oil prices rather than the annual changes. The other advantage of using biannual changes is that we can regress individual revisions in inflation forecasts on the changes in food prices over the same time period. Consider the revisions to inflation expectations over the next year $E_t^i[\pi_{t\to t+4}]$. Since we would like to examine the manner in which inflation expectations are revised, the forecast horizon of a dependent variable should overlap between $E_t^i[\pi_{t\to t+4}]$ and $E_{t-k}^i[\pi_{t-k\to t-k+4}]$. In this case, the forecast horizon can overlap only when $k \leq 3$. Once we choose a k that is three or below, the corresponding changes in food (or oil) prices should be $\pi_{t-k,t}$. We take the middle value between one and three. Thus, the dependent variables are $E_t^i[\pi_{t\to t+4}] - E_{t-2}^i[\pi_{t-2\to t+2}]$ and the independent variables are the biannual changes in prices $\pi_{t-2,t}$ rather than $\pi_{t-4,t}$.

revisions, significantly. The results suggest that Japanese consumers' forecasts respond to the changes in food prices and not energy prices.

The results here are consistent with Coibion and Gorodnichenko (2015), which show that consumer's inflation forecasts in the United States respond to the price of oil closely because consumers emphasize the prices they observe frequently. Furthermore, they document that the more the consumers spend energy on energy, the more their inflation forecasts will respond to the price change of oil. However, Japanese consumers revise inflation forecasts in response to changes in food prices.

The results may imply that changes in the retail prices of food items serve as one of the main sources of information on price changes for Japanese consumers. In order to check the validity of the implication, we link the survey data on consumers' inflation expectations with the data on consumers' purchase records, using the monthly purchase volume of each consumer as the proxy for how consumers observe a change in price. The data on consumers' consumption expenditure are the panel data (SCI-personal) from Japan collected by a marketing company, Intage.[17] Intage asks over 50,000 individuals to report the items they buy on a daily basis. The data allow us to identify who bought what, when, where, how much, and at what price. These data cover items that consumers purchase frequently, such as food (except for fresh food, prepared food, and lunch boxes), beverages, daily miscellaneous goods, cosmetics, pharmaceutical products, and cigarettes.[18][19] Thus, the data record details of the buyer, items purchased, time of purchase, and the price of the items. We assume that consumers purchasing a high volume of daily commodities have more opportunities to observe a change in food prices than those who do not, and hence, data on purchase volume predicts the degree of sensitivity of revisions in consumers' inflation forecasts.[20]

Using the quarterly-based purchase volume of each consumer, we construct a dummy

[17] Diamond et al. (2020) also use the panel data (SCI-personal) that we use here.

[18] Since our scanner data cover daily necessities, they do not cover housing, utilities, durables, clothing, and services.

[19] The data suggest that food items including beverages and alcohol account for 74.4% of the total volume of daily commodity purchases.

[20] The assumption is supported by the data in Section 3.2.

variable D^{Volume} that takes one if a respondent purchases more volume than the median values; otherwise zero: The estimating equation is the following;

$$E_t^i[\pi_{t\to t+k}] - E_{t-2}^i[\pi_{t-2\to t+k-2}] = c_i + \beta \times \pi_{p,t-2\to t}^{Food} + \gamma \times \pi_{p,t-2\to t}^{Food} \times D_{i,t}^{Volume} + \varepsilon_t^i, \quad (3)$$

Our focus is on the sign of γ; if a respondent who buys more food in retail stores is more sensitive to a change in food prices, γ is significantly positive.

Table 8 shows the estimation result for Equation (3) and supports our intuition. The table shows significant and positive γ in all the cases. The positive and significant γ shows a higher sensitivity of forecast revisions to a change in the food price when consumers make high-volume purchases than those who do not. The high sensitivities are found in not only the shorter-term forecasts but also in the longer-term forecasts. These results suggest that the changes in food prices, which consumers regularly and predominantly observe in their consumption experiences, determine the forecast revisions of inflation expectations.

