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Responses of Households' Expected Inflation to Oil Prices and the Exchange Rate: Evidence from Daily Data[1]

Etsuro Shioji
(Hitotsubashi University)[2,3]

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[3] Department of Economics, Hitotsubashi University, 2-1 Naka, Kunitachi, Tokyo, 186-8601, Japan. E-mail: shioji (at) econ.hit-u.ac.jp.

Abstract

This paper asks if daily data can help us predict monthly changes in inflation expectations of households. I utilize the mixed-data sampling (MIDAS) method (Ghysels et. al. (2004)) to study determinants of a monthly survey-based measure of household inflation expectations in Japan. I incorporate two types of higher-than-monthly frequency variables into the analysis. The first is a group of "traditional" daily indicators such as the exchange rate and crude oil prices. The second consists of more unconventional measures such as a scanner-data-based price index and (weekly) retail gasoline prices. I find that, although both groups of variables help explain *actual* CPI inflation, only the latter turn out to be significant when the dependent variable is *expected* inflation. This finding suggests that people's perceptions are affected predominantly by prices that they actually observe in their everyday lives, at supermarkets and gasoline stations.

1. Introduction

This paper asks if daily (and weekly) data can help us predict monthly changes in inflation expectations of households. Our recent experiences suggest that, when actual prices are moving rapidly, people's perceptions about the future course of inflation could also shift dramatically, even within a month. It would be beneficial for policy makers if they could detect early signs of such changes.

For that purpose, they might be able to take advantage of the recent influx of newly developed daily data. In the literature, it has long been argued that household expectations about inflation are heavily influenced by their perceived inflation (Jonung (1981)). More recently, a growing number of studies point to importance of prices of items that households purchase frequently in forming their expectations (D'Acunto et. al. (2021), D'Acunto et. al. (2022)). If that is indeed the case, we could hope that daily observations on those prices, as well as those on factors that affect them, could be useful in anticipating changes in people's expectations.

This paper applies the mixed-data sampling (MIDAS) method (Ghysels et.al. (2004)) to the Japanese data[4]. I conduct two types of studies. The first study examines which of the various daily (or weekly) indicators help explain monthly indices of actual inflation. Then I ask if the same set of variables could explain at least a part of movements in households' expected inflation.

As regressors, I incorporate two types of higher-than-monthly frequency variables. The first is a group of "traditional" daily indicators, or market-based measures, such as the exchange rate and crude oil prices. The second consists of more unconventional and direct measures such as a scanner-data-based price index and (weekly) retail gasoline prices.

I find that, although both groups help explain *actual* CPI inflation, only the latter turns out to be significant when the dependent variable is *expected* inflation. This finding suggests that people's perceptions are affected predominantly by prices that they actually observe in their everyday lives, at places such as supermarkets and gasoline stations. Oil prices and the exchange rate might help predict how those prices would evolve in near

[4] An example of an application of this methodology which tries to answer macroeconomic questions is Andreou et.al. (2013), who study how information contained in daily financial variables help forecast quarterly GDP growth.

future, but do not directly influence households' expectations.

The rest of the paper is organized as follows. Section 2 reviews the related literature, focusing on work that study expectation formation about inflation by households in Japan. Section 3 explains the methodology. Section 4 provides an overview of the data on actual as well as expected inflation and higher frequency variables. In section 5, I will explain the results on the determinants of actual inflation. Section 6 reports those for expected inflation. Section 7 concludes.

2. Related literature: studies on household inflation expectations in Japan

The literature on inflation expectations has grown rapidly in the past twenty years or so. Here, I will focus on studies that deal with expectations of households in Japan.

There are two relevant data sources published by the public sector in Japan. *Consumer Confidence Survey*, which is conducted by the Ministry of Internal Affairs and Communications, includes questions regarding the respondent's outlook for future inflation. *Opinion Survey* by the Bank of Japan also contains questions about inflation expectations. In addition, some researchers have conducted their own questionnaire surveys to gain insights into the mechanisms of expectation formation.

Features of inflation expectations

Some studies have examined characteristics of inflation expectations of Japanese households. Kamada (2013) studies the micro data from the Opinion Survey. He argues that there is a downward rigidity in survey responses. That is, respondents, when their true expected inflation is negative, tend to choose "zero percent" as an answer. Hori and Kawagoe (2012) utilize micro level data from the Consumer Confidence Survey and conclude that household inflation expectation formation in Japan is not fully rational.

Diamond, Watanabe and Watanabe (2020) employ a questionnaire survey to construct a panel data on inflation expectations. It is shown that expected rate of inflation increases with age. They find evidence that an individual's inflation expectations are influenced by past experiences through their lives.

