Cabinet Office

ESRI Discussion Paper Series No.403

Subjective Monetary Policy Shocks

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August 2025

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Abstract

We introduce a new concept of monetary policy shocks—subjective monetary policy shocks—defined at the household level as the residual from a Taylor rule-style regression that uses each household's own macroeconomic expectations. Using a unique panel dataset that links household survey-based expectations with high-frequency scanner data on expenditure in Japan, we identify cross-sectional heterogeneity in perceived policy shocks and estimate their effects on consumption behavior. Our findings reveal striking heterogeneity in consumption responses. Households with outstanding loans sharply reduce consumption following a perceived tightening, while asset holders increase theirs—consistent with redistribution channels emphasized in heterogeneous-agent models. These effects are likely to be mediated by macroeconomic attentiveness: households that actively update their information sets about interest rates tend to exhibit more significant and timely consumption responses. These results suggest that differences in attention and financial exposure jointly shape how households perceive and respond to monetary policy, offering micro-level evidence on the heterogeneity of monetary policy transmission.

JEL Classification: D12; D15; D84; E21; E52

Keywords: consumption; monetary policy; rational inattention; subjective belief; subjective monetary policy shocks;

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*We thank the discussant, Naohito Abe and Prachi Srivastava for invaluable inputs and Natsuki Arai, Masahiro Hori, Hirokazu Ishise, Rui Ota, Qing-Yuan Sui, Michio Suzuki, Takayuki Tsuruga, and Tomoaki Yamada, Francesco Zanetti, and participants in the Japanese Economic Association 2022 Spring Meeting, the 1st PhD Workshop on Expectations in Macroeconomics in Barcelona School of Economics, the 24th Annual Macro Conference, and seminars at the Economic and Social Research Institute, the Government of Japan and Osaka University for their comments and suggestions. Tango acknowledges financial support from JST, the establishment of university fellowships towards the creation of science technology innovation, Grant Number JPMJFS 2140. Nakazono acknowledges financial support from Institute of Social and Economic Research, Osaka University, and JSPS KAKENHI Grant Numbers 22K01438, 23K17553, and 25H00544.

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1 Introduction

In standard macroeconomic models, monetary policy shocks are treated as aggregate, unanticipated innovations that are orthogonal to the state of the economy. However, recent work in behavioral macroeconomics and information rigidity suggests that agents often form expectations under incomplete or outdated information. In such settings, even when policy outcomes are identical, households may hold divergent expectations about future interest rates, leading to heterogeneous forecast errors. Motivated by this observation, we shift the focus from aggregate monetary policy shocks to household-level subjective surprises. This approach allows us to examine how heterogeneity in perceived monetary policy shifts influences household consumption responses.

We construct a novel household-level measure of subjective monetary policy shocks. The shock is defined as the residual from a household-specific Taylor rule-style regression, where the realized nominal interest rate is regressed on each household's own forecasts of inflation and macroeconomic conditions. This residual captures the component of the observed interest rate that is unexpected from the household's perspective, given its information set at the time of expectation formation. This residual captures an unanticipated shift in perceived policy stance that is orthogonal to the household's information set at the time expectations are formed. Using a unique panel dataset that links household-level interest rate expectations with high-frequency consumption data, we estimate consumption responses to these subjective shocks using local projection methods. Our empirical results reveal strong heterogeneity in both the direction and timing of responses. Households with outstanding debt significantly reduce consumption following a perceived tightening, whereas asset holders increase consumption—consistent with redistribution effects emphasized in heterogeneous-agent models. These asymmetries are further amplified by attentional differences: only attentive households—those who frequently update their interest rate expectations—respond significantly to policy shocks. These findings suggest that variation in attentiveness and financial position jointly shape how households perceive and respond to monetary policy, offering micro-level foundations for heterogeneous transmission mechanisms.

Our analysis draws on a unique panel survey of Japanese households conducted between 2015 and 2019. The survey, designed and implemented in collaboration with a major research firm, collects quarterly data on individuals' expectations about interest rates, inflation, and stock prices, along with demographic characteristics and household behavior. Critically, this period overlaps with Japan's effective lower bound (ELB) episode, during which the Bank of Japan emphasized control over long-term interest rates. Accordingly, we use 10-year government bond yields as the primary policy indicator relevant to household perceptions. The survey responses are linked to scanner data that record household purchases at the daily level. This data linkage enables joint analysis of expectations and behavior, offering micro-level evidence on the transmission of subjective monetary policy shocks.

This study makes three primary contributions. First, we propose a new conceptual framework: the subjective monetary policy shock at the household level. This concept captures how the same policy action can generate different perceived surprises across households, due to heterogeneity in macroeconomic attentiveness. Using household-level forecast data, we construct a household-specific monetary policy shock as the residual from a Taylor-rule-type regression, where expected interest rates are modeled as a function of the household's own forecasts of inflation and macroeconomic conditions. Our empirical findings show that households who are more attentive—often due to factors such as financial exposure or life-cycle position-exhibit significant consumption responses to these shocks, whereas inattentive households exhibit muted or no reaction. This suggests that subjective shocks reflect not random noise or bias, but systematic differences in information acquisition. Our measure thus provides a tractable method for quantifying how attentional frictions influence the household-level transmission of monetary policy.

Second, our measure of subjective monetary policy shocks helps reconcile theoretical predictions with observed heterogeneity in household consumption behavior. Although representative agent models predict consumption behavior consistent with the permanent income or life-cycle hypothesis, our empirical findings reveal systematic heterogeneity in household responses. Specifically, we find that borrowers reduce consumption, while asset holders increase it, in response to the same perceived policy shock. This divergence is consistent with the redistribution channels emphasized in heterogeneous-agent New Keynesian (HANK) models. By identifying policy shocks at the household level, our approach reveals how household financial exposure, attentiveness to policy, and life-cycle stage jointly mediate the transmission of monetary policy—offering new micro-foundations for aggregate dynamics.

Third, our survey-based identification strategy is particularly effective under unconventional monetary policy regimes. The survey data allow us to address the censoring (or truncation) problem associated with the ELB on nominal interest rates: while observed nominal rates rarely fall below zero, survey-based forecasts can and often do take on negative values (Braun and Ikeda, 2025; Mavroeidis, 2021). Furthermore, forecasts of macroeconomic variables reflect households' perceptions of the effectiveness of unconventional policy tools such as forward guidance, inflation targeting, and asset purchase programs. The availability of household-level forecasts on both interest rates and macroeconomic conditions enables the identification of monetary policy shocks even in ELB environments.

Our study is related to three strands of the literature. First, it contributes to the literature on the identification of monetary policy shocks. The identification of monetary policy shocks and their real effects are central questions in macroeconomics.[1] Unlike earlier research relying on aggregate time-series or high-frequency financial data, our identification strategy relies on household survey data on interest rate expectations, eliciting a subjective monetary policy shock from forecast errors.[2] This novel identification strategy is enabled by a unique household survey capturing both interest rate expectations and broader macroeconomic beliefs. To our knowledge, this is the first study to identify household-level monetary policy shocks using micro data on expectations.

Second, our approach is based on previous studies on information rigidity and behavioral macroeconomics. The full-information rational expectations (FIRE) hypothesis assumes that every economic agents makes decisions using updated information sets. However, past studies strongly reject the FIRE hypothesis while supporting the perspectives of information rigidity and behavioral macroeconomics. In fact, economic agents are not always fully attentive to incoming news, rather, they are inattentive. In contrast to the FIRE hypothesis, even professional forecasters submit their forecasts based on old information sets (Andrade and Le Bihan, 2013).[3] This study sheds light on the attentiveness of households to financial variables and examines whether attentiveness matters for the transmission mechanism of monetary policies. We document heterogeneous household responses to monetary policy under imperfect information.

Third, we build on a growing strand of research on households' subjective expectations (D'Acunto et al., 2022; Malmendier and Nagel, 2016; Cavallo et al., 2017). Malmendier and Nagel (2016) find that lifetime experiences predict inflation expectations. Using subjective changes in inflation expectations, Crump et al. (2022) estimate the value of the elasticity of intertemporal substitution. Further, Andre et al. (2022) provide evidence on experts' beliefs about the effects of macroeconomic shocks. Kuchler and Zafar (2019) show that recent personal experiences influence the expectation formation about aggregate economic outcomes. We contribute to this research area by proposing a cross-sectionally heterogeneous monetary policy shock, paired with household-level expenditures, to estimate the causal effects of policy changes on consumption.[4]

[1] Many prior studies have identified conventional and unconventional monetary policy shocks, from Romer and Romer (2004) to Mavroeidis (2021).

[2] This approach builds on earlier work by Kuttner (2001), Cochrane and Piazzesi (2002), and Bernanke and Kuttner (2005), and has been extended by Swanson (2006), Nakamura and Steinsson (2018), and Andrade and Ferroni (2021). High-frequency approaches typically define policy shocks as forecast errors—differences between futures-implied and realized policy rates. A parallel literature has employed survey-based expectations to measure policy surprises (Romer and Romer, 2004; Honda and Kuroki, 2006). Auerbach and Gorodnichenko (2013) use forecast errors of professional forecasters to identify fiscal shocks.

[3] Dupor et al. (2010) develop a model that integrates sticky prices and information and find that both rigidity types are present in the U.S. data. Coibion and Gorodnichenko (2012) and Coibion and Gorodnichenko (2015) provide broader evidence of information rigidity.

[4] Using administrative data in Norway, Holm et al. (2021) provide evidence on the cross-sectionally heterogeneous

The remainder of this paper is organized as follows. Section 2 discusses the theoretical motivation. Section 3 describes the survey data used in our study and outlines the identification strategy for the subjective monetary policy shock. Section 4 outlines the identification strategy for the subjective monetary policy shock. Section 5 presents the impulse response estimates. Section 6 concludes.