For a robustness check, we control income effects on the total volume purchased and examine whether a respondent who buys more food is more sensitive to a change in food prices. We construct a dummy variable $D^{HighIncome}$ that takes the value one if households' annual income is 7 million yen and above; otherwise, it takes the value zero.[21] The estimating equation is the following;

$$\begin{aligned} E_t^i[\pi_{t\to t+k}] - E_{t-2}^i[\pi_{t-2\to t+k-2}] = c_i + \beta \times \pi_{p,t-2\to t}^{Food} + \gamma \times \pi_{p,t-2\to t}^{Food} \times D_{i,t}^{Volume} \\ + \delta \times \pi_{p,t-2\to t}^{Food} \times D_{i,t}^{HighIncome} + \varepsilon_t^i, \end{aligned}$$

Again, our focus is on the sign of γ; if a respondent who buys more food in retail stores is more sensitive to a change in food prices, γ is significantly positive.

Table 9 shows the sensitivity of forecast revisions to a change in the food price. The table shows a significant and positive γ in all cases. The positive and significant γ shows higher sensitivity of forecast revisions to a change in the food price among consumers who

[21] Since a consumer with higher income is likely to purchase more than a consumer with lower income, we include a dummy variable $D^{HighIncome}$ to control for income effects on the total volume purchased.

make high-volume purchases than among those who do not. The table also shows that the coefficient δs of the cross term between π^{Food} and $D^{HighIncome}$ is significantly negative for short-term horizons. The table shows that while forecast revisions of a consumer with higher income is less subject to a food price change, consumers' inflation forecasts respond to the price of food even when income effects are controlled. The evidence supports the view that consumers' inflation forecasts in Japan respond to the price of food closely because consumers emphasize the prices they observe frequently.

3.2 Who update their information sets?

Our next strategy also provides evidence that consumers that pay attention to the prices they frequently and dominantly observe respond to a change in the food price more than those who do not. The fact that consumers purchasing a higher volume of food items have a higher sensitivity of forecast revisions to a food price change implies that they update their information sets more frequently than those who purchase lesser volume. In order to examine the chief factors that predominantly determine the renewal of information sets, we use a probit model. In the model, a dummy variable ($D^{updated}$) that represents the individual who updates an information set is regressed on a set of respondents' covariates, which comprise all indicator variables.[22] Table 10 shows the result of the probit model. It shows that the independent variables predict whether consumers update price information—the impacts are all significantly positive (except for constant). The probability of updating price information is larger when a respondent is male, highly educated, earns more, married, and purchases a higher volume. Notably, the table shows that the purchase volume most significantly impacts the probability of updating an information set. The higher the purchase volume of consumers, the higher will be the probability of updating price information. This suggests that consumers see (food) price changes in retail stores, such as supermarkets and convenience stores, and the price changes induce them to update their information sets, in turn, shaping their inflation expectations.

[22] As we introduce in Section 2, our online survey asks respondents how often they collect information on prices. $D^{Updated}$ takes one when a respondent collects information on prices when submitting an inflation forecast; otherwise zero.

The above results in this section suggest that respondents purchasing a higher volume update their information sets more frequently and have a higher sensitivity of forecast revisions to changes in food prices. This may suggest that Japanese consumers collect information about prices in retail stores. In sum, food prices play a significant role in the formation of inflation expectations of Japanese consumers. While typical consumers are inattentive to overall inflation rates, they may use a change in food prices which they frequently observe as a signal of fluctuations in overall inflation rates.

4 Conclusion

We examine how consumers form their inflation expectations, combining a unique survey for inflation expectations with their actual expenditure data. Our measure to capture inflation expectations can not only alleviate the problem arising from the rounding behavior but also mitigate the response bias resulting from providing scales.

There are three findings. First, disagreements on inflation forecasts among consumers are larger for the shorter-term horizons than those for the longer-term horizons. Inflation forecasts for the shorter-term horizons are widely dispersed, while those for the 10-year horizon are anchored at 1%. We also find that cross-sectional disagreements decline after respondents update their information sets on price levels.

Second, consumers heterogeneously update their information sets on prices. Only 40% of the consumers collect information about the consumer price index at least once a quarter, and more than half of the consumers never obtain this information. The existence of inattentive consumers to the nationwide price levels casts doubt on the transmission mechanism of the monetary policy through the management of expectations.

Third, forecast revisions are sensitive to a change in food prices and a respondent who buys more food is more sensitive to the price change. Additional analysis reveals that consumers that purchase large quantities of daily food update their information sets more frequently than those who do not make such purchases. The evidence implies that a change in food prices influences the formation of inflation expectations and inattentive consumers may use a change in food prices as a signal of fluctuations in overall inflation rates. It also suggests that the literature should incorporate rational inattention models as well as the sticky information model.

