Marginal Propensity to Consume and Personal Characteristics:
Evidence from Bank Transaction Data and Survey

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October 25, 2024

Abstract

The marginal propensity to consume (MPC) is heterogeneous and depends on liquidity, while liquidity is affected by both temporary circumstances and persistent characteristics. Using bank account transaction data and a survey of its account holders, this study aims to distinguish the sources of MPC heterogeneity. The results indicate that individuals with higher levels of risk aversion and time discount rates tend to exhibit a higher MPC, whereas lower wealth is also linked to a higher MPC. These findings suggest that MPC heterogeneity is influenced by both temporary and persistent factors.

JEL Classification Number: D14, E21

Keywords: marginal propensity to consume; special cash payment program; heterogeneity

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1 Introduction

The marginal propensity to consume (MPC) is one of the most important variables in macroeconomics, frequently referenced in the evaluation of policy effects and in the development of macroeconomic models. Previous studies have shown that the magnitude of the MPC is closely linked to liquidity constraints, which determine whether an individual's asset holdings are sufficient to meet current payments. However, liquidity constraints are endogenous variables. Recent research has emphasized the need to distinguish between temporary circumstances and persistent characteristics when analyzing liquidity levels (e.g., Jappelli and Pistaferri 2020, Gelman 2021, and Aguiar, Bils, and Boar 2023). For instance, liquidity may be limited because of persistent characteristics such as high time discount rates that lead to a consistently low propensity to save. Alternatively, liquidity may be constrained because of time-varying economic conditions such as temporary adverse income shocks, where time discount rates remain constant.

This study's main contribution is analyzing the sources of heterogeneity in the MPC by combining transaction data from one of Japan's major banks with a survey of its account holders. To estimate the MPC, this study uses bank transaction data and examines outflow changes in response to two types of income shocks: the large-scale special cash program (SCP) implemented by the Japanese government during the COVID-19 pandemic and the receipt of bonuses (which are widely distributed in Japan twice a year among most regular workers). These findings are then combined with a new survey that aims to obtain information on personal characteristics such as age, gender, education, and factors that may affect consumption and investment behaviors, such as risk aversion and time discount rates. The relationships between these personal characteristics and the magnitude of the MPC are investigated.

The main results of the study are as follows. First, utilizing two-way fixed effects regression to estimate the change in consumption in response to income shocks, I find that the magnitude of the MPC is approximately 0.2 (i.e., 20%) during the week of an income shock. The income effect on consumption is short-lived, lasting only for a couple of weeks. The magnitude of the MPC is similar across different types of income shock (i.e., not just the SCP and bonus payments but also salary payments), despite the different intrinsic natures of these income shocks.

Second, the study finds that heterogeneity in the MPC is related to both temporary circumstances and persistent characteristics. The estimation of the MPC is conducted by including cross-terms of income shocks and various explanatory variables on the right-hand side of the equation. Temporary circumstances, represented by time-varying wealth (deposits) and liquidity constraint dummy (whether wealth is smaller than monthly income) based on the transaction data, have significant relations with the magnitude of the MPC, suggesting that smaller liquidity is associated with a higher MPC. Meanwhile, persistent characteristics, represented by higher risk aversion and higher time discount rates based on the survey data, are also associated with a higher MPC, particularly for the income shock of a bonus. Some variables that appear to be significant as persistent characteristics, such as gender and education, do not yield significant results, although age is positively correlated with the MPC.

The estimation results suggest that the extent to which these temporary circumstances and persistent characteristics are associated with the MPC is considerable. Specifically, the estimation results indicate that an increase of one standard deviation in risk aversion and discount rate increases the MPC to the income shock of a bonus by 0.020 (i.e., 2.0 percentage points) and 0.053, respectively, whereas an increase of one standard deviation in log wealth decreases the MPC by 0.041.