2 Theoretical Motivation

Understanding heterogeneity in household consumption responses to monetary policy requires acknowledging that expectations are subjective and shaped by individual characteristics. We conceptualize two distinct layers of heterogeneity. The first concerns the *perception* of monetary policy shocks: due to differences in information attention, financial exposure, and life-cycle stage, households form different expectations and interpret the same policy action differently (Sims, 2003). The second layer relates to *behavioral responses*: even when faced with similar perceived shocks, households differ in how they adjust consumption, depending on liquidity constraints, interest rate sensitivity and marginal propensities to consume (Cloyne et al., 2020). This dual framework motivates our analysis. The following paragraphs discuss first the heterogeneity in perceived shocks (first layer), and then the heterogeneity in consumption responses (second layer). By linking both layers to predictions from heterogeneous-agent models, we aim to clarify the micro-foundations of monetary transmission.

2.1 Heterogeneity in Perceived Policy Shocks

Household expectations of macroeconomic variables are inherently subjective and diverse. While traditional models assume rational and homogeneous expectations, surveys show households hold biased, dispersed, and volatile beliefs. These expectations were once dismissed as noise, but are now seen to reflect systematic differences in information and cognition (Manski, 2004). Such heterogeneity influences economic behavior, including consumption, saving, and investment decisions (Weber et al., 2022; Kuchler and Zafar, 2019).

Heterogeneity in expectations often stems from differences in attentional allocation. Households vary in the effort they dedicate to monitoring macroeconomic conditions. Rational inattention models assume that attention is costly and selectively applied (Sims, 2003). The rational inattention theory similarly posits that agents process only a subset of available signals. Such frictions

responses to a monetary policy shock. However, they use an aggregate shock.

are influenced by factors including time constraints, financial literacy, and prior macroeconomic exposure.

Financial exposure also influences attention. Households with mortgages or market-traded assets have stronger incentives to follow economic news. In contrast, less-exposed households may rationally ignore macro signals. Empirical studies show that price experience and financial literacy predict attention and belief accuracy (D'Acunto et al., 2021; Malmendier and Nagel, 2016; Weber et al., 2022). For instance, those exposed to price volatility or past inflation revise expectations more actively. This is the first layer of heterogeneity we examine.

2.2 Heterogeneity in Consumption Responses

Because attention and expectations vary, behavioral responses to policy shocks also differ. Attentive households adjust behavior promptly, while inattentive ones respond weakly or with delay. This aligns with models where information frictions lead to dispersed consumption and labor responses (Mackowiak and Wiederholt, 2009). Thus, the effectiveness of monetary policy depends on who absorbs and reacts to new information.

Consumption responses also differ by financial position. Borrowers face higher costs when interest rates rise, particularly with variable-rate debt, and tend to cut spending. Lenders, by contrast, may benefit from higher interest income and increase consumption. Empirical evidence confirms this asymmetry (Cloyne et al., 2020; Di Maggio et al., 2017), and theory shows such redistribution effects are central to monetary transmission (Auclert, 2019).

Finally, financial roles vary systematically over the life cycle. Young households are often borrowers, while older households tend to be net savers. As a result, monetary policy affects age groups differently: older savers may benefit from rate hikes, while younger borrowers face rising debt burdens (Braun and Ikeda, 2025; Auclert, 2019; Kaplan et al., 2018). Even within the working-age population, mortgage holders respond more strongly than debt-free households. This is the second layer of heterogeneity we examine.

3 Data

This section describes the data we use. First, we summarize the survey data on consumer's economic outlooks and updating frequency of the information sets to identify monetary policy shock at the micro level. Second, we summarize home-scanner data on consumption expenditure. Since this data is collected from the same respondents as the forecast data, we combined the two via unique identifiers. Finally, we explain the consumption imputation. One shortcoming of home-scanner data is that the coverage of the data relative to Japanese households consumption is not large. To address the issue, we impute total (nondurable) consumption according to Blundel et al. (2004) and Blundel et al. (2008).

3.1 Consumers' Economic Outlooks and Updating Frequency of the Information Sets

The survey data used in this study were developed and implemented jointly by the authors and Intage Inc., a prominent Japanese market research firm. It was administered online on a quarterly basis from 2015, targeting individuals aged 15 to 79 nationwide. Each wave comprised approximately 30,000 respondents drawn from Intage's nationally representative consumer panel, stratified by age, gender, and geographic region.

The survey's panel structure permits natural attrition over time. Respondents who drop out or become inactive are regularly replaced by new participants drawn from the same nationally representative sampling frame. This replenishment strategy maintains a stable sample size of approximately 50,000 individuals across survey waves. Although attrition is non-negligible, the rotating panel design facilitates continuity in the sample while preserving representativeness over time.

Respondents were invited without prior notice of the questionnaire's content. To encourage broad participation, Intage provided modest fixed incentives (e.g., point-based rewards), irrespective of respondents' interest in or familiarity with economic topics. While we acknowledge the potential for selection bias due to unobserved characteristics, the combination of stratified sampling and neutral recruitment procedures helps mitigate this concern. Importantly, survey responses are linked via unique identifiers to scanner-based panel data on household consumption (SCI). This linkage enables analysis of how household-level expectations translate into actual spending behavior, offering micro-level evidence on the transmission mechanism of subjective monetary policy shocks. The same SCI dataset is employed in Diamond et al. (2020).

To assess individual information updating behavior and economic expectations, respondents are asked the following survey questions:

(A) Interest in the development of interest rates:

- "How interested are you in information about interest rates?"

(B) Frequency of updating information on interest rates:

- "How often do you collect information on interest rates?"

(C) Expectations about inflation and stock prices:

- "What do you expect the Consumer Price Index (CPI) level to be over the next one, three, and ten years, assuming a current CPI level of 10,000? Please provide price level estimates for each horizon, excluding the effects of consumption tax hikes."
- "What do you expect the Nikkei 225 index level to be in three and six months? Please provide point estimates (in yen) for each horizon."

Regarding Question (A), respondents select the most appropriate option from the following list: (1) Very interested, (2) Somewhat interested, (3) Neither interested nor uninterested, (4) Not very interested, (5) Not at all interested.

Regarding Question (B), respondents select the most appropriate option from the following list: (1) Almost every day, (2) Four or five times a week, (3) Two or three times a week, (4) Once a week, (5) One or more times a week, (6) Two or three times a month, (7) Once a month, (8) Once every two to three months, (9) Once every six months, (10) Once a year, (11) Less than once a year, (12) Do not collect.

Questions (A) and (B) capture consumers' interest in and self-reported attention to macroeconomic information—specifically interest rate developments. These measures allow us to assess the extent to which individuals are aware of and attentive to monetary policy-related information, which is a key determinant of how frequently and effectively they update their information sets. The FIRE hypothesis assumes that economic agents make decisions based on fully updated information sets. However, prior research supports the sticky information hypothesis, which posits that agents revise their information sets infrequently (Carroll, 2003). In contrast to FIRE, the sticky information framework suggests that agents—including professional forecasters—may base decisions on outdated information (Andrade and Le Bihan, 2013).[5]

In the empirical analysis that follows, we use the frequency of information updating as a proxy for consumer attentiveness to interest rates. Heterogeneous attentiveness may help explain why monetary policy shocks propagate unevenly across households, particularly under unconventional policy regimes. Table 1 presents the distribution of attention frequency among consumers. About 50% of respondents report collecting information at least once a month. In contrast, the remaining half either collect information less frequently than once a month or not at all. [6]

For inflation expectations (Question (C)), our survey elicits numeric forecasts of the CPI level

[5]For example, Carroll (2003) provides microfoundations for the sticky information theory and derives a tractable empirical model. Dupor et al. (2010) develop a framework integrating both sticky prices and sticky information, finding evidence for both forms of rigidity in U.S. data. Using Japanese data, Hori and Kawagoe (2013) and Kikuchi and Nakazono (2023) empirically test the sticky information hypothesis in the context of consumer inflation expectations.

[6]From a theoretical perspective, the finding that many consumers do not regularly update their information sets is inconsistent with the full-information rational expectations (FIRE) hypothesis and instead supports the presence of information frictions.

over the next one, three, and ten years. These forecasts enable the computation of annualized inflation expectations at the household level. Unlike surveys that rely on qualitative categories (e.g., “prices will rise” or “prices will fall”), our approach yields continuous, respondent-specific measures. For example, if a respondent forecasts CPI levels of 10,080, 10,600, and 11,000 for the next 1, 3, and 10 years, respectively, these correspond to annualized inflation rates of 0.80%, 1.96%, and 0.96%.[7]

Similarly, we use household-level forecasts of the Nikkei 225 index as a proxy for growth expectations. Specifically, we compute the one-quarter-ahead expected return as the log difference between the forecasted and current index levels.[8] These expectation measures serve as key inputs in our identification strategy for subjective monetary policy shocks, as detailed in Section 4.

3.2 Survey on Consumption Expenditure

3.2.1 Home Scanner Data

This subsection describes the data used to examine the impact of subjective monetary policy shocks on household consumption. We utilize panel data from the SCI (Home Scanner Panel), collected by Intage Inc., a Japanese marketing research firm. The SCI dataset captures day-to-day shopping behavior from over 50,000 consumers aged 15 to 79 across Japan, using a continuous data collection process. The scanner data consist of detailed household-level purchase histories. Respondents use a handheld scanner to record the barcode of every item they purchase. For each transaction, they report the quantity purchased, purchase price, and retail channel (e.g., supermarket or convenience store). This enables us to observe who bought what, when, where, how much, and at what price. The dataset primarily covers frequently purchased consumer goods, including food (excluding fresh food, prepared meals, and boxed lunches), beverages, daily necessities, cosmetics, over-the-counter pharmaceuticals, and cigarettes.[9] The sample period spans January 2015 through December 2019. In addition to transaction records, the SCI dataset includes detailed respondent profiles with demographic, educational, and financial characteristics. This allows us to identify each respondent’s age, gender, educational attainment, and income level.

The SCI panel data are notable in two key respects: a significantly larger sample size and a substantially longer survey duration. Most studies on private consumption using micro-level data

[7] See Kikuchi and Nakazono (2023) for methodological details.