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Table 1: Basic statistics of consumers' inflation forecasts: "Spot" forecasts

	1-year average			3-year average			10-year average		
	Mean	Median	Obs.	Mean	Median	Obs.	Mean	Median	Obs.
All	2.5%	0.5%	143,612	2.1%	0.9%	144,806	1.5%	1.0%	144,835
Female	2.8%	0.8%	69,474	2.4%	1.0%	69,843	1.6%	1.0%	69,802
Male	2.2%	0.5%	73,694	1.8%	0.6%	74,517	1.3%	1.0%	74,589
High school graduate or below	2.8%	1.0%	64,212	2.3%	1.0%	64,650	1.6%	1.0%	64,671
Four-year college graduate or above	2.2%	0.5%	73,706	1.8%	0.6%	74,340	1.3%	1.0%	74,159
Annual income below 4 million yen	2.7%	0.9%	63,077	2.3%	1.0%	63,570	1.6%	1.0%	63,625
Annual income 7 million yen and above	2.2%	0.5%	54,290	1.8%	0.6%	54,742	1.3%	1.0%	54,676
Information set updated	2.6%	0.8%	88,539	2.1%	1.0%	89,257	1.4%	1.0%	89,011
Information set NOT updated	2.4%	0.5%	55,073	2.1%	0.6%	55,549	1.5%	1.0%	55,824

Note: The forecasts of inflation above 25 and below −5 percent are trimmed. The data cover from 2015Q4 to 2019Q1.

Table 2: Basic statistics of consumers' inflation forecasts: "Forward" forecasts

	1 to 3-year average			3 to 10-year average		
	Mean	Median	Observation	Mean	Median	Observation
All	1.8%	0.4%	141,686	1.1%	0.6%	141,667
Female	2.0%	0.7%	68,192	1.1%	0.6%	68,131
Male	1.7%	0.4%	73,058	1.0%	0.6%	73,107
High school graduate or below	2.0%	0.9%	63,139	1.1%	0.6%	63,061
Four-year college graduate or above	1.6%	0.4%	73,062	1.0%	0.5%	72,975
Annual income 7 million yen and above	2.0%	0.7%	61,986	1.2%	0.6%	61,865
Annual income below 4 million yen	1.6%	0.4%	53,782	0.9%	0.6%	53,822
Information set updated	1.8%	0.7%	87,517	1.0%	0.6%	87,270
Information set NOT updated	1.9%	0.4%	54,169	1.1%	0.6%	54,397

Note: The forecasts of inflation above 25 and below -5 percent are trimmed. The data from 2015Q4 to 2019Q1.

Table 3: Variance ratio test: Forecasts for shorter- and longer horizons

$$H_0: \ \sigma^2_{longer\ horizon}/\sigma^2_{shorter\ horizon} > 1$$

			F-statistics		
Forecast horizon	Standard deviation		1-year	3-year	10-year
1-year	4.364%	1-year	—	—	—
3-year	3.241%	3-year	1.813***	—	—
10-year	2.395%	10-year	3.321***	1.832***	—

Note: We test whether variance of forecasts for longer horizons is larger than that for shorter horizons. For example, F-statistics, which tests whether variance of forecasts for the three-year horizon is larger than those for the one-year horizon, is 1.813, which is significant at the 1% level. Here, *** indicates 1% significance.