Kikuchi and Nakazono (2023) conduct a large-scale quarterly questionnaire survey of inflation forecasts of households, along with their other characteristics. They find that households vary greatly in terms of the frequency with which they update their information sets related to prices. They also find that their expectations revisions are sensitive to food prices.

Some researchers have conducted randomized experiments on respondents of their own questionnaire surveys to better understand the nature of inflation expectation formation. First, all the respondents are asked to give their own estimates for future inflation. Then, some of them (the treatment group) are given certain pieces of information that are possibly relevant for the future course of inflation. The others (the control group) do not receive such information. Afterwards, they are asked to state their expected inflation again. How the answers to the second question of the treatment group might differ from those of the control group could shed light on the mechanism of expectation formation. Such studies include Abe and Ueno (2015, 2016) and Niizeki (2022).

Determinants of inflation expectations

Most directly related to the current analysis are the studies that explore determinants of inflation expectations. Ueda (2010) estimates VAR models that involve output gap, the interest rate, and actual as well as expected inflation, for both the US and Japan. Nishiguchi, Nakajima and Imakubo (2014) estimate a VAR model which consists of inflation rate of items frequently purchased by household, that of items less frequently purchased, households' perceived inflation and their expected inflation. The find that expectations are much more sensitive to prices of goods and services that households purchase frequently. Kamada, Nakajima and Nishiguchi (2015) analyze how inflation expectations (not only their means across households but also other moments) react to monetary policy announcements and actual inflation. Shintani and Yamamoto (2023) estimate how household expectations respond to newspaper articles about prices.

Inflation expectations and household expenditures

Others have studied the role of inflation expectations as a driver of household expenditure. Ichiue and Nishiguchi (2015) utilize micro data from the Opinion Survey. Ito and Kaihatsu (2016) use data from the Questionnaire Survey on Work and Life of Workers, conducted by the Japanese Trade Union Confederation Research Institute for Advancement of Living Standards, which asks its respondents not only about inflation expectations but their wage expectations. Niizeki (2021) constructs a pseudo panel data of cohorts by combining micro data on inflation expectations data from the Consumer Confidence Survey with other sources of information. Kikuchi and Nakazono (2020) combine their questionnaire surveys on inflation expectations with scanner data on consumption spending by individual households to tackle the issue. Jinnai, Mikami, Okuda and Nakajima (2021) study a panel data set from Osaka University's Preference Parameter Survey: they find that the effect of inflation expectations on consumption varies depending on the source of the revisions in their forecasts.

3. Empirical methodology

This section gives a brief description of the MIDAS-based approach used in this paper. Let us denote a measure of the monthly price level, either actual or expected, in month m as P_m. Its rate of change is written as ΔP_m. Throughout the paper, I define this as the rate of change from the same month of the previous year: this is because my measure of expected inflation is derived from a survey about the respondent's expectation for year-on-year inflation. My baseline model is specified as:

$$\Delta P_m = a_1 \Delta P_{m-1} + a_2 \Delta P_{m-2} + D_m + \varepsilon_m \tag{1}$$

where ε_m is the error term. Its distinct feature is the presence of D_m, which is the "daily part". For simplicity of exposition, assume that this part involves a single daily variable denoted X_{m_d}, where m_d is a date in month m (for example, the 15th day of each month). The daily part takes the following form:

$$D_m = f(0) \cdot X_{m_d} + f(1) \cdot X_{m_d - 1} + f(2) \cdot X_{m_d - 2} + \cdots \tag{2}$$

where $f(i)$ is a function of i, the index for a daily lag. I specify this as a polynomial distributed lag (or PDL: I assume the number of lags to be two throughout the paper):

$$f(i) = \theta_0 + \theta_1 \cdot i + \theta_2 \cdot i^2 \tag{3}$$

where θ_0, θ_1 and θ_2 are parameters to be estimated. The entire model is estimated by non-linear least squares. I use Eviews' built-in commands for the estimation.

4. Data

Actual Inflation

We study various measures of inflation within the category of the Consumer Price Index (CPI) compiled by the Japanese Government, as follows:

CPI_HEAD: all items (100)*

CPI_CORE: all items, less fresh food*

CPI_FRESH: fresh food

CPI_CORECORE: all items, less food and energy*

CPI_FOOD: food, less fresh food

CPI_ENERGY: energy

CPI_GOODS: goods, less fresh food

CPI_SERVICE: services

CPI_FREQ: frequently purchased items (see below) *.