Empirical studies on the MPC have used various methodological approaches to estimate the magnitude and determinants of the MPC. These approaches have advantages and disadvantages, and researchers have selected them depending on the availability of data and the research questions they want to answer. Group (1) studies, into which this study falls, use actual transaction data and particular events and can capture actual consumption behavior following an income shock, but they may be limited in terms of the types of income shocks they can analyze.[1] Group (2) studies use surveys and can cover a wider range of income shocks but may be limited in terms of the accuracy of consumption measures (e.g., Shapiro and Slemrod 1995, 2003; Jappelli and Pistaferri 2020).[2] Group (3) studies use household panel data and can provide information on how

[1]The examples of income shocks are lottery wins (Olafsson and Pagel 2019; Fagereng, Holm, and Natvik 2021) and government transfers during the COVID-19 pandemic (Baker et al. 2024; Kaneda, Kubota, and Tanaka 2021; Kubota, Onishi, and Toyama 2021; Lewis, Melcangi, and Pilossoph 2021; Yannelis and Amato 2022). The estimation of the MPC is relatively simple because income shocks are often transitory, salient, and unexpected.

[2]Group (2) studies also use particular events to estimate the MPC, such as government transfers during COVID-19 (Coibion et al. 2020; Parker et al. 2022) and other stimulus payments (Johnson, Parker, and Souleles 2006; Agarwal, Liu, and Souleles 2007; Parker et al. 2013; Parker 2017; Kueng 2018; Fuster, Kaplan, and Zafar 2021).

the MPC varies over time and across different groups but require identifying restrictions on household income and consumption, because the income in the data is not necessarily transitory, salient, or unexpected (e.g., Bodkin 1959; Blundell, Pistaferri, and Preston 2008; Olafsson and Pagel 2018; Gelman 2021, 2022; Crawley and Kuchler 2023; Patterson 2023). A meta-analysis can provide a comprehensive summary of the existing evidence (e.g., Havranek and Sokolova 2020).

Gelman (2021), Jappelli and Pistaferri (2020), and Aguiar, Bils, and Boar (2023) have shown that both temporary circumstances and persistent characteristics play a significant role in determining the MPC. Specifically, Gelman (2021) uses household panel data from a personal finance app to estimate the MPC to the arrival of a tax refund and finds that both temporary circumstances and persistent characteristics account for roughly half of the MPC variance. Jappelli and Pistaferri (2020) use household surveys in Italy conducted twice in 2010 and 2016 and report that unobserved heterogeneity exaggerates the sensitivity of the self-reported MPC to cash on hand, but the size of the bias is moderate, which suggests that both temporary circumstances and persistent characteristics are important. Aguiar, Bils, and Boar (2023) do not estimate the MPC and instead, use data from the Panel Study of Income Dynamics to point out that hand-to-mouth households do not display higher growth in spending, which shows the importance of persistent characteristics. Patterson (2023) shows that an MPC is heterogeneous by demographics (race, age, gender, and earning history), but also argues that these characteristics are likely correlated with other underlying economic circumstances, particularly liquidity. The contribution of this study compared to those above lies in using a combination of bank transaction and survey data to estimate the MPC. In other words, whereas Jappelli and Pistaferri (2020) falls in group (2) and Gelman (2021) and Patterson (2023) fall in group (3), this study falls in group (1), which is beneficial in estimating the MPC without relying on self-reporting surveys (group (2)) or structural models (group (3)).[3]

[3] It should be noted that, in this study, MPC heterogeneity is captured only as the correlation between the MPC and observable characteristics. Thus, the decomposition of the MPC to various factors such as temporary circumstances and persistent characteristics is difficult, unlike in earlier studies. Jappelli and Pistaferri (2020) and Fuster, Kaplan, and Zafar (2021) use a survey to obtain the distribution of the MPC, which is compared with the observable characteristics of individuals. Gelman (2021) and Aguiar, Bils, and Boar (2023) generate MPC distribution in the model and perform a variance decomposition. Another approach is adopted by Lewis, Melcangi, and Pilossoph (2021), who estimate the unconditional distribution of the MPC in a non-restricted way and compute how much of the overall MPC variance

There has been a steady increase in studies using bank transaction data. Baker and Kueng (2022) provide a review of household financial transaction data. Kubota, Onishi, and Toyama (2021) and Ueda (2024) use the same Mizuho Bank data as I do. I follow Kubota, Onishi, and Toyama (2021) in most of the analysis, where the largest difference is that I combine the survey data.

The remainder of this paper is structured as follows. Section 2 describes the data. Section 3 explains estimation methodology and results and Section 4 concludes.