[8] For example, if the current Nikkei 225 level is 20,000 and a respondent forecasts 20,200 three months ahead, the implied return is $\log(20{,}200) - \log(20{,}000) \approx 1.0\%$.

[9] Because the scanner data focus on daily necessities, they do not include categories such as housing, utilities, durable goods, clothing, or services. O’Connell et al. (2021) also use household scanner data comparable to those employed in our study.

rely on the Family Income and Expenditure Survey (FIES), administered by Japan's Ministry of Internal Affairs and Communications. While the FIES—one of the official sources for national accounts and GDP compilation—is based on a relatively small sample, the SCI panel covers over 50,000 respondents. Moreover, the duration of participation differs markedly between the two datasets. Each household in the FIES is surveyed for a maximum of six months, whereas the average participation length in the SCI panel is approximately 49 months.

Furthermore, we are able to link the home scanner data with the online survey on consumers' economic outlooks. Since both datasets contain individual identifiers, we can perform respondent-level matching.[10] The linkage is valid because both datasets are drawn from the same population of respondents. Although the expectations survey is administered to approximately 30,000 individuals per wave, the final analytic sample consists of approximately 95,000 observations. This reduction primarily reflects restrictions imposed by our identification strategy. To compute subjective monetary policy shocks, we require non-missing forecast responses for two variables—stock prices and inflation—as well as corresponding socioeconomic information. In addition, a non-negligible number of observations are excluded due to unsuccessful linkage with the scanner-based consumption data (SCI), which occurs when individual identifiers are missing or when purchasing records are incomplete or unavailable. These restrictions ensure the internal consistency of shock measurement and the reliability of the final matched panel used in the analysis.

There are two caveats regarding the SCI data on consumption expenditures. First, as shown in Table 2, women outnumber men in the sample, in which expenditure amounts are compared. Consistent with findings in Kaplan and Schulhofer-Wohl (2017) and D'Acunto et al. (2021), our data also indicate that expenditures reported by women are larger than those reported by men. Second, the coverage of the SCI data relative to total household consumption in Japan is limited. Using the SCI dataset, Diamond et al. (2020) report that the included items account for approximately 30% of the total weight of the Japanese CPI.[11]

However, scanner data offer several advantages. First, the panel data on consumption expenditures include detailed demographic and socioeconomic information on respondents, such as age, occupation, education, income, wealth, and geographic location. These rich covariates enable researchers to control for household-level heterogeneity in the empirical analysis. Second, the panel

[10] Both the economic outlook survey and the SCI are collected and managed by Intage Inc. using the same underlying panel. As such, the same individuals participate in both components of the data. Each dataset includes a persistent anonymized respondent ID, enabling exact matching of expectations and consumption records at the individual level, without relying on demographic variables. This one-to-one linkage forms the foundation for our household-level analysis of belief formation and consumption behavior.

[11] D'Acunto et al. (2021) use similar scanner data from U.S. consumers and report that the data cover roughly 25% of U.S. household consumption.

structure allows the data to be matched with other surveys tailored to researchers' objectives. A growing literature combines scanner data with survey-based inflation expectations from the same individuals. For example, Diamond et al. (2020), Kikuchi and Nakazono (2023), and D'Acunto et al. (2021) examine how consumers form inflation expectations, while Kikuchi and Nakazono (2020) documents a relationship between inflation expectations and consumption behavior.[12] This study links the scanner data with a survey on interest-rate forecasts. This linkage enables us to identify perceived monetary policy shocks and estimate their causal effects on household consumption.

3.2.2 Imputed Consumption

One limitation of home scanner data is their incomplete coverage of total household consumption in Japan. Diamond et al. (2020) use the SCI dataset and report that the items included account for approximately 30% of the weight of the Japanese CPI.[13] Failure to account for total consumption may lead to biased estimates, as scanner data capture only a limited subset of household consumption categories.

To address the limitation of partial consumption coverage, we construct panel data on total (nondurable) consumption using an imputation procedure based on food demand estimates from a representative consumption dataset. Following Blundel et al. (2004) and Blundel et al. (2008), we impute total consumption in the SCI dataset using a procedure closely aligned with their approach. First, we estimate a food demand function—based on an item common to both datasets—using the Family Income and Expenditure Survey (FIES), a rotating panel survey covering approximately 9,000 households per month.[14] The FIES, conducted by the Statistics Bureau of Japan, collects consumption expenditure data from approximately 6,000 households per month, based on household heads. We use FIES data from January 2015 to March 2019 and exclude single-person and agricultural households.[15] In addition, we exclude households whose head is aged 60 or older, as their (pension) income is generally lower than that of wage earners.[16] Second, under the as-

[12] Kikuchi et al. (2023) match the same panel data used here with a survey on the effects of the COVID-19 pandemic, examining how fear of contagion influences consumption expenditures.

[13] D'Acunto et al. (2021) use similar scanner data from U.S. households and report that the data cover about 25% of total household consumption in the United States.

[14] See Stephens and Unayama (2011) and Stephens and Unayama (2012) for details on the FIES.

[15] As of the 2015 FIES, single-person households composed 14.5% of the population, while agricultural households accounted for 0.9%. Single-person households are excluded due to accessibility issues for interviewers, which may introduce sampling bias—particularly an overrepresentation of the elderly. Agricultural households are excluded because their food expenditures are substantially lower than those of non-agricultural households, given that many consume their own harvests. This self-consumption introduces downward bias in the estimation of food demand.

[16] As discussed below, the food demand function is estimated using the annual income of the household head. To avoid underestimating food demand due to lower pension income, we exclude potential retirees by removing households with heads aged 60 or older.

sumption of monotonicity in food demand, the estimated function is inverted to obtain a measure of nondurable consumption in the SCI dataset. The resulting imputed consumption panel enables us to examine the relationship between total consumption growth and subjective monetary policy shocks.

To implement the imputation procedure, we pool the monthly FIES data from January 2015 to March 2019. We then estimate a food demand function of the form:

$$f_{j,t}^{FIES} = \gamma\left(D_{j,t}\right) \times c_{j,t}^{FIES} + \mathbf{X}\alpha + \mathbf{p}\theta + \delta_t + e_{j,t}, \tag{1}$$

where f is the log of food expenditure for household j at time t, which is available in both the FIES and SCI datasets. The variable $c_{j,t}$ denotes the log of total nondurable consumption expenditure, which is observed only in the FIES. The term $\mathbf{X}$ includes socio-economic household characteristics that are common to both datasets (e.g., age, household size, education), $\mathbf{p}$ is a vector of relative prices, and δ_t represents month fixed effects. The coefficients on $\mathbf{p}$ can be interpreted as price elasticities of food demand, while $\gamma(D_{j,t})$ captures the budget elasticity, which we allow to vary flexibly with time and observable household characteristics $D_{j,t}$. To address the potential endogeneity of total consumption ($c_{j,t}$) with respect to food expenditure, we instrument $c_{j,t}$ using the household head's annual income, as well as its interactions with month dummies and a dummy for the presence of children in the household. Table 3 reports the estimation results for Equation (1). The estimated budget elasticity is 0.75, and the price elasticity is -1.66, both of which have the expected signs.

Using the estimated parameters, we invert the demand function to derive a series of imputed nondurable consumption values for all households in the SCI dataset. Before inverting the food demand function, we adjust the distribution of SCI food expenditures so that their mean and variance match those of nondurable expenditures in the FIES. This adjustment is necessary because the SCI does not cover certain food items, such as fresh foods and products without barcodes, whereas the FIES includes all food expenditures. In practice, average food expenditures reported in the FIES are more than twice those in the SCI. Specifically, we scale the SCI food expenditure data so that the adjusted SCI distribution aligns with the mean and variance of FIES food expenditures. We then apply the inverted demand function to this rescaled data to obtain the imputed nondurable consumption series for SCI households.[17]

[17] Figure 1 compares actual FIES consumption with the imputed SCI consumption. The figure shows that the imputed series closely tracks the observed consumption levels in the FIES.

4 Identification Strategy

4.1 Estimating the Taylor Rule

Using an online survey of economic outlooks, we identify subjective monetary policy shocks based on a Taylor-rule-type framework. Specifically, we construct unexpected changes in interest rates that are orthogonal to forecast errors in inflation and output growth. The following equation is used to identify monetary policy shocks:[18]

$$i_t^{Policy} = \bar{i} + \beta i_{t-1}^{Policy} + \phi \left(\mathbb{F}_{t-1}^j \left[\pi_t \right] - \bar{\pi} \right) + \kappa \left(\mathbb{F}_{t-1}^j \left[y_t \right] - \bar{y} \right) + \varepsilon_t^j, \quad (2)$$

where i^{Policy} and $\bar{i}$ denote the respondent's forecast of the policy rate and the equilibrium (nominal) interest rate, respectively. Similarly, π_t (with target $\bar{\pi}$) and y_t (with equilibrium level $\bar{y}$) represent the inflation and output growth rates. The terms $\mathbb{F}_{t-1}^j [\pi_t]$ and $\mathbb{F}_{t-1}^j [y_t]$ denote household j's forecasts at time $t-1$ for inflation and output growth in period t. By estimating Equation (2), we obtain the residuals $\hat{\varepsilon}_t^j$, which serve as household-level measures of the subjective monetary policy shock.