Asterisks mean that, for those series, starting from January 2020, I estimate and subtract influences of mobile telecommunications fees and lodging: those two price series have been subject to large distortions from peculiar governmental policy changes, and thus exhibited highly irregular movements. CPI_HEAD is the overall index which includes all the items. It can be decomposed into CPI_CORE and CPI_FRESH. The former (which is conceptually different from the core CPI in the US) excludes fresh food, while the latter is the index for fresh food. In turn, CPI_CORE can be divided into CPI_CORECORE, CPI_FOOD, and CPI_ENERGY. The first one (which corresponds to the core CPI in the US) excludes all the food items and energy, the second one is for food other than fresh food, and the third one is for energy such as gasoline and electricity fees. CPI_CORE can alternatively be decomposed into CPI_GOODS and CPI_SERVICE.

In this paper, I shall pay a particular attention to the last index, namely CPI_FREQ. It is based on a section of the official CPI statistics called the *Indices of Annual Purchase Frequency Classes*. As the name suggests, items are classified according to frequency with which they are purchased by the average Japanese household. Within the same frequency class, items are weighted according to their expenditure shares, as in regular CPI statistics (that is, they are not weighted according to their purchase frequencies), to form an index specific to that class. In this paper, I define "frequently purchased items" as those items that are bought once in two months or more frequently. From the official index, I estimate and subtract contributions of fresh food. I also adjust for influences of mobile telecommunications fees and lodging, as mentioned earlier. The resulting index is my CPI_FREQ.

As discussed in the introduction, and also suggested by the estimation results in

Nishiguchi, Nakajima and Imakubo (2014), inflation expectations of households are often supposed to be under heavy influences of prices of items that they purchase frequently. It is thus of particular intertest to examine their determinants. In Figure 1, I plot evolution of CPI_FREQ, along with that of CPI_CORE. The two series are apparently very highly correlated, but CPI_FREQ tends to be more volatile.

In a mixed frequency analysis, it is important to recognize the timing at which a lower frequency variable is observed. Japanese CPIs are based on a survey of retail prices that is conducted during the week that contains the 12^{th} day of the month: specifically, either Wednesday, Thursday or Friday of that week.

Expected Inflation

Consumer Confidence Survey, conducted monthly, contains a few questions regarding the outlook for inflation. Since April 2004, the following question is included: "What do you think about prices of goods that your household regularly purchases frequently one year from now?" Note that the respondents are not asked to predict the official CPI but to state their views on the items they often buy. They are asked to choose an answer from various intervals of price changes. They are given nine choices of those intervals, as shown in the first column in Table 1[5,6]. To convert this into a numerical value for expected inflation, I assign a specific number to each range of answers, as shown in the second column of the same table. I take a weighted average of those values using the share of respondents who picked each of the ranges. Figure 2 plots the resulting estimates for inflation expectations.

Higher frequency variables (1) *Oil prices*

For the first set of variables in the daily part of the MIDAS model, I include the exchange rate and world oil prices.

Previous studies have emphasized an important role played by oil prices in forming inflation expectations of households, especially because they impact prices of gasoline,

[5] Prior to April 2009, only seven choices were given: inflation number was top- and bottom-coded at + and -5% instead of + and -10%.

[6] Starting April 2016, the respondents were explicitly asked to answer about prices that are *tax inclusive*. The instruction was less clear until then.

which many consumers observe on daily basis. Most notably, Coibion et. al. (2015) argue that incorporating this effect into an expectation-augmented Phillips Curve goes a long way toward explaining "missing disinflation" in the post-Global Financial Crisis era in the US. Kilian et. al. (2022) downplay the importance of oil prices during this period, but still find that they have significant influences on household inflation expectation.

Oil prices could be especially important in the Japanese context. Shioji (2021) reports that pass-through from world oil prices to domestic gasoline prices is surprisingly fast in Japan: when oil prices increase due to a news shock to the supply side of the oil market, retail gasoline prices in Japan start to go up almost immediately, and about 70% of the entire adjustment process is completed within just 18 days. This probably reflects a specific way the dominant Japanese refiners determine their sales prices of gasoline. In such a case, incorporating daily movements in oil prices into a model for monthly domestic consumer prices could be vitally important.

In addition to gasoline prices, oil prices could also have a sizable impact on other consumer goods that are oil-intensive, such as plastic products. In this study, as an indicator of world oil prices, I use the closing price of Brent Futures (CO1).

Higher frequency variables (2) *Exchange rates*

The exchange rate could affect prices of imported consumer goods directly, especially if the pass-through is immediate. I use the USD/JPY exchange rate taken from the FRED data base of the Federal Reserve Bank of St. Louis.

Higher frequency variables (3) *CPINOW*

Nikkei CPINOW is a scanner-based data on daily consumer goods prices, produced by NOWCAST, Inc. It is constructed from information collected from 1,200 supermarkets around Japan. I use their T Index (T stands for Törnqvist), which is provided in the form of y-o-y rate of change. The index is based on before tax prices. Refer to Watanabe and Watanabe (2014) and Imai and Watanabe (2015) for detailed analyses of the underlying scanner data.