2 Data

I use survey and transaction data thanks to the collaboration with Mizuho Bank. Mizuho Bank is one of the three largest banks in Japan, with approximately 24 million accounts held by individual customers (one out of every five people).[4] The data were made available through a strict contract between Mizuho Bank and Waseda University, and were analyzed in a setting where measures were taken to prevent the identification of individuals, such as masking and other anonymous processing.

2.1 Survey

I conducted the survey in November and December, 2022. Mizuho Bank sent 400,000 bank account users an email to ask them to answer the survey, stating that we would give an Amazon gift card worth 500 Japanese yen (JPY) to 1,000 respondents. The 400,000 bank account users were selected randomly from those who received their salary regularly. In total, I collected 5,282 responses (the response rate is 1.32%).[5]

The timing of individuals' transactions in this analysis precedes the timing of the survey. In this regard, there is no pathway through which the implementation of the survey affects the estimation of the MPC.

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is explained by observables. In addition, the multiple testing problem may spuriously reject the null hypothesis for the coefficient on an observable. Despite these technical differences, this study reaches a similar conclusion in one thing: unobserved drivers are important for MPC heterogeneity (e.g., Lewis, Melcangi, and Pilossoph 2021).

[4] https://www.mizuho-fg.co.jp/investors/individual/strength/index.html

[5] Schnorpfeil, Weber, and Hackethal (2023) conduct a survey to account users of a German bank and the overall response rate is 1.8%. They further argue that this response rate is comparable to other surveys of the bank.

In the survey, I asked respondents widely-used questions to infer their personal characteristics related to their saving/investment decisions. Specifically, I referred to the Japan Household Panel Survey on Consumer Preferences and Satisfaction conducted by Osaka University.[6] In the questions, I allowed respondents to select the option "I do not know or do not want to answer." When respondents choose this answer, I exclude it from the estimation (see Online Appendix A for details). After asking respondents' basic characteristics such as gender, age, household type, house type, education, occupation type (Q1 to 7), I collected the following variables.

Risk Aversion I calculate the Arrow–Pratt measure of absolute risk aversion σ for each respondent following Pratt (1964) and Cramer et al. (2002). I ask respondents whether they would buy a lottery ticket for various probabilities to win (Q8 to 13) and calculate $\sigma = -U''/U'$ as $\frac{2(\alpha Z-p)}{\alpha Z^2-2\alpha Zp+p^2}$, where α, Z,and p represent the probability of winning, the prize value, and the price of a lottery ticket, respectively. In the survey, Z and p equal 100,000 and 10,000 JPY, respectively, and α is obtained from a respondent's answer such that I set $\alpha = 0.9$ if the respondent answers that they would buy a ticket if the probability to win is 0.9, but would not buy it if it is 0.5. I set $\alpha = 1$ if the respondent would not buy the ticket even if the probability of winning is 0.9. Consequently, the absolute risk aversion σ in the study ranges from -4.5 (when $\alpha = 0.01$) to 0.891 (when $\alpha = 1$). When $\alpha = 0.1$, σ equals zero, which means that the respondent is risk neutral.

Further, I calculate other measures of risk aversion by directly asking respondents whether they are risk averse or risk taking (Q18 and 19, each denoted by risk aversion A and B, respectively, hereafter). The answer takes an integer from one to five, where a larger value indicates a higher risk aversion.

Time Discount Rate I calculate time discount rate δ for each respondent from Q14 to 16. In the questions, I ask respondents about the minimum amount of money they are willing to wait one week, one year, or ten years to receive. To be more precise, I ask respondents to compare 100,000 JPY one week later, not now, and a certain amount after one week, one year, or ten years plus one week, considering hyperbolic discounting. I then calculate δ as $X/100,000$ if a respondent answers that the minimum amount of money is $100,000 + X$ JPY. I set $X = 10,000,000$ if a respondent answers that "even if I can receive 1,100,000 JPY in 10 years, I would like to receive it now." Consequently,

[6] https://www.iser.osaka-u.ac.jp/survey_data/top_eng.html

the time discount rate δ in this study ranges from 0.01 (when $X = 100$) and 100 (when $X = 10,000,000$).