Table 4: Determinants of Consumers' Inflation Expectations

$$E_t^i[\pi_{t\to t+k}] = \alpha + \gamma \times X_t^i + \varepsilon_t^i,$$

	"Spot"			"Forward"	
	1 year	3 year	10 year	1 – 3 year	3–10 years
Female	0.455***	0.404***	0.248***	0.273***	0.129***
	(0.112)	(0.088)	(0.045)	(0.058)	(0.020)
Age	−0.240***	−0.294***	−0.230***	−0.220***	−0.081***
	(0.064)	(0.052)	(0.044)	(0.039)	(0.026)
Age^2	0.015***	0.017***	0.013***	0.012***	4.83e-03**
	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)
Annual income 7 million yen and above	−0.297***	−0.272***	−0.207***	−0.235***	−0.113***
	(0.046)	(0.023)	(0.006)	(0.012)	(0.005)
Four-year college graduate or above	−0.452***	−0.371***	−0.246***	−0.281***	−0.123***
	(0.021)	(0.023)	(0.026)	(0.019)	(0.013)
Marital Status	−0.241***	−0.136***	−0.103***	−0.106**	−0.060***
	(0.022)	(0.022)	(0.023)	(0.035)	(0.001)
Constant	3.660***	3.410***	2.530***	2.920***	1.490***
	(0.100)	(0.093)	(0.132)	(0.087)	(0.068)
Observations	130,299	131,374	131,335	128,600	128,517

Note: Standard errors in parentheses are clustered at individual levels, * indicates 10%, ** indicates 5% and *** indicates 1% significance.

Table 5: The fraction of consumers who update information sets on the aggregate price levels at least once a quarter.

	Information set		
	Updated	NOT Updated	Total
All	46%	54%	100%
Female	49%	51%	100%
Male	52%	48%	100%
High school graduate or below	43%	57%	100%
Four year college graduate or above	52%	48%	100%
Annual income 7 million yen and above	44%	56%	100%
Annual income below 4 million yen	51%	49%	100%
Purchase volume above median	45%	55%	100%
Those who purchase less items than median	62%	38%	100%

Note: "Updated" means the fraction of consumers who update information sets on the aggregate price levels at least once a quarter.

Table 6: Variance ratio test: Do cross-sectional disagreements among forecasters decrease when the information set is updated?

	Information set	Standard deviation
1-year ahead forecast	Updated	4.346%
	NOT updated	4.393%
3-year ahead forecast	Updated	3.151%
	NOT updated	3.382%
10-year ahead forecast	Updated	2.292%
	NOT updated	2.550%
1 to 3-year forecast	Updated	2.969%
	NOT updated	3.256%
3 to 10-year forecast	Updated	1.722%
	NOT updated	1.830%

$$Ratio = \sigma^{Old}/\sigma^{Updated}$$

$H_0 : Ratio > 1$	F statistics
1-year ahead forecast	1.022***
3-year ahead forecast	1.153***
10-year ahead forecast	1.238***
1 to 3-year forecast	1.202***
3 to 10-year forecast	1.130***

Note: *** indicates 1% significance.

Table 7: Which price changes influence forecast revisions?

	"Spot"			"Forward"	
	1 year	3 year	10 year	1 – 3 year	3 – 10 year
Panel (A): $E_t^i[\pi_{t\to t+k}] - E_{t-2}^i[\pi_{t-2\to t+k-2}] = c_i + \beta_1 \times \pi_{p,t-2\to t}^{Oil} + \varepsilon_t^i.$					
$\beta_1 : \pi_{p,t-2\to t}^{Oil}$	0.003	0.005	0.000	0.007	-0.002
	(0.013)	(0.010)	(0.005)	(0.008)	(0.004)
Fixed effect	YES	YES	YES	YES	YES
Observations	59,791	60,468	60,144	58,893	58,643
Panel (B): $E_t^i[\pi_{t\to t+k}] - E_{t-2}^i[\pi_{t-2\to t+k-2}] = c_i + \beta_2 \times \pi_{p,t-2\to t}^{Food} + \varepsilon_t^i.$					
$\beta_2 : \pi_{p,t-2\to t}^{Food}$	0.179**	0.162**	0.086**	0.156***	0.052**
	(0.076)	(0.055)	(0.032)	(0.047)	(0.020)
Fixed effect	YES	YES	YES	YES	YES
Observations	59,791	60,468	60,144	58,893	58,643
Panel (C): $E_t^i[\pi_{t\to t+k}] - E_{t-2}^i[\pi_{t-2\to t+k-2}] = c_i + \beta_3 \times \pi_{p,t-2\to t}^{FLF} + \varepsilon_t^i.$					
$\beta_3 : \pi_{p,t-2\to t}^{FLF}$	0.164*	0.142**	0.072**	0.120***	0.027
	(0.088)	(0.046)	(0.031)	(0.032)	(0.029)
Fixed effect	YES	YES	YES	YES	YES
Observations	59,791	60,468	60,144	58,893	58,643

Note: $\pi_{p,t-2\to t}^{Oil}$, $\pi_{p,t-2\to t}^{Food}$, and $\pi_{p,t-2\to t}^{FLF}$ are denoted as percent changes in energy price, food price, and food price less fresh foods in the previous two quarters in prefecture p where individual i resides, respectively. Standard errors in parentheses are clustered at individual levels; * indicates 10%, ** indicates 5%, and *** indicates 1% significance.