I estimate that about 90% of the total weights within this index is given to processed foods.

Other items included are, for example, toilet papers, tissue papers, detergents, etc[7].

Higher frequency variables (4) *Weekly Gasoline prices*

If much of the influences of oil prices are transmitted through their effects on gasoline prices, especially in the short run, including the latter prices could also prove to be important. The Japanese government surveys retail gasoline prices across the country each week: usually, the survey is conducted on Monday. I convert this into a daily series by assuming that, between Tuesday and Friday of the same week, the price was the same as that on Monday. The data is tax-inclusive.

Higher frequency variables (5) *Others (that do not appear in the final specification)*

I also tried including other daily variables such as: break-even inflation rate, JEPX (Japan Electric Power Exchange) price index, world wheat prices and the index of geopolitical risk, but they turned out to be not systematically related to either actual or expected inflation. Those variables are excluded from the following analyses.

Another notable variable I tried was a daily business cycle indicator called the Nikkei-UTEcon Daily Business Climate Index. According to the web site of UTokyo Economic Consulting Inc. (UTEcon), this index "is constructed using algorithms developed by the University of Tokyo's Economic Consulting, Inc." and the data is based on the morning edition of the Nikkei Newspaper. It is also stated that "(a)cademic knowledge of natural language processing and macroeconomics is applied" in its construction.

Business cycle condition could be an important driver of both actual and perceived (and therefore expected) inflation. In fact, Goshima, Ishijima, Shintani and Yamamoto (2020) construct their own daily business cycle indicator based on a text analysis of another major newspaper in Japan. They estimate a Phillips-curve model at a daily frequency and demonstrate that their indicator helps predict daily inflation, as measured by the Nikkei CPINOW.

I tried incorporating the above-mentioned index into my MIDAS model. The sample period was shortened slightly (until the end of 2022) due to data availability.

[7] Another important source of higher frequency data on retail prices in Japan is the SRI-Hitotsubashi Consumer Purchase Index's POS-CPI, which is a weekly series.

Unfortunately, this variable did not turn out to be significant, and was dropped from the final empirical model. In future, I intend to further pursue potential usefulness of this indicator in predicting monthly inflation, both actual and expected.

Details of estimation

The sample period is April 2005-March 2023 throughout the paper. The daily part of the model consists of weekdays only: observations on weekends are eliminated. When missing values are encountered due to, for example, national holidays, I assume that their values are the same as those on the most recent business days. Prior to the estimation, all the higher frequency variables are transformed into log differences from 261 weekdays (approximately one year) ago, with the exception of CPINOW, which is already in the y-o-y rate of change form. I also tried taking 260-weekdays differences, in the hope of reducing any day-of-the-week effect, and the results were quite similar.

5. Results for actual inflation

I first estimate determinants of various CPIs. As monthly explanatory variables, I include the first and the second lags of the dependent variable as well as two dummy variables for the consumption tax rate changes: one for the tax hike in April 2014 (which is equal to 1 between that month and March 2015, and zero elsewhere) and another for the further increase in October 2019 (which is equal to 1 for the twelve months starting that month). The daily part of the model starts from the 10th business day of the month (that is, I set m_d in equation (2) to be equal to 10). This means that around the 14th day of the month. As stated earlier, CPIs are based on surveys that are conducted around the middle period of each month, and my choice of m_d reflects this fact.

As already stated, I specify the "*f*" function in equation (2) as a distributed lag polynomial (PDL, with two lags). The results are presented in Table 2.

Oil is found to be significant except for CPI_FRESH, CPI_FOOD and CPI_SERVICES. A similar tendency can be found for gasoline prices, except that it is insignificant in the CPI_CORECORE equation (which makes sense as gasoline is excluded from this indicator), and is significant for CPI_FOOD. The latter result could be because gasoline is used for transporting food items, but it requires a further scrutiny. Results for the exchange rate are somewhat disappointing: the only significant coefficient can be found for the quadratic term for CPI_FOOD. Upon further analysis, I have found that it becomes significant for CPI_FREQ, if I shorten the sample and end it before July of 2022. It seems that the exchange rate fails to predict the rapid acceleration of inflation that occurred in year 2022. CPINOW is significant, at least at the 10% level, for CPI_HEAD, CPI_FRESH, CPI_FOOD, CPI_GOODS, and CPI_FREQ. This likely reflects the fact that most of the items that constitute CPINOW are food[8]. I also tried estimating the same model for the food component of CPI_FREQ (results are not shown), and CPINOW turned out to be very significant.

The estimated PDLs for the case of CPI_FREQ are plotted in Figure 3. We find that, in terms of the sizes of the coefficients, those on CPINOW and gasoline prices are much larger than those for the exchange rate and world oil prices.