Further, I obtain another measure of time discount by directly asking respondents which is more important between now and the future (Q20). The answer takes an integer from one to four, where a larger value indicates that the future is more important (i.e., a smaller δ).

Other Variables Because the liquidity constraint matters for the MPC, I ask respondents whether they can pay the same amount of their household income by withdrawing their savings, selling their assets, or borrowing from financial institutions, friends, or relatives (Q17). Real interest rates likely influence the MPC by influencing saving decisions. As a proxy, I ask respondents about their views on inflation perceptions in the latest year, inflation expectations one year from now, and wage expectations one year from now (Q21 to 23).

Further, I ask respondents how concerned they are about fiscal debt after I explain that Japan's government debt is at a historically extremely high level (Q24). The answer takes an integer from one to five, where a smaller value indicates a greater concern.

2.2 Transaction Data

Transaction data of Mizuho Bank record all transactions involving Mizuho Bank, including automatic teller machine (ATM) cash withdrawals, payroll receipts, utility bill payments, and bank transfers, all of which are assigned identification codes and remarks in Japanese. In addition, the data record the balance of deposits and annualized income at the end of each month and information on personal characteristics such as the year of birth, gender, and registered address data at the municipal level. The time frame is from January 2019 to November 2022, including the period of the COVID-19 pandemic. The time unit is one week.

Outflows are defined as all the transactions that decrease the amount of their deposits. Although outflows are a clear candidate for the measure of consumption, they include expenditures unrelated to consumption. First, certain outflows represent saving rather than consumption. While the data lack information on financial assets such as stocks because of the unobservability of transactions conducted through securities companies, outflows may be directed toward investments. Furthermore, outflows may arise from loan repayments, particularly mortgage payments. Second, certain outflows are regular and not necessarily discretionary. Specifically, account users often use direct debit (direct withdrawal), in which an organization withdraws an undetermined amount of money automatically from users' accounts given the pre-authorization of payments at the bank account. Outflows using direct debit include regular automatic payments such as withdrawals of utility bills, rent, and school fees. Because the time unit of this analysis is a week, while the frequency of direct debit payments is often a month, these regular payments may cause a spurious result in the estimation of the MPC even if I control individual and week fixed effects.[7] However, certain direct debit is likely discretionary, most notably credit card payments.

In this study, I proxy consumption by the sum of the following outflows: credit card payments in direct debit, transfers, debit card payments, and cash withdrawals from ATMs (see Online Appendix B.1 and B.2 for details).[8] For robustness, I employ two other measures of consumption: total outflows excluding saving and cash withdrawals from ATMs. As discussed in Ueda (2024), cash continues to be a major payment method in Japan.

There are caveats in the data. The account users are dispersed across the country but are concentrated in metropolitan areas when compared to the census. All outflows are recorded, but we cannot know the purpose of the outflows. Kaneda, Kubota, and Tanaka (2021) use a personal finance management app, which enables them to investigate the types of consumption. Information on transactions at other financial institutions, especially securities companies and postal savings accounts, is not available. Since many account users hold accounts with institutions other than Mizuho Bank, the deposits and withdrawals recorded in this data do not necessarily capture all of an individual's

[7]For example, the timing of salary and direct debit is predetermined, which may make the estimate of the MPC to regular monthly salary significantly different from zero. In Online Appendix B.1, I illustrate daily transaction patterns in a month.

[8]There is a possibility that credit card payments are used for debt repayments for past credit card spending, which can be conceptually different from the MPC. For example, Kosar et al. (2023) show that MPC heterogeneity is substantially different from that in the marginal propensity to repay debt (see also Agarwal, Liu, and Souleles 2007). However, in Japan, such debt repayments are rare. According to the Japan Consumer Credit Association, credit card spending in 2022 is 80 trillion JPY, of which only 5 trillion JPY (6%) is repaid over two months. In other words, most credit card spending is repaid within a month or two. See https://www.j-credit.or.jp/information/statistics/download/statistics_domestic_2022.pdf (in Japanese).

transactions. In particular, it should be noted that there is a large omission of information on non-liquid financial assets, such as stocks, which are often invested in securities companies.