However, estimating Equation (2) is not straightforward. Because the Japanese economy remained in a liquidity trap for much of the sample period, short-term nominal interest rates were near zero. As a result, we use long-term interest rates as proxies for policy rates in our identification strategy. Our approach does not rely on information about short-term interest rates or the size of the Bank of Japan's balance sheet. Specifically, we do not use the overnight call rate, which has been near zero since 1999, nor do we incorporate changes in excess reserves, which served as a primary policy indicator before March 2006. Although the Bank of Japan adjusted the level of excess reserves and conducted government bond purchases between 2003 and 2006, its apparent goal was to reinforce the interest rate channel rather than to target reserves directly. For instance, the Bank employed forward guidance—referred to as "commitment policy"—to lower long-term interest rates.[19] Asset purchases during this period were similarly aimed at reducing longer-term

[18]To validate the identification strategy, we estimate monetary policy shocks at the macro level using Equation (2). Specifically, we regress policy interest rates on macro-level forecasts of inflation and growth using data from Consensus Forecasts over the period 1994–2014. As the policy interest rate (i_t^{Policy}), we use the 3-month yen certificate of deposit rate through 2000Q2, and the 10-year Japanese government bond yield from 2000Q3 onward. First, we compute the correlation between macro-level shocks and the cross-sectional average of our micro-level shocks for the period 2016Q1–2019Q4. The resulting correlation is 0.87 and statistically significant. Second, we estimate impulse responses to identified monetary policy shocks using Local Projections (Jordà, 2005). Figure B.1 in the Appendix shows that contractionary shocks lead to declines in GDP, consumption, investment, and core CPI. These results provide empirical support for the validity of our identification strategy.

[19]In October 2003, the Bank of Japan enhanced the transparency of its monetary policy stance by clarifying its intentions regarding the future path of interest rates.

interest rates. To manage the increase in excess reserves and prevent volatility in key policy rates, the Bank sought to ensure the smooth functioning of the interest rate channel. Given the consistent policy objective of lowering long-term rates under the effective lower bound for short-term nominal rates, our identification strategy is based on information embedded in long-term interest rate expectations.

Instead of estimating Equation (2), we consider the following alternative specification:

$$i_t^{\text{10year}} = \rho \cdot i_{t-1}^{\text{10year}} + \beta_1 \cdot \mathbb{F}_{t-1}^{j}\left[\pi_{t-1,t+3}\right] + \beta_2 \cdot \mathbb{F}_{t-1}^{j}\left[q_t^{\text{Nikkei225}}\right] + \mathbf{X}_t \boldsymbol{\delta} + \varepsilon_t^{j}, \tag{3}$$

where i_t^{10year} denotes the yield on a 10-year (risk-free) Japanese government bond at time t. We treat long-term interest rates as proxies for policy rates. The term $\mathbb{F}_{t-1}^{j}[\pi_{t-1,t+3}]$ represents household j's inflation expectations over the next four quarters, and $\mathbb{F}_{t-1}^{j}[q_t^{\text{Nikkei225}}]$ captures the household's expectation of the Nikkei 225 stock index level at time t.[20] The vector $\mathbf{X}_t$ includes household-level controls such as age, education, and income. The residual term ε_t^{j} captures household-specific deviations from predicted long-term interest rates. $\mathbf{X}$ includes control variables such as quarterly time dummies, individual fixed effects, and respondents' socio-economic characteristics, including age, income level, and educational attainment (coded as a dummy variable). The equation also includes the lagged value of the dependent variable to account for the persistence of monetary policy expectations. Estimating Equation (3) yields the residuals $\hat{\varepsilon}_t^{j}$, which we interpret as household-level subjective monetary policy shocks.[21] Figure 3 shows the development of macro-level monetary policy shocks (constructed using professional forecasts) and the cross-sectional average of household-level subjective monetary policy shocks. The two series exhibit a strong positive correlation. This suggests that the household-level shocks are reasonably identified and broadly aligned with aggregate measures of policy surprises.

[20] As described in Section 3, our survey collects both inflation expectations and stock index forecasts from individual respondents. While the expectations survey is administered during the first or second week of the middle month of each quarter—namely, in February, May, August, and November—Equation (3) also uses realized values, such as i_t^{10year}, from the second month of each quarter. To estimate Equation (3), we use the 10-year Japanese government bond yield (i_t^{10year}) at the end of the second month of the quarter. Although the exact survey response date is not available at the individual level, we verify that our results are robust to using the interest rate at the end of the next quarter (e.g., end of June for Q1) as the realized value.

[21] Table 4 reports summary statistics for the household-level monetary policy shocks identified in our analysis. Figure 2 depicts the histogram of household-level monetary policy shocks.

5 Empirical Results: Consumption Responses to Subjective Monetary Policy Shocks

5.1 Average Effects and Baseline Dynamics

This section presents the micro-level responses to a subjective monetary policy shock. The estimation strategy relies on simple local projections following Jordà (2005):

$$\log c^j_{t+h} - \log c^j_{t-1} = \beta^h \hat{\varepsilon}^j_t + \sum_{k=1}^{K} \gamma^h_k X_{t-k} + c_j + \delta_t + \eta^j_{t+h},$$

where $h = 0, 1, \ldots, 4$ corresponds to the projection horizons in quarters. $\hat{\varepsilon}^j_t$ denotes the subjective monetary policy shock, and $\log c^j_{t+h}$ is the logarithm of household j's consumption at horizon h, which we imputed in Section 3. The estimated coefficients β^h represent the response of consumption at horizon h to a micro-level monetary policy shock. X_t denotes a vector of control variables, including fixed effects, age, income level, educational attainment, the stock market returns' expectations ($\mathbb{F}^j_{t-1}\left[q^{\text{Nikkei225}}_t\right]$), and lagged values (lag 1) of both the monetary policy shock and the dependent variable. The estimated impulse response is shown in Figure 4. The figure shows that consumption increases by approximately 0.7% in the two quarters following a monetary tightening shock, defined as an unexpected 100 basis point increase in interest rates. Such an unanticipated rate hike induces both substitution and income effects, and the overall direction of the consumption response depends on which effect dominates. If the income effect prevails, average consumption may rise in response to the tightening.

5.2 Heterogeneity by Attention and Financial Exposure

However, this average response may mask substantial heterogeneity across households, particularly in how they perceive the shock in the first place. Figure 5 examines this first layer of heterogeneity—variation in the perception of monetary policy shocks—by distinguishing households based on their attentiveness to interest rate information. The left panel shows that attentive households, as identified by those who reported updating their information sets at least once per month in Question (B) in Section 3, exhibit a statistically significant increase in consumption following a monetary tightening shock. This pattern is consistent with the interpretation that attentive households were more likely to perceive the shock and adjust their behavior, although causality cannot be inferred. In contrast, the right panel shows no significant response among inattentive households, indicating limited recognition or cognitive processing of the shock. This contrast underscores how differences in attention contribute to heterogeneous perceptions of monetary policy, forming the first layer of transmission heterogeneity discussed in Section 2.

Figure 6 further explores heterogeneity in the perception of monetary policy shocks by comparing households with and without financial exposure—either through outstanding loans or asset holdings. The results mirror those in Figure 5: households with loans (left panel) and those with substantial financial assets (right panel) both exhibit significant consumption responses following a monetary tightening shock. This pattern is consistent with the notion that financially exposed households tend to be more attentive to macroeconomic developments and, therefore, may form more accurate perceptions of policy changes. These findings reinforce the first layer of heterogeneity—differences in the perception of monetary policy shocks—driven by variation in financial stakes and information acquisition.

Beyond differences in perception, Figure 6 also highlights the importance of heterogeneity in behavioral responses—the second layer discussed in Section 2. Despite experiencing the same tightening shock, borrowers and asset holders respond in opposite directions: consumption declines significantly among households with outstanding loans (left panel), while it rises among those with financial assets (right panel). This asymmetry reflects the redistribution effects of monetary policy, wherein higher interest rates increase debt servicing costs for borrowers but raise income from interest-bearing assets for lenders. These divergent responses underscore that even when households perceive policy shocks similarly, their behavioral adjustments can vary markedly depending on their financial positions. Such evidence lends empirical support to heterogeneous-agent models emphasizing balance sheet effects and marginal propensities to consume.

5.3 Heterogeneity by Lifecycle Position

The relevance of the second layer of heterogeneity—differences in behavioral responses—is further illustrated in Figure 7, which separates households by age. The left panel shows that younger households (under age 50) reduce their consumption following a monetary tightening shock, whereas the right panel reveals that older households (age 50 and above) increase their consumption in response to the same shock. This age-dependent divergence aligns with the life-cycle hypothesis: younger individuals are more likely to be net borrowers and therefore face higher debt-servicing costs when interest rates rise, prompting them to cut back on spending. In contrast, older households are more likely to be net lenders, benefiting from higher interest income, which allows for increased consumption. These findings emphasize that even when monetary policy shocks are similarly perceived, their impact on consumption crucially depends on where households stand in the life cycle, reflecting structural differences in balance sheets and consumption-savings motives.[22]

5.4 Robustness Checks

Figure 8 provides a robustness check for the first layer of heterogeneity, reaffirming the importance of attention in shaping household responses to monetary policy shocks. For robustness checks, we adopt an alternative definition of attentive households: those who selected either "Very interested" or "Somewhat interested" in response to Question (A) in Section 3, which asks about interest in information on interest rates. This alternative classification is used to verify that our main findings are not sensitive to how attentiveness is defined. The figure focuses on younger households with outstanding loans—a group that, in theory, is expected to reduce consumption when faced with a tightening shock. The left panel restricts the sample to attentive borrowers—those who selected either "Very interested" or "Somewhat interested" in Question (A)—and shows a statistically significant decline in consumption. This pattern is consistent with the interpretation that households who express greater interest in interest rate developments, particularly those with loan exposure, are more likely to perceive monetary tightening and respond by adjusting consumption. The results suggest that the perceived impact of monetary policy is systematically associated with the level of attentiveness. These findings confirm that the heterogeneity in perception identified earlier is not an artifact of sample composition but reflects systematic differences in information processing.