Table 8: Do purchase volumes have an impact on forecast revisions?

$$E_t^i[\pi_{t\to t+k}] - E_{t-2}^i[\pi_{t-2\to t+k-2}] = c_i + \beta \times \pi_{p,t-2\to t}^{Food} + \gamma \times \pi_{p,t-2\to t}^{Food} \times D_{i,t}^{Volume} + \varepsilon_t^i.$$

	"Spot"			"Forward"	
	1 year	3 year	10 year	1 – 3 year	3 – 10 year
β: $\pi_{p,t-2\to t}^{Food}$	0.154**	0.147**	0.068*	0.148***	0.039
	(0.069)	(0.053)	(0.035)	(0.046)	(0.024)
γ: $\pi_{p,t-2\to t}^{Food} \times D_{i,t}^{Volume}$	0.062***	0.038**	0.036***	0.020*	0.032**
	(0.020)	(0.013)	(0.010)	(0.010)	(0.011)
Fixed effect	YES	YES	YES	YES	YES
Observations	59,791	60,468	60,144	58,893	58,643

Note: $\pi_{p,t-2\to t}^{Food}$ is denoted as a percent change in food price in the previous two quarters in prefecture p where individual i resides. $D_{i,t}^{volume}$ takes one when purchase volume by consumer i is larger than median; otherwise zero. Standard errors in parentheses are clustered at individual levels; * indicates 10%, ** indicates 5%, and *** indicates 1% significance.

Table 9: Do purchase volumes have an impact on forecast revisions?: robustness check

$$E_t^i[\pi_{t\to t+k}] - E_{t-2}^i[\pi_{t-2\to t+k-2}] = c_i + \beta \times \pi_{p,t-2\to t}^{Food} + \gamma \times \pi_{p,t-2\to t}^{Food} \times D_{i,t}^{Volume} + \delta \times \pi_{p,t-2\to t}^{Food} \times D_{i,t}^{HighIncome} + \varepsilon_t^i.$$

	"Spot"			"Forward"	
	1 year	3 year	10 year	1 – 3 year	3 – 10 year
β: $\pi_{p,t-2\to t}^{Food}$	0.177**	0.162**	0.072*	0.160***	0.035
	(0.072)	(0.056)	(0.036)	(0.050)	(0.026)
γ: $\pi_{p,t-2\to t}^{Food} \times D_{i,t}^{Volume}$	0.061***	0.037**	0.036***	0.019*	0.032**
	(0.020)	(0.013)	(0.010)	(0.010)	(0.011)
δ: $\pi_{p,t-2\to t}^{Food} \times D_{i,t}^{HighIncome}$	−0.056***	−0.034***	−0.009	−0.031**	0.009
	(0.010)	(0.009)	(0.007)	(0.011)	(0.006)
Fixed effect	YES	YES	YES	YES	YES
Observations	59,791	60,468	60,144	58,893	58,643

Note: $\pi_{p,t-2\to t}^{Food}$ is denoted as a percent change in food price in the previous two quarters in prefecture p where individual i resides. $D_{i,t}^{Volume}$ takes one when purchase volume by consumer i is larger than median; otherwise zero. $D_{i,t}^{HighIncome}$ takes one when households' annual income is 7 million yen and above; otherwise zero. Standard errors in parentheses are clustered at individual levels; * indicates 10%, ** indicates 5%, and *** indicates 1% significance.

Table 10: Who updates their information sets: a probit analysis

Dependent Variable: Dummy variable ($D^{Updated}$)	
Independent Variables	
Purchase volume above median	0.445***
	(0.005)
Male	0.210***
	(0.004)
Four-year college graduate or above	0.159***
	(0.004)
Households' annual income 7 million yen and above	0.070***
	(0.004)
Marital status	0.226***
	(0.005)
Constant	−0.518***
	(0.005)
Observations	389,026

Note: Standard errors are in parentheses; *** indicates 1% significance. $D^{Updated}$ takes one when a respondent's information set is updated in forecasting inflation rates; otherwise zero.