I collect the transaction records of the survey respondents, such as the amount of outflows and cash withdrawals weekly. Wealth and annualized income, which are provided monthly, are merged using the values at the end of the previous month. In this study, wealth is defined as the balance of deposits at the Mizuho Bank, which is the sum of demand deposits, time deposits, other banking accounts, public bonds, mutual funds, and life and non-life insurance balances. The majority of the deposits are demand deposits because the deposit rate is effectively zero, even for time deposits, and most non-liquid financial assets (e.g., stocks) are invested outside the bank. Annualized income is labor earnings based on either the actual amount of salary and bonus in the last year (after tax and social contribution) paid to users' accounts or the self-reported amount. The latter information is often collected when users open their bank accounts or apply for a mortgage. The liquidity constraint dummy is defined following Kubota, Onishi, and Toyama (2021) as the variable takes one if the end-of-month wealth in the previous period is below the individual's monthly income (annualized income divided by 12).

2.3 Two Types of Income Shock

In this study, I consider two types of income shock, SCP and bonus payments, to calculate the MPC.

SCP The first type of income shock is SCPs by the government. The government launched the first wave of SCPs around mid-2020, which provided 100,000 JPY, approximately equivalent to 800 US dollars, for each resident in Japan. Then, the government rolled out the second wave of SCPs from the end of 2021 to the beginning of 2022, which targeted households with children under 18 and an annual income below a specified threshold (9.6 million JPY annually), providing 100,000 JPY per eligible child.

SCP receipts are identified in the following way. Using transaction remarks in Japanese, I choose the transactions of inflows that include the keywords related to special payments. Then, I restrict the transactions of inflows to those that were multiples of

50,000 JPY.[9] SCP payments were mostly paid to head-of-household accounts.

The SCP is likely to be a one-time income shock, in which the timing is unknown *ex ante*. The government provided SCPs to soften the adverse effects of the COVID-19 pandemic on household finances. The SCPs, including the first one distributed around June–July 2020, were temporary, although the government provided the second SCP from the end of 2021 to the beginning of 2022. The left-hand panel of Figure 1 shows the histogram for the timing of the SCPs for the survey respondents. The distribution is bimodal: one mode around June to July 2020 (the first wave) and the other around December 2021 to February 2022 (the second wave; a dip exists because of New Year holidays). This figure further shows that the timing was dispersed within the same SCP wave. Kubota, Onishi, and Toyama (2021) document that the timing was unpredictable and nearly random and exogenous to individuals' characteristics (except for the area of residence) because of the administrative overburdening that occurred at local offices.

Approximately half of the respondents received the SCP payments in their bank accounts. The number of respondents who received the second-wave SCP is much smaller, because the government restricted recipients to households that had a child under 18 and earned income below a certain threshold (9.6 million JPY annually).

Bonus The second type of income shock is a bonus. Most regular employees (not part-time workers) receive bonuses twice a year in Japan, whereas bonuses are often limited to executive classes in the United States (Ito and Hoshi 2020). The bonus accounts for around $15 - 30\%$ of employees' annual income and is determined based on their performance and the performance of the company that they work for. I collect the data on bonuses from inflow transactions that include the remark "shoyo (bonus)." The right-hand panel of Figure 1 shows the histogram for the timing of bonuses for the survey respondents. The histogram has two modes in a year: one from June to August (summer bonus) and the other in December (winter bonus). The timing of bonuses is dispersed among individuals (i.e., some receive in June, whereas others receive in

[9] Specifically, transaction remarks should include the words "tokubetsu kyufu (special payments)," "teigaku kyufu (fixed-amount payments)," or "tokubetsu teigaku (special fixed-amount)," whereas transaction remarks that include the words "jizoku (continuous)" or "sumai (housing)" are excluded because they do not appear to be related to SCPs. In the two waves of the SCPs, the government provided multiples of 100,000 JPY to individuals; however, some local offices divided the payments into two installments of 50,000 JPY each per child in the second wave of the SCPs. Moreover, local offices provided additional special payments to individuals for less than 100,000 JPY.

August; some receive in the first week of December, whereas others receive in the third week of December), which helps us estimate the MPC using the time dummy effect. The amount of the bonus is not necessarily known until it is received, although employees usually know in advance when they will receive the bonus.