Figure 9 further supports the robustness of the first layer of heterogeneity by focusing on older households with substantial financial assets. The left panel, which isolates attentive households, shows that these households show an immediate and statistically significant increase in consumption following a monetary tightening shock. In contrast, the right panel shows that inattentive asset holders display no significant response in the short run, with consumption rising only after a delay.[23] This divergence highlights how differences in attentiveness influence the timing of consumption adjustments. While attentive households may incorporate expected future interest income into current decisions, inattentive households appear to update their behavior less promptly. These results underscore that attentiveness is systematically associated with differences in the timing and direction

[22]This result is consistent with institutional features of the Japanese mortgage market. Younger households tend to select variable-rate mortgages, whereas older cohorts are more likely to hold fixed-rate loans. According to (MLIT, 2024), the share of fixed-rate residential loans fell from 64.0% in March 2009 to 41.5% in March 2019. This implies that younger borrowers are more exposed to interest rate fluctuations. As a result, the consumption response to monetary tightening is more immediate and significantly negative for younger households.

[23]One possible interpretation is that inattentive households adjust their consumption only after receiving the actual cash flow from higher interest income, rather than in anticipation. This behavior would be consistent with the excess sensitivity hypothesis and is reminiscent of findings from the COVID-19 period. For example, Baker et al. (2023) and Chetty et al. (2024) show that many households increased spending immediately after receiving stimulus checks.

of consumption adjustments and suggest that cognitive frictions can introduce meaningful delays in the transmission of monetary policy—even among financially well—positioned households.

Figures 8 and 9 together underscore the robustness of the second layer of heterogeneity—differences in behavioral responses to perceived monetary policy shocks. Despite both groups being attentive to interest rate information, their consumption responses move in opposite directions: as shown in Figure 8, attentive young borrowers reduce consumption significantly following a tightening shock, while as seen in Figure 9, attentive older asset holders increase consumption immediately. This divergence reflects the asymmetric transmission of monetary policy across financial positions. When interest rates rise, debt servicing costs increase for borrowers, inducing a contraction in consumption, whereas lenders benefit from higher expected interest income and expand their spending. The consistency of this pattern across age and balance sheet profiles highlights that even when perception is held constant, the direction of consumption adjustment depends fundamentally on household financial exposure. These findings reinforce the theoretical predictions of heterogeneous-agent models such as Auclert (2019) and Kaplan et al. (2018), where redistribution effects and marginal propensities to consume jointly shape the transmission of monetary policy at the micro level.

6 Conclusion

This paper introduces a novel approach to measuring monetary policy shocks—subjective monetary policy shocks—defined at the household level as residual forecast errors derived from a Taylor-rule-style regression based on individual expectations. Using a unique dataset that links household-level forecasts of macroeconomic variables with high-frequency scanner data on consumption in Japan, we uncover substantial heterogeneity in both the perception of monetary policy and the behavioral response to it. Our findings offer three key insights. First, we document that households form expectations under asymmetric information and varying levels of attention. These differences lead to subjective policy shocks that differ meaningfully across households. Attentive households—those who update interest rate expectations more frequently—tend to respond more strongly to policy signals, while inattentive households show limited reaction. This suggests that attention is closely associated with how monetary policy shocks translate into consumption adjustments at the micro level. Second, we show that household financial positions shape the direction of consumption responses to the same policy shock. Borrowers tend to cut consumption following a perceived tightening, while asset holders increase theirs. These asymmetric responses are consistent with redistribution channels emphasized in HANK models and provide direct micro-level support for such mechanisms. Third, we highlight the importance of life-cycle heterogeneity. Younger households—typically net borrowers—respond differently from older households, who are more likely to be savers. This distinction reinforces the notion that household characteristics mediate not only the perception but also the behavioral consequences of monetary policy shocks.

Taken together, our results show that heterogeneity in attention, financial exposure, and lifecycle stage jointly influence how monetary policy is perceived and how it affects consumption. These findings contribute to the growing literature on behavioral macroeconomics and provide empirical foundations for modeling the micro-level transmission of monetary policy. Future research may extend this framework to other domains such as labor supply, housing decisions, or investment responses under subjective policy beliefs.

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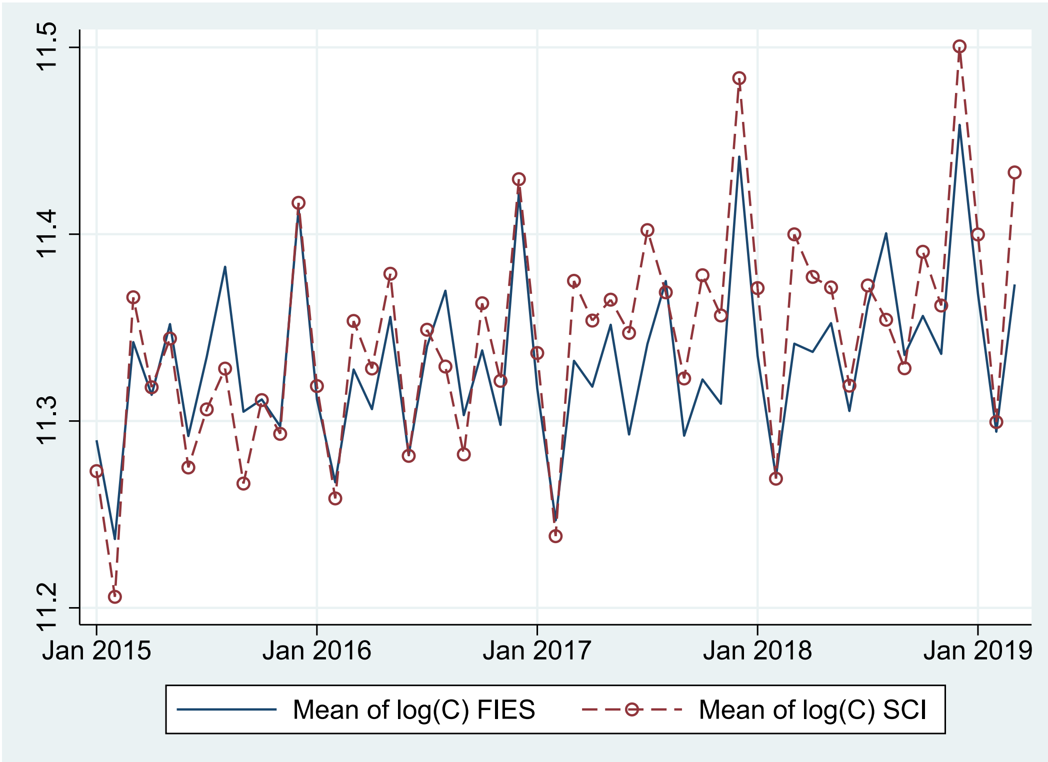

Figure 1: FIES consumption and imputed SCI consumption: equivalence-scaled non-durable expenditures.

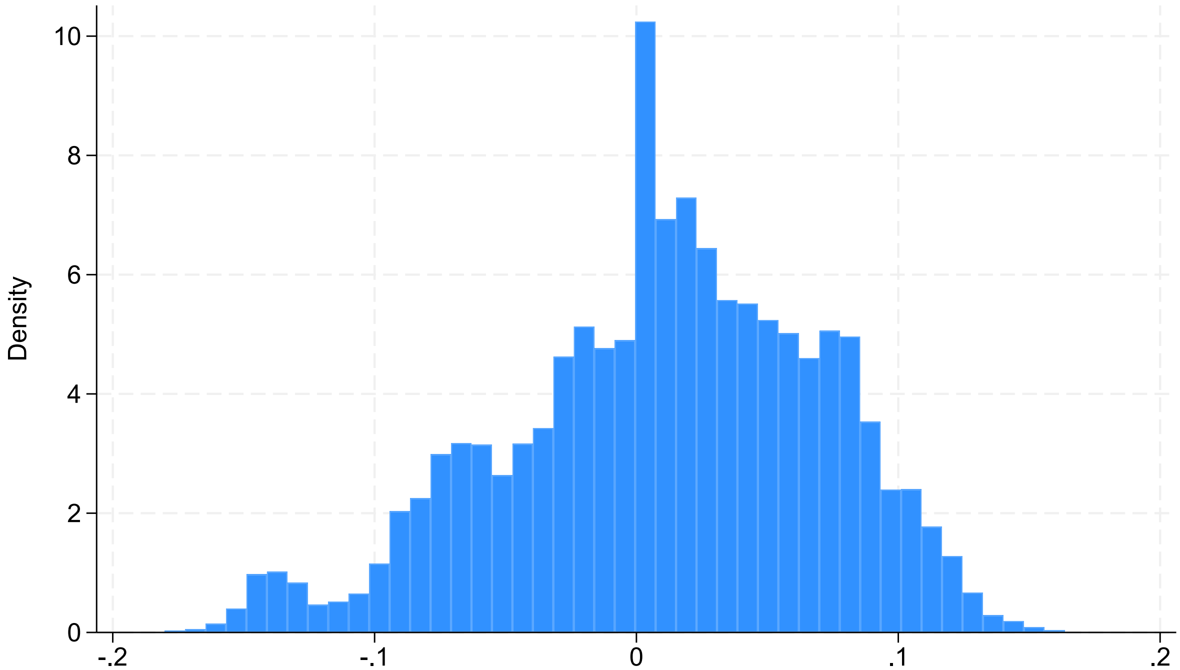

Figure 2: Histogram of subjective monetary policy shocks across households j ($\hat{\varepsilon}_t^j$).