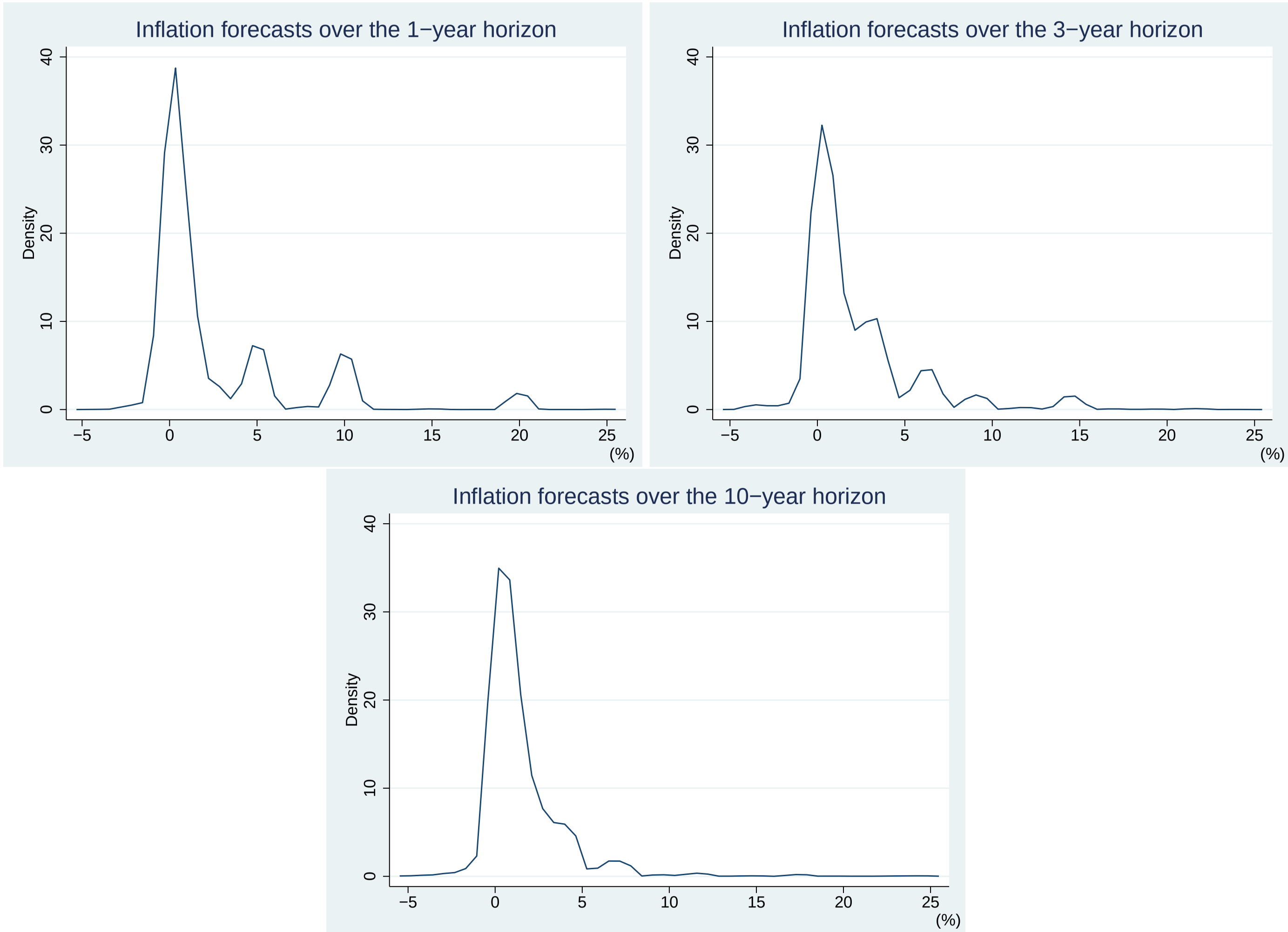

Figure 1: Kernel density estimates of inflation expectations for the 1-year (top panel), 3-year (middle panel), and 10-year (bottom panel) horizons. We use an Epanechnikov kernel as a kernel function. The bandwidth of the kenel is set to be 0.005.