6. Results for expected inflation

Next, I study determinants of the household expected inflation. On top of the first and the second lags of the dependent variable and the two consumption tax dummies, I add two dummy variables for survey design changes. One is equal to 1 until April 2009, when they changed the number of choices for ranges of expected inflation (refer to footnote 5). The other is set to be equal to 1 since that month until April 2013, when they switched from direct-visit and self-completion style to the mail survey method.

First, I included all the four higher frequency variables in the analysis: only CPINOW was significant. Next, I excluded the exchange rate and re-estimated the model: still, only CPINOW was found to be significant. Then, I tried omitting either oil prices or gasoline prices. When oil prices were dropped, gasoline prices turned significant. When I took out gasoline prices from the model, oil prices did not become significant. Hence, I decided the model with CPINOW and gasoline prices to be my final specification. The results are shown in the first column of Table 3. In the second column of the same table, I try adding CPI_FREQ as an explanatory variable. As households' inflation expectations are said to be influenced by how prices of the items they purchase frequently have evolved in the recent past, it might be worth trying to include this variable. The variable is lagged by

[8] However, very few of its items (such as eggs) fall into the category of fresh food. Hence, it is not immediately clear why CPINOW turns out to be so significant in the estimation for CPI_FRESH.

two months considering that, at the time when the respondents answer to the survey in the middle of a month, they have not seen the official statistics from the previous month. The variable indeed turns out to be significant, though the coefficient is relatively small. In Figure 4, I plot the PDLs based on the results from the first column of Table 3. We can see that the effect of CPINOW far outweighs that of Gasoline prices.

7. Summary and work ahead

In this paper, I asked if daily and weekly data help us predict actual as well as expected inflation of households. I found that, although the exchange rate and world oil prices do help us anticipate changes in actual inflation that those households face in their everyday lives, they are not reflected in their expected inflation. Only those variables that are directly related to the prices they observe on daily bases have significant (though small) impacts on their expectations.

In future work, I intend to include more higher-than-monthly frequency variables into the analysis. Of particular interest are variables that are generated through text mining of, for example, newspaper articles (Goshima, et.al. (2020)). Shintani and Yamamoto (2023), based on a text analysis of a major newspaper in Japan, demonstrate that appearances of certain phrases, such as “price hike” and “price increase”, are strongly correlated with households’ inflation expectations.

Also, it would be beneficial if one could employ an objective way to determine which of the daily variables from a potentially vast pool of candidates should be included, and how many lags to be used: a machine-learning based approach could be useful in such an attempt. The above-mentioned article by Shintani and Yamamoto employs a LASSO-based approach for variable selection. A similar methodology could be adopted in the context of the current study.

Another important task would be to improve the way we extract information on inflation expectations from the Consumer Confidence Survey, which is admittedly rather crude at the moment. Nishiguchi, Nakajima and Imakubo (2014) stress heterogeneity among households and the need to pay attention to evolution of dispersion and other distributional characteristics of the data. Extending the analysis along those lines would enrich our understanding of the issue.

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Table 1 Survey structure and conversion to a numerical value

Range (x denotes expectation)	Assigned value
$x \leq -10\%$	-10%
$-10\% < x \leq -5\%$	-7.5%
$-5\% < x \leq -2\%$	-3.5%
$-2\% < x \leq 0\%$	-1%
Around 0%	0%
$0\% < x \leq 2\%$	1%
$2\% < x \leq 5\%$	3.5%
$5\% < x \leq 10\%$	7.5%
$10\% < x$	10%

Table 2A Estimation results for CPIs

		CPI_HEAD		CPI_CORE		CPI_FRESH	
		Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
LHS(-1)		0.857	12.62	0.819	12.84	0.839	11.86
LHS(-2)		-0.134	-2.02	-0.078	-1.26	-0.185	-2.66
Oil	Intercept	6.E-04	2.70	6.E-04	3.22	-2.E-03	-0.43
	Slope	-4.E-05	-1.85	-4.E-05	-2.38	3.E-04	0.78
	Quadratic	6.E-07	1.52	6.E-07	2.13	-5.E-06	-0.98
Exchange Rate	Intercept	-2.E-04	-0.24	5.E-04	0.75	-2.E-02	-1.59
	Slope	3.E-05	0.31	-3.E-05	-0.52	2.E-03	1.29
	Quadratic	-3.E-07	-0.20	6.E-07	0.54	-2.E-05	-1.09
CPINOW	Intercept	0.024	2.87	0.010	1.60	0.269	2.11
	Slope	-0.002	-2.19	0.000	-0.66	-0.023	-2.00
	Quadratic	0.000	1.90	0.000	0.32	0.000	1.90
Gasoline	Intercept	0.004	3.82	0.005	6.12	-0.007	-0.43
	Slope	0.000	-4.23	0.000	-6.69	0.000	0.40
	Quadratic	0.000	4.39	0.000	6.84	0.000	-0.32
Adjusted R-squared		0.956		0.973		0.561	