While salary constitutes the major component of income, caution is needed when estimating the MPC to the income shock of salary because it is largely expected and persistent. Furthermore, the weekly data exhibit a bump in my consumption measure, which often synchronizes with the timing of salary income and may cause a spurious estimate of the MPC. In Online Appendix B and C, I discuss the estimation results of consumption responses to salary payments.

2.4 Overview of the Data

Table 1 shows the descriptive statistics of the transaction data at the individual level as of 2020 for 5,282 survey respondents. To maintain anonymity, the maximum and minimum values are not shown. The first to eighth rows of the table show the descriptive statistics of different types of outflows. Particularly, according to the first to third rows, the median amount of consumption, outflows excluding saving, and cash withdrawals is around three million, five million, and one million JPY, respectively, which indicates that the amount of consumption varies considerably depending on what I include in consumption. The SCP dummy takes the value one if respondents received the SCP in 2020 based on the bank transaction data. The mean of the SCP dummy is 0.47, which suggests that 47% of respondents received the SCP in their Mizuho bank account that year. The mean, median, and top 25% of the SCP (which includes that for non-recipients of the SCP) are 110,000, zero, and 200,000 JPY, respectively, where the last value implies that the household consists of two family members because one person received 100,000 JPY. The mean amounts of the bonus and salary are around 700,000 and 3,400,000 JPY, respectively. The median log wealth and log annual income are 7.4 and 8.3, respectively, which suggests that median wealth and annual income are 1,595 thousand and 4,125 thousand JPY. The median wealth in this study is greater than that in Kubota, Onishi, and Toyama (2021), 444 thousand JPY. The mean age is 48, whereas it is 53 in Kubota, Onishi, and Toyama (2021). As the next table shows, the fraction of male respondents is 65%, whereas it is 74% in Kubota, Onishi, and Toyama (2021). These differences reflect that I sent the survey to bank account users who received a regular salary to their

Mizuho bank account. Table 2 shows the descriptive statistics of the survey data.

I compare the age, wealth, and income distribution of survey respondents with that of all salary recipients in the Mizuho Bank users and that of representative Labor Force Survey (Statistics Bureau). Online Appendix B.3 shows that survey respondents are relatively older (highly concentrated around age 50) and have higher wealth and income levels.

Before estimating the MPC, I examine how respondents' wealth and income are associated with the variables I collect from the survey at the individual level, where respondents' wealth and income are their means from January 2019 to November 2022. In Table 3, column (1) shows that wealth is significantly associated with the following variables at the 5% level: positively with age, education, the inverse of discount rate (direct), and risk aversion A, and negatively with the discount rate for one year and ten years and inflation perception in the latest year. Regarding the time discount rate, this result suggests that myopic individuals (with a high discount rate) tend to have a smaller amount of wealth, which is consistent with the standard models of intertemporal substitution. Individuals who perceive higher past inflation tend to have a smaller amount of wealth, which may imply that hand-to-mouth households are attentive to price increases. Meanwhile, risk aversion measures are insignificant except for risk aversion A. Since a difference in wealth can stem not only from a difference in discount rate but also a difference in income, I control for income in column (2), which shows that the coefficient on income is positive and significant, but the estimation result of column (1) is still robust. These estimation results show that liquidity (wealth) is endogenous and associated with personal characteristics, which endorses my research question.

In column (3), I use income as the dependent variable and the estimation result shows that income is significantly associated with the following variables at the 5% level: positively with age, male dummy, and education and negatively with inflation perception in the latest year. Here, all measures of discount rate and risk aversion are insignificant.

In Online Appendix B, I present the correlation coefficients between three measures of risk aversion and two measures of the discount rate, all derived from the survey. Additionally, I provide the correlation coefficients between the liquidity constraint dummy, log wealth, and log income from the transaction data, along with the liquidity constraint measure from the survey.

3 Estimation

In this section, I explain estimation strategy and estimation results.