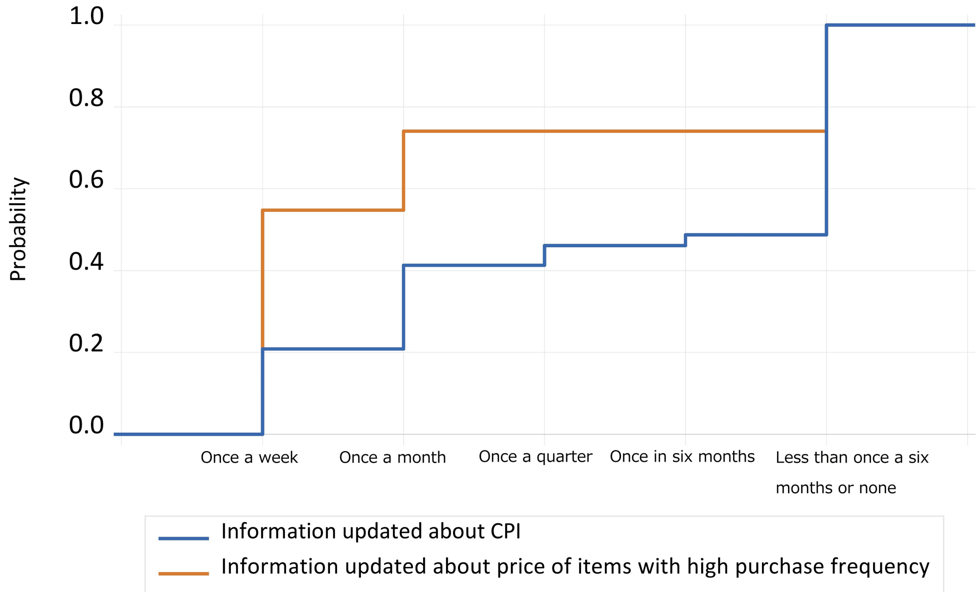

Figure 2: Cumulative relative frequency of information updated

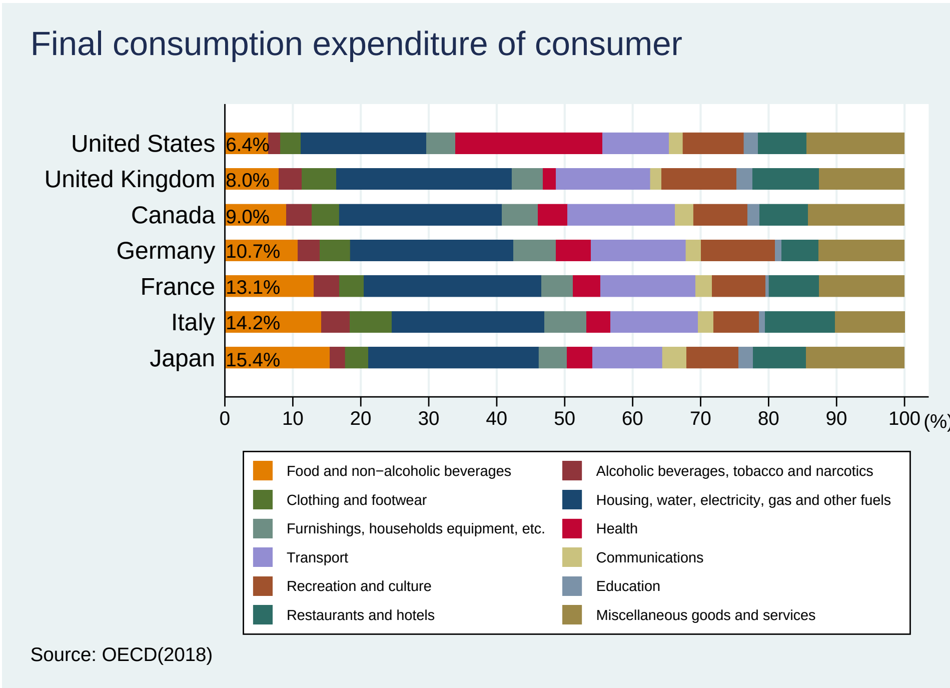

Figure 3: International comparison of final consumption expenditure of consumer