Table 2B Estimation results for CPIs (continued)

		CPI_CORECORE		CPI_FOOD		CPI_ENERGY	
		Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
LHS(-1)		0.673	9.98	0.607	9.04	0.960	14.25
LHS(-2)		0.045	0.72	0.038	0.67	-0.080	-1.13
Oil	Intercept	4.E-04	2.08	1.E-04	1.30	4.E-03	3.33
	Slope	-3.E-05	-1.70	2.E-04	1.13	-3.E-04	-2.55
	Quadratic	4.E-07	1.57	2.E-04	1.90	4.E-06	2.22
Exchange Rate	Intercept	3.E-04	0.39	2.E-04	0.63	1.E-03	0.23
	Slope	-3.E-05	-0.49	-3.E-04	-0.75	7.E-05	0.18
	Quadratic	7.E-07	0.68	9.E-04	2.90	-2.E-06	-0.37
CPINOW	Intercept	0.004	0.65	0.028	8.64	-0.034	-0.85
	Slope	0.000	-0.31	-0.007	-1.29	0.004	1.22
	Quadratic	0.000	0.27	0.002	0.49	0.000	-1.43
Gasoline	Intercept	0.001	0.93	0.001	1.28	0.044	8.82
	Slope	0.000	-1.09	-0.002	-3.31	-0.004	-9.73
	Quadratic	0.000	1.08	0.001	2.25	0.000	9.94
Adjusted R-squared		0.939		0.977		0.972	

Table 2C Estimation results for CPIs (continued)

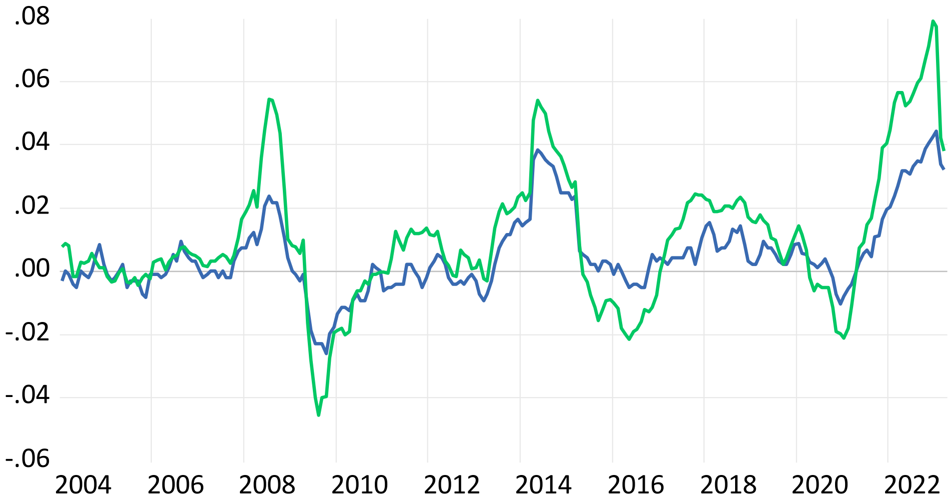
		CPI_GOODS		CPI_SERVICE		CPI_FREQ	
		Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
LHS(-1)		0.944	14.72	0.844	11.95	1.027	16.28
LHS(-2)		-0.150	-2.34	-0.020	-0.28	-0.177	-2.74
Oil	Intercept	1.E-03	4.25	-1.E-02	-0.56	1.E-03	3.20
	Slope	-9.E-05	-3.51	1.E-03	0.51	-7.E-05	-2.45
	Quadratic	1.E-06	3.25	-2.E-05	-0.52	1.E-06	2.18
Exchange Rate	Intercept	1.E-03	1.30	1.E-03	0.01	7.E-04	0.58
	Slope	-1.E-04	-1.11	-1.E-03	-0.16	-3.E-05	-0.25
	Quadratic	2.E-06	1.12	3.E-05	0.24	2.E-07	0.12
CPINOW	Intercept	0.018	1.71	0.833	0.97	0.020	1.76
	Slope	-0.001	-0.85	-0.037	-0.48	-0.001	-0.76
	Quadratic	0.000	0.50	0.000	0.23	0.000	0.26
Gasoline	Intercept	0.009	6.84	0.087	0.85	0.010	7.09
	Slope	-0.001	-7.49	-0.007	-0.90	-0.001	-8.13
	Quadratic	0.000	7.67	0.000	0.93	0.000	8.52
Adjusted R-squared		0.974		0.860		0.973	

Note: In all the estimations for Table 2, two consumption tax dummies and the constant term are also included in the estimation, but are omitted from the table.