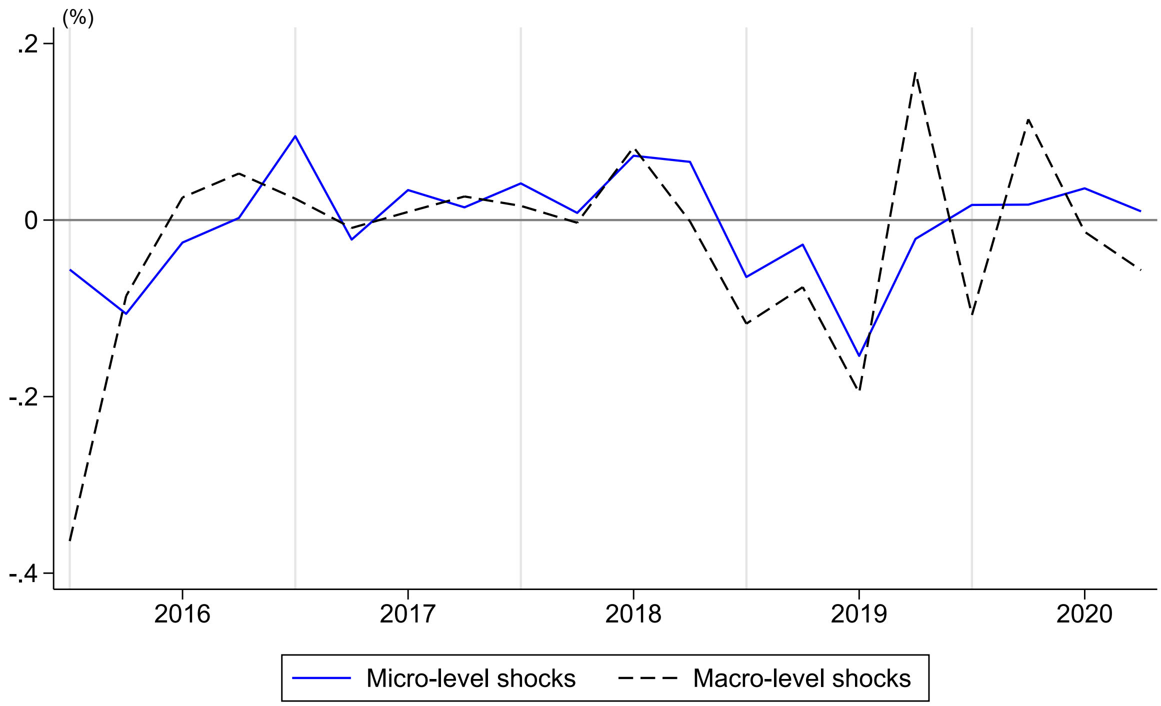

Figure 3: Development of macro-level monetary policy shocks identified from professional forecasts and the cross-sectional average of household-level subjective monetary policy shocks ($\hat{\varepsilon}_t^j$).

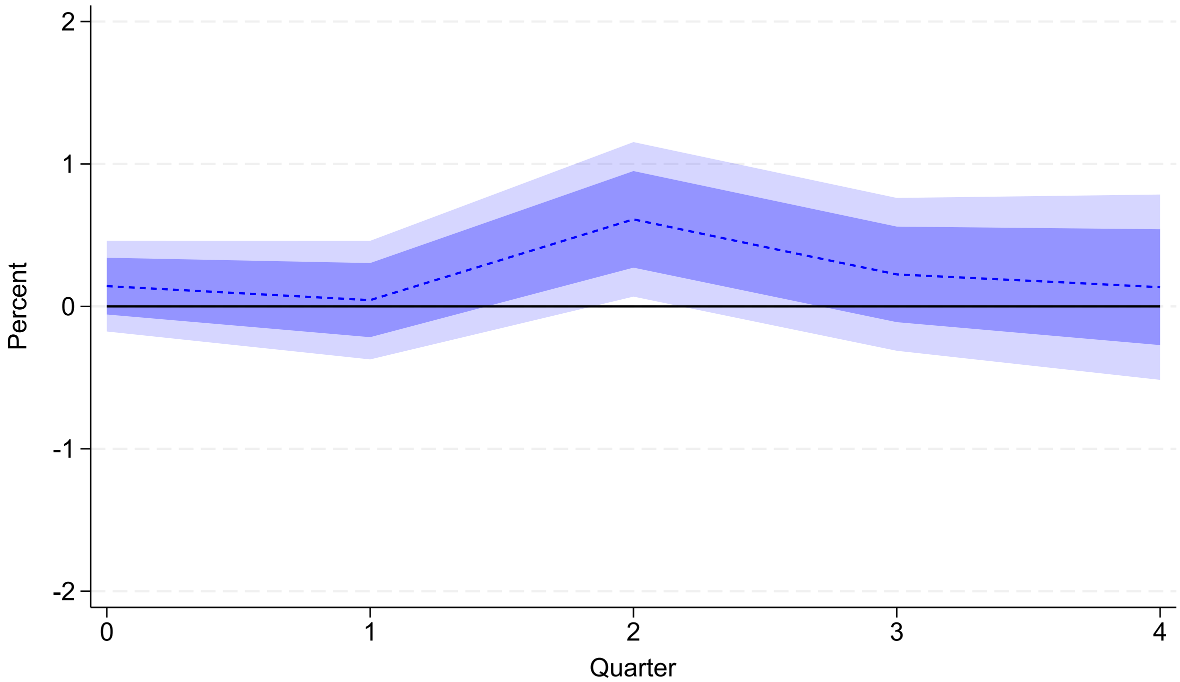

Figure 4: Impulse responses of imputed consumption to a one-percentage-point subjective monetary policy shock at the micro level ($\hat{\varepsilon}_t^j$), using the full sample. Shaded areas indicate 68% and 90% confidence intervals computed using the robust standard errors of Driscoll and Kraay (1998).

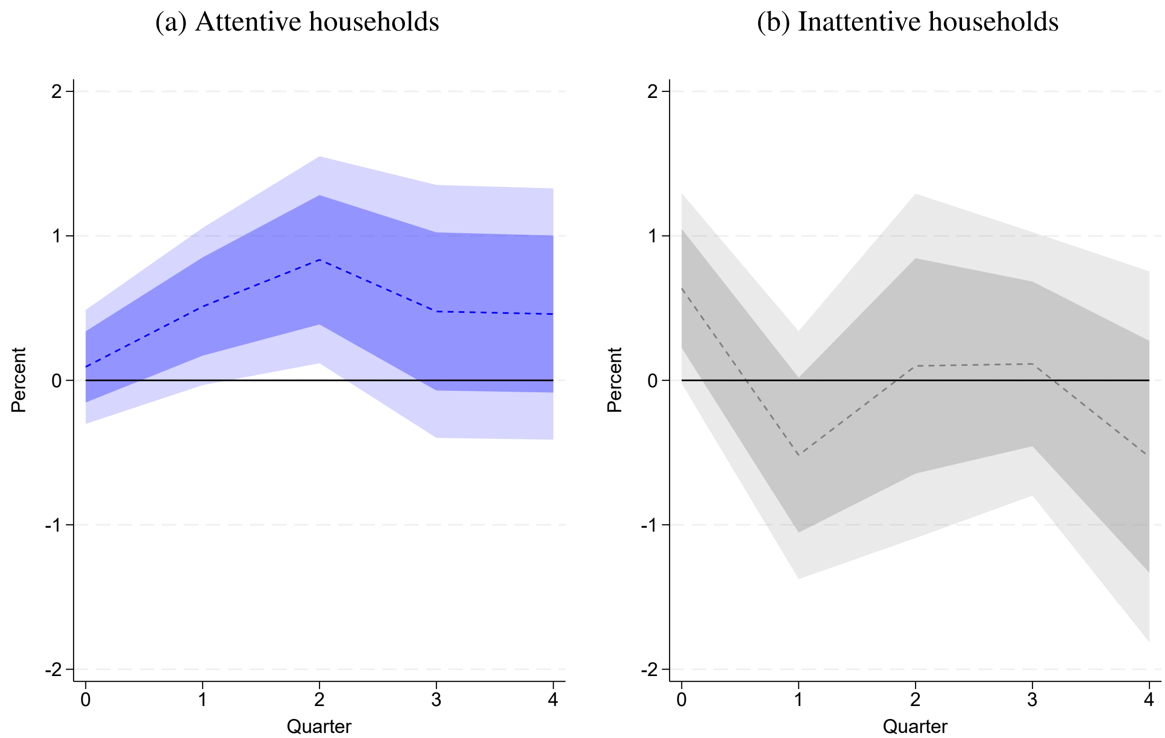

Figure 5: Households that update information sets about interest rates: Impulse responses of imputed consumption to a one-percentage-point subjective monetary policy shock at the micro level ($\hat{\varepsilon}_t^j$), estimated separately for those who updated their information sets (left panel) and those who did not (right panel). We classify attentive households as those who report updating their information sets on interest rates at least once per month. Shaded areas indicate 68% and 90% confidence intervals computed using the robust standard errors of Driscoll and Kraay (1998).

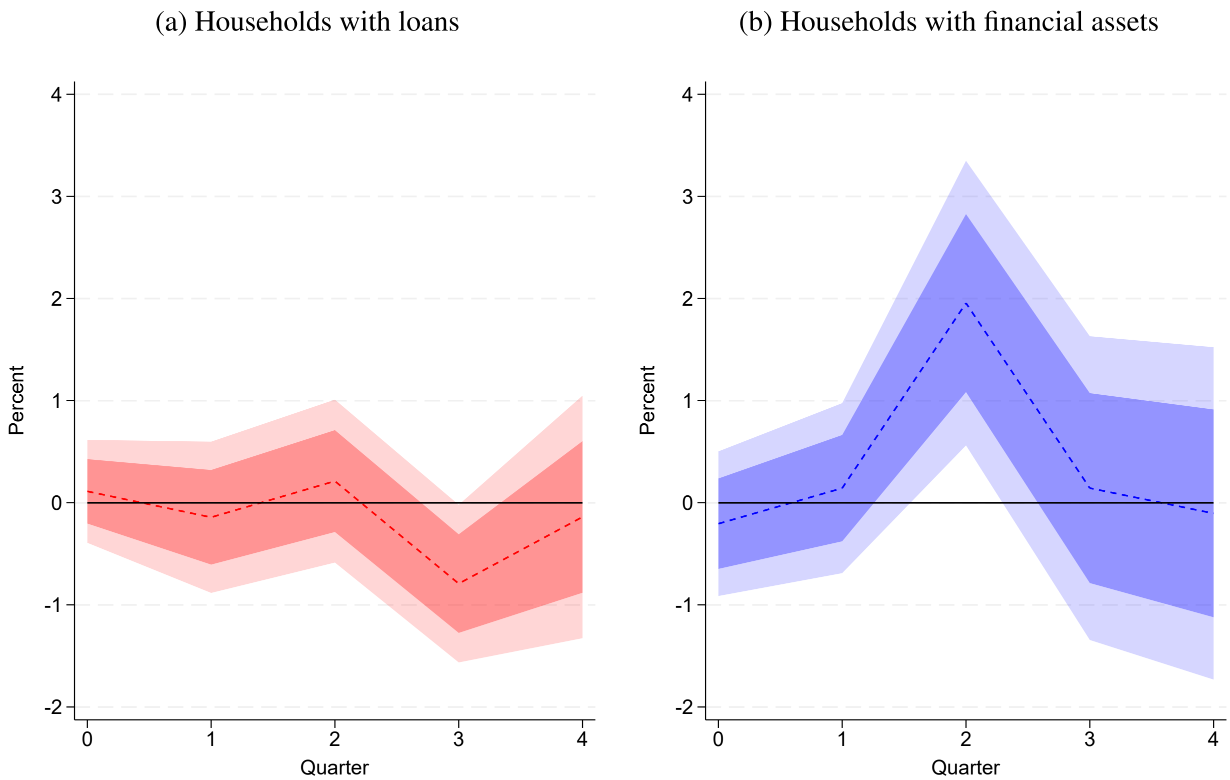

Figure 6: Impulse responses of imputed consumption to a one-percentage-point subjective monetary policy shock at the micro level ($\hat{\varepsilon}_t^j$), estimated separately for households with loans (left panel) and households with financial assets (right panel). Shaded areas indicate 68% and 90% confidence intervals computed using the robust standard errors of Driscoll and Kraay (1998).

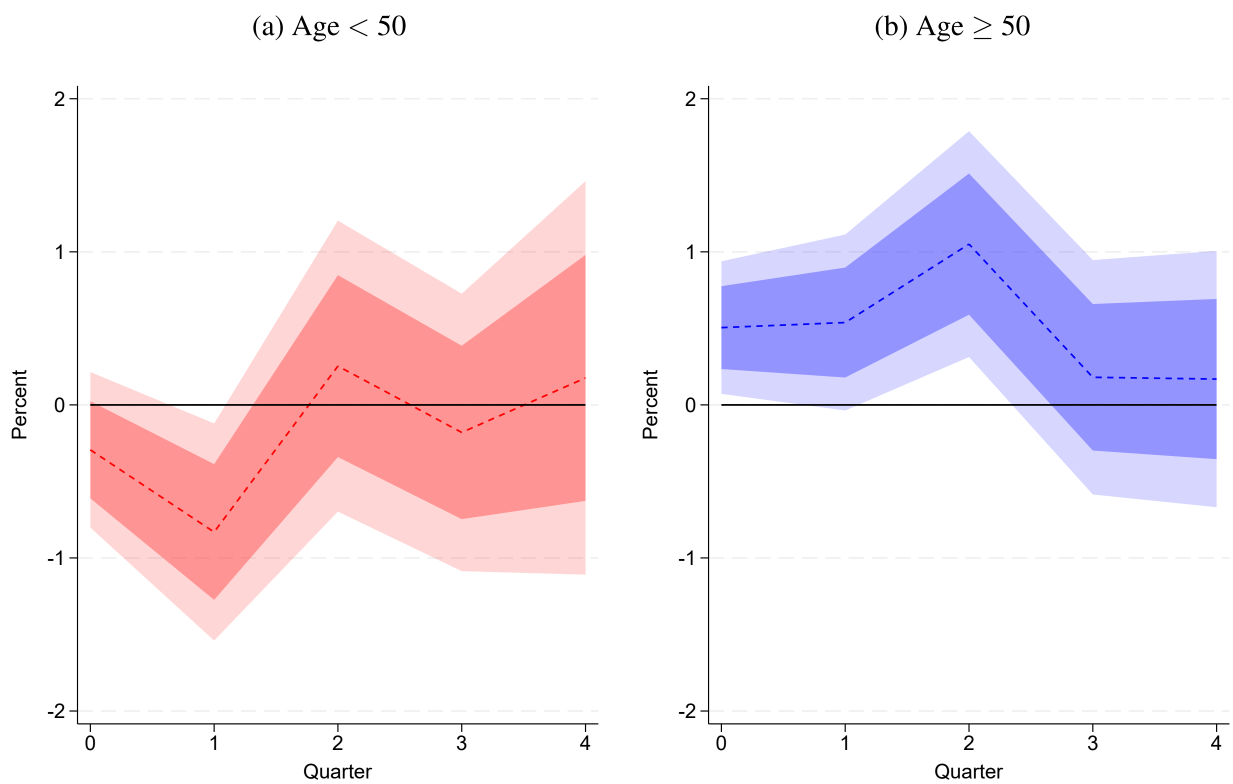

Figure 7: Impulse responses of imputed consumption to a one-percentage-point subjective monetary policy shock at the micro level ($\hat{\varepsilon}_t^j$), estimated separately for those aged under 50 (left panel) and those aged 50 or older (right panel). Shaded areas indicate 68% and 90% confidence intervals computed using the robust standard errors of Driscoll and Kraay (1998).

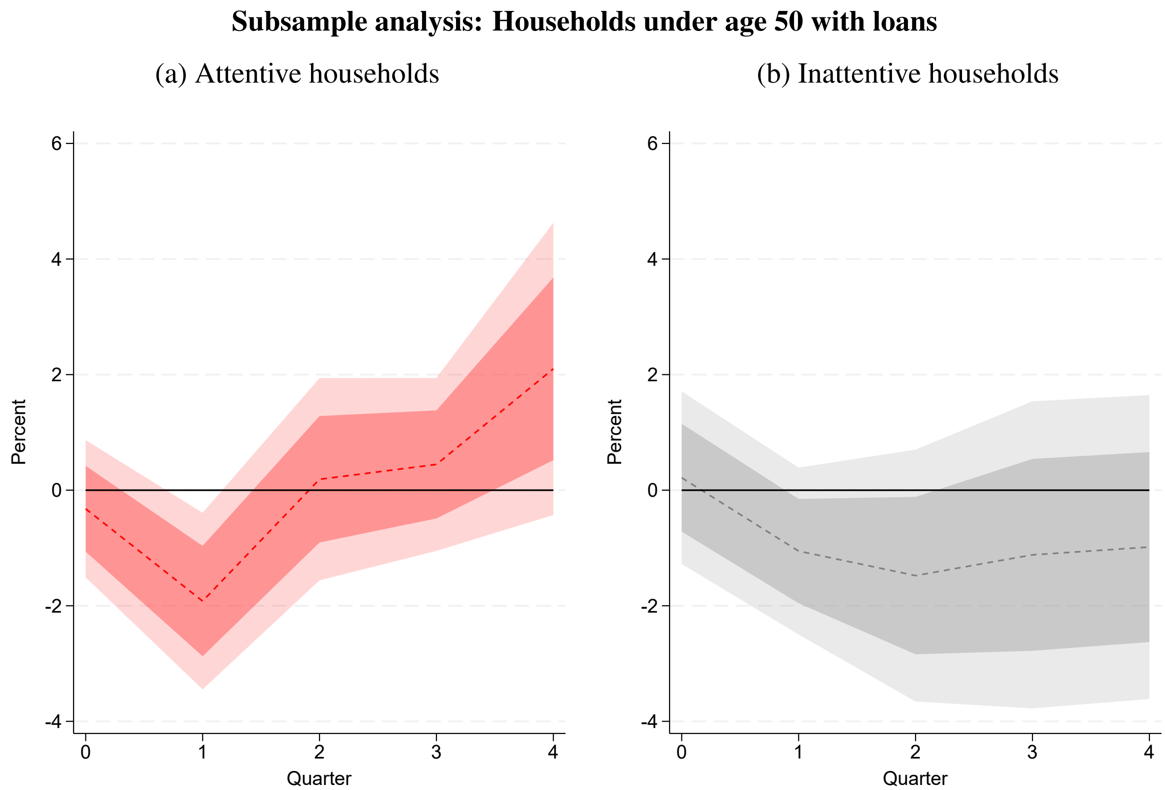

Figure 8: Robustness check (1) using subsamples of respondents under age 50 with loans: Impulse responses of imputed consumption to a one-percentage-point subjective monetary policy shock at the micro level ($\hat{\varepsilon}_t^j$), estimated separately for attentive (left panel) and inattentive (right panel) households who reported outstanding loans. We classify attentive households as those who selected either "Very interested" or "Somewhat interested" in response to Question (A) in Section 3, which asks about interest in information on interest rates. Shaded areas indicate 68% and 90% confidence intervals computed using the robust standard errors of Driscoll and Kraay (1998).