Table 3: Estimation results for expected inflation

		EXPECTED_INFLATION			
		Coef	t-Stat	Coef	t-Stat
LAG 1		1.078	15.42	1.040	14.92
LAG 2		-0.105	-1.44	-0.120	-1.67
CPI_FREQ(-2)				0.057	3.04
CPINOW	Intercept	1.E-02	2.20	1.E-02	2.11
	Slope	-1.E-03	-2.10	-1.E-03	-1.92
	Quadratic	2.E-05	1.97	2.E-05	1.69
Gasoline	Intercept	1.E-03	1.91	1.E-03	2.35
	Slope	-9.E-05	-1.77	-1.E-04	-2.16
	Quadratic	1.E-06	1.74	2.E-06	2.03
Adjusted R-squared		0.973		0.974	

Figure 1 Evolution of the Japanese CPI (y-o-y rate of change)



Blue: CPI_HEAD (all items less fresh food).

Green: CPI_FREQ (frequently purchased items, less fresh food and mobile phone fees).

Starting from January 2020, I estimate and exclude the effects of mobile phone fees and lodging from CPI_HEAD.

Effects of consumption tax changes (in April 2014 and October 2019) have not been removed.

Figure 2: Evolution of households' inflation expectations

Figure 3: Estimated PDL for CPI_FREQ

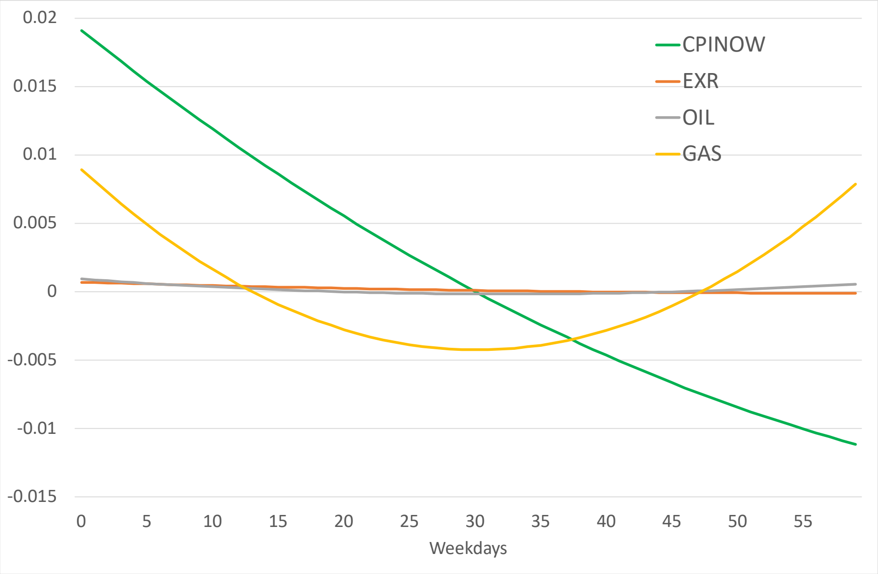
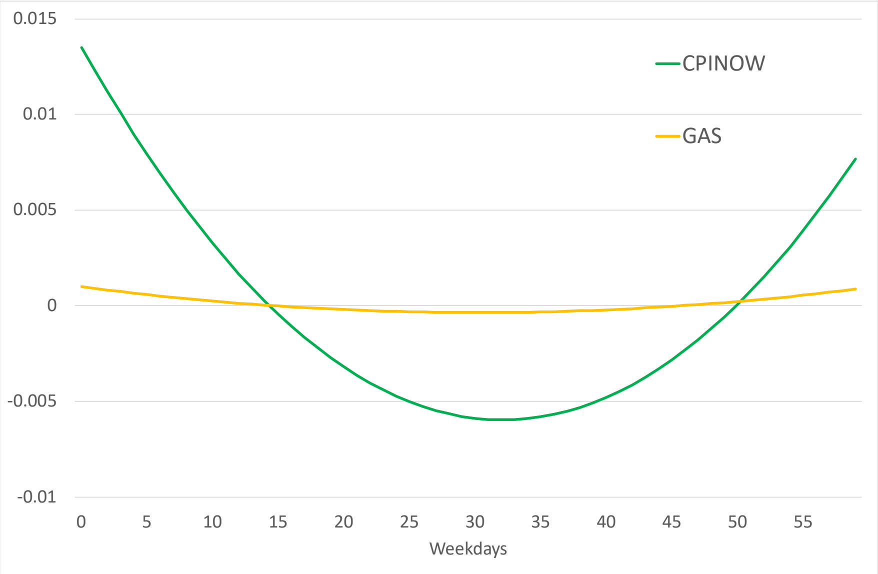


Figure 4: Estimated PDL for expected inflation



<u>**Appendix: Inflation expectations by age group**</u>

Data on expected inflation is available by the respondents' age groups. Since 2004, data exists for three broadly defined age groups; those who are below 29, those aged between 20 and 59, and those who are 60 or older.

Figure A1 plots evolution of inflation expectation for those three groups. We can see that the oldest group almost always has the highest expectation, which is consistent with the finding by Diamond, Watanabe and Watanabe (2020). It is interesting to observe that the gap between the groups seems to have widened in the course of the most recent inflation. Other than that, however, it is difficult to detect any systematic difference in the way those expectations evolve over time.

Table A-1 reports the MIDAS estimation results for the three groups. The results are similar between them. We see that gasoline prices are marginally significant only for the oldest group. As those are the least likely to be travelling around by automobiles, it is rather difficult to interpret this result.

Figure A1: Inflation expectations by age group

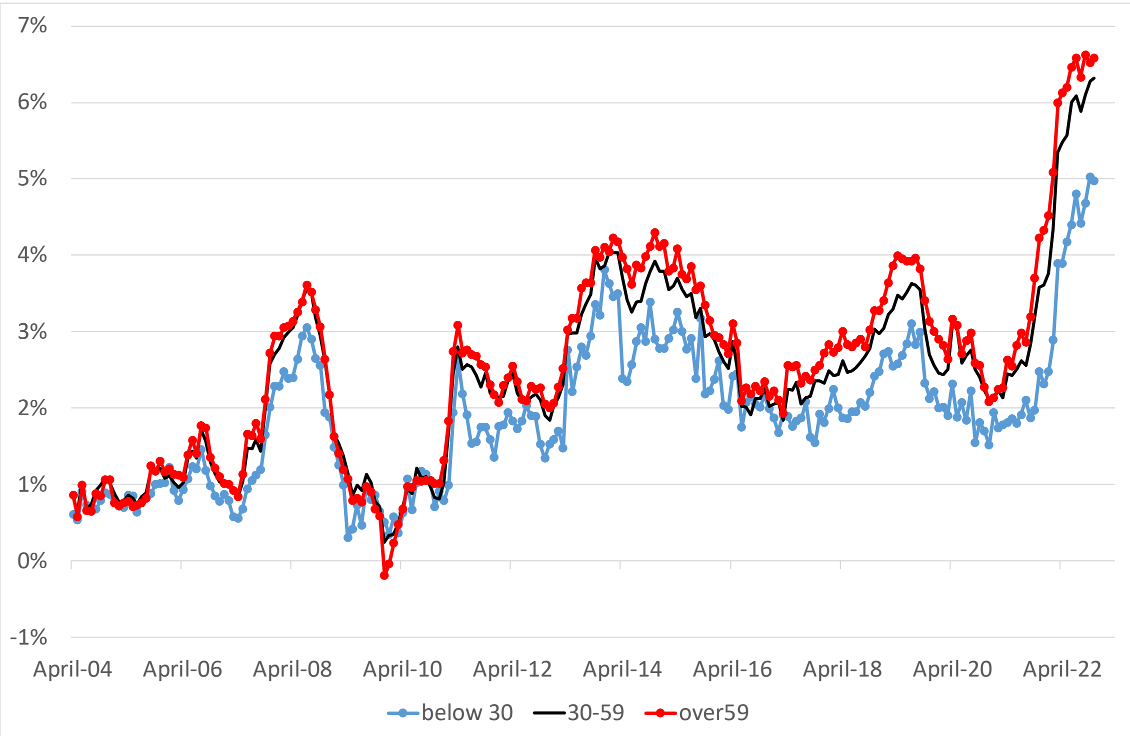


Table A-1: MIDAS estimation results for age groups

		Below 30		30-59		Over 59	
		Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
LHS(-1)		0.718	10.49	1.154	16.61	1.099	15.68
LHS(-2)		0.164	2.29	-0.184	-2.54	-0.124	-1.69
CPINOW	Intercept	0.019	2.10	0.015	2.25	0.014	2.06
	Slope	-0.001	-1.29	-0.001	-2.13	-0.001	-2.06
	Quadratic	0.000	0.80	0.000	1.99	0.000	1.98
Gasoline	Intercept	0.000	0.28	0.001	1.28	0.001	1.90
	Slope	0.000	-0.33	0.000	-1.19	0.000	-1.75
	Quadratic	0.000	0.38	0.000	1.19	0.000	1.71
Adjusted R-squared		0.920		0.973		0.974	