Subsample analysis: Households aged 50 or older with financial assets

(a) Attentive households (b) Inattentive households

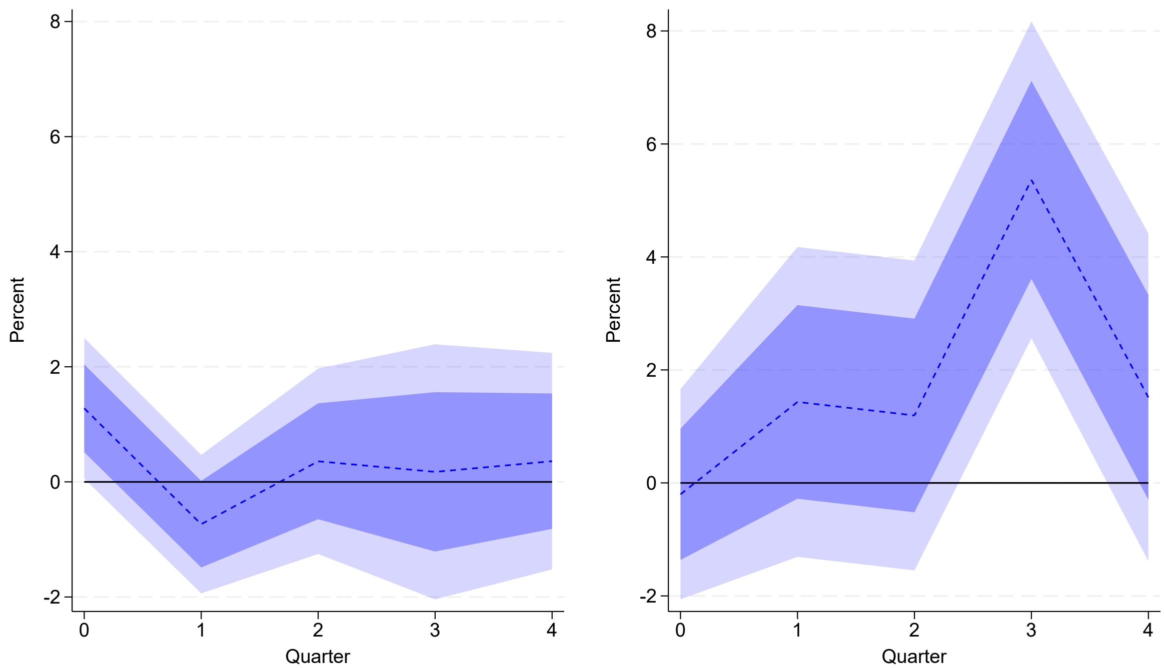

Figure 9: Robustness check (2) using subsamples of respondents aged 50 or older: Impulse responses of imputed consumption to a one-percentage-point subjective monetary policy shock at the micro level ($\hat{\varepsilon}_t^j$), estimated separately for attentive (left panel) and inattentive (right panel) households who reported holding financial assets. We classify attentive households as those who selected either “Very interested” or “Somewhat interested” in response to Question (A) in Section 3, which asks about interest in information on interest rates. Shaded areas indicate 68% and 90% confidence intervals computed using the robust standard errors of Driscoll and Kraay (1998).

Table 1: The fraction of households that update information sets about interest rates

	Information set updated			
	YES		NO	Total
	Once a month or more	less than once a month		
All	58%	24%	18%	100%
Female	48%	31%	21%	100%
Male	62%	21%	17%	100%
Age below 50	55%	25%	20%	100%
Age over 50	60%	24%	16%	100%
Non-college grad	51%	26%	23%	100%
College grad	63%	22%	15%	100%
Less than 5 million yen	52%	26%	22%	100%
More than 5 million yen	66%	21%	13%	100%
With loans	59%	24%	17%	100%
With assets	68%	20%	12%	100%

Table 2: Descriptive statistics of monthly household expenditure (yen)

	Purchase amount		Observations
	Mean	Median	
All	21,014	17,248	95,634
Female	28,710	25,702	32,397
Male	17,071	13,570	63,237
Age below 50	18,507	14,471	47,190
Age over 50	23,456	19,992	48,444
Non-college grad	23,743	20,434	36,057
College grad	19,362	15,581	59,577
Less than 5million yen	21,318	17,703	40,228
More than 5 million yen	20,793	16,884	55,406
With loans	21,251	17,712	27,496
With assets	22,021	18,056	23,111
Attentive households	21,046	17,193	56,209
Inattentive households	20,968	17,319	39,425

Note: The data are from 2015Q4 to 2019Q4.

Table 3: The demand for food in the FIES

Variable	Estimate	Variable	Estimate
$\ln c$	0.754	$\ln p_{transports}$	−0.860
	(0.013)		(6.411)
$\ln c \times$ one child	0.091	$\ln p_{fuel+utils}$	−3.655
	(0.015)		(1.619)
$\ln c \times$ two children	0.031	$\ln p_{alcohol+tobacco}$	17.870
	(0.012)		(7.371)
$\ln c \times$ three children+	−0.024	Born 1955–59	−0.028
	(0.016)		(0.004)
One cild	−1.106	Born 1960–64	−0.047
	(0.169)		(0.007)
Two children	−0.409	Born 1965–69	−0.051
	(0.129)		(0.009)
Three children+	0.198	Born 1970–74	−0.020
	(0.174)		(0.010)
Age	0.016	Born 1975–79	0.008
	(0.002)		(0.011)
Age^2	−0.000	Born 1980–84	0.013
	(0.000)		(0.012)
Family size	0.009	Born 1985–89	0.001
	(0.001)		(0.014)
$\ln p_{food}$	−1.655	Born 1990–94	0.009
	(9.762)		(0.016)
$\bar{R}^2$	0.477	Observations	202,524

Note: This table reports IV estimates of the demand equation for food spending using data from the FIES. The log of total nondurable expenditure—along with its interactions with monthly time dummies and child dummies—is instrumented using the log of the household head's annual income and its corresponding interactions. For brevity, we omit the estimated coefficients on the interactions between total nondurable expenditure and monthly time dummies. Robust standard errors are reported in parentheses.

Table 4: Basic statistics of monetary policy shocks at the household level

	MP shocks $\hat{\varepsilon}_{j,t}$			
	Mean	Median	Standard deviation	Observations
All	0.000%	0.007%	0.062	98,273
Female	0.000%	0.005%	0.061	32,831
Male	0.000%	0.008%	0.063	65,442
Age below 50	−0.000%	0.006%	0.062	48,764
Age over 50	0.000%	0.009%	0.063	49,509
Non−college grad	0.000%	0.006%	0.062	36,920
College grad	−0.000%	0.008%	0.063	61,353
Less than 5 million yen	−0.000%	0.006%	0.062	41,242
More than 5 million yen	0.000%	0.008%	0.063	57,031
With loans	−0.000%	0.008%	0.064	28,043
With assets	−0.000%	0.009%	0.064	23,593
Attentive households	−0.001%	0.007%	0.063	57,754
Inattentive households	0.001%	0.008%	0.061	40,519

Note: The data are from 2015Q4 to 2019Q4.

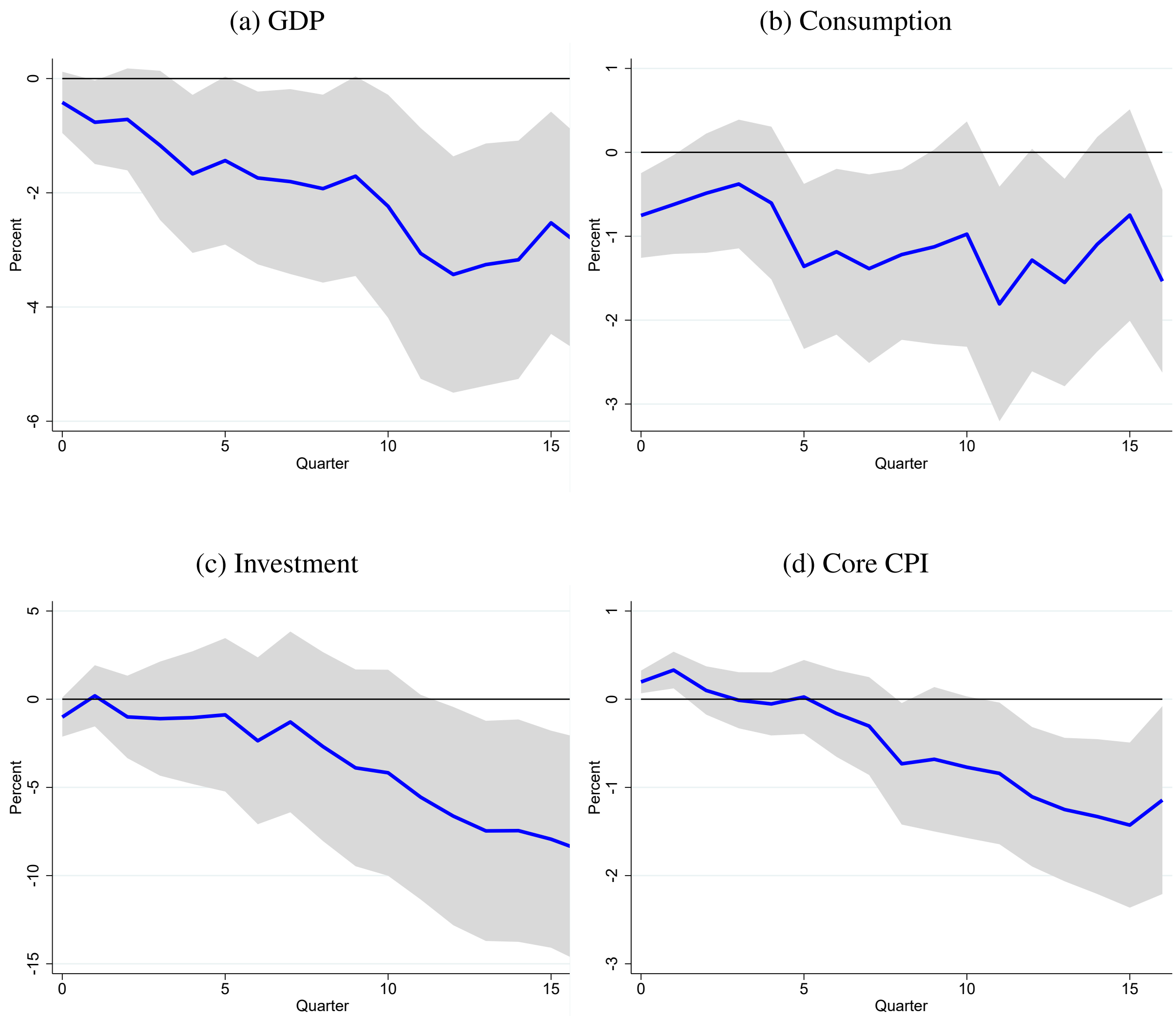

Figure B.1: Macro-macro responses to a monetary policy at a quarterly frequency from 1994 to 2019. The figure shows impulse responses to a one percentage point contractionary monetary policy shock. The confidence bands are calculated using the 68% interval based on the robust standard errors.