3.1 Estimation Strategy

To estimate the MPC to an income shock, I run the following two-way fixed effect regression:

$$C_{it} = \alpha_i + \alpha_{tr} + \sum_j \sum_{k=a}^{b} \gamma_j^k X_{ijt}^k + \varepsilon_{it}, \tag{1}$$

where C_{it} represents the amount of outflows, a proxy for consumption, for individual i in week t; X_{ijt}^k is the income shock that takes the amount of the income ($j \in$ SCP and bonus) in week T_i if $t - T_i = k$, where T_i denotes the week in which individual i received the income; and X_{ijt}^k takes zero otherwise. Further, I denote $X_{ijt} \equiv X_{ijt}^0$. By including $k < (>)0$, I consider the effect of the income shock on consumption $|k|$ weeks before (after) the event. Coefficient γ_j^k indicates the extent to which C_{it} has changed before and after j's income shock. The lead terms for $k < 0$ are used to test the presence of the pre-trend before the income shock. I normalize the coefficient γ_j^k for $j =$SCP and $k = -1$ to zero and set $a = -9$ and $b = 9$ weeks. Two-way fixed effects α_i and α_{tr} control time-invariant heterogeneity across individuals and the effects of aggregate time-series developments such as the state of emergency declaration and the number of COVID-19 infections on aggregate consumption. More precisely, the time fixed effects are multiplied by the region fixed effects using prefecture r in which individual i lives. I estimate the equation by including two kinds of income shocks together, rather than using a single equation for each of the income shocks because it has the advantage of constraining the fixed effects at the same values for both the SCP and bonus analyses.

This regression is different from that in Kubota, Onishi, and Toyama (2021), where they take differences from the same week in the previous year for the dependent variable in order not to use the individual fixed effect because of the enormous sample size. I cluster the standard error at the individual level. The data are a balanced panel, where there are 194 weeks from January 2019 to November 2022.

Income shocks may have lagged effects on consumption (i.e., $\gamma_j^k > 0$ for $k > 0$), whereas some income shocks, particularly salary, are anticipated, yielding positive effects beforehand (i.e., $\gamma_j^k > 0$ for $k < 0$). In such a case, as illustrated by Kaplan and Violante

(2014), using the explanatory variables of X_{ijt}^k for $k \neq 0$ is important to obtain γ_j^k that can be properly interpreted as the MPC.

A bias in the average treatment effects can arise in the case when treatments occur in multiple periods and treatment effects are heterogeneous across groups or periods. While de Chaisemartin and D'Haultfœuille (2020), Callaway and Sant'Anna (2021), Sun and Abraham (2021) propose robust methods for estimating treatment effects, their methods are not directly applicable because the size of treatments (i.e., income shocks) varies so that I do not use a 0 or 1 dummy variable but X_{ijt}^k as a variable of treatment. However, I do not claim that this bias is unimportant. On the contrary, heterogeneity is important in considering the MPC. In what follows, I provide various robustness checks of estimation results.

3.2 Estimation Results of the MPC

Table 4 and Figure 2 show the estimation results. Columns (1) and (2) in the table are the cases where the dependent variable is consumption based on my definition and cash withdrawals, respectively. Figure 2 shows the change in the MPC over weeks (coefficient γ_j^k), where the horizontal axis is k before/after j's income shock.

Column (1) in Table 4 and the two left-hand panels of Figure 2 show that coefficient γ_j^0 on X_{ijt}^0 is significant at the 5% level for both SCP and bonus shocks. More precisely, the on-impact MPC is similar: 0.17 and 0.18 for SCP and bonus shocks, respectively. This suggests that average individuals spent approximately 20% of the SCP or bonus payments in the week they received it.

The size of the MPC around 0.2 suggests excess sensitivity. Based on the permanent income hypothesis and infinite horizon, an unexpected income shock increases consumption by interest rate r times the amount of SCP payments; and thus, the MPC should be only r, which is effectively zero in Japan. Based on the permanent income hypothesis and finite horizon with $r = 0$, an unexpected income shock induces the MPC of $1/T$, where T is the remaining lifetime. If T is 30 years multiplied by 52 weeks, the weekly on-impact MPC should be only 0.0006. One reason for the excess sensitivity is liquidity (precautionary savings or borrowing constraints), which is further decomposed into persistent characteristics and temporary circumstances.

The estimated size of the MPC is comparable to that obtained in early studies. For Japan, the on-impact MPC to SCP is 0.19 in Kubota, Onishi, and Toyama (2021) and

0.15 in Kaneda, Kubota, and Tanaka (2021). Baker et al. (2024) document that the MPC in response to the 2020 CARES Act stimulus payments in the U.S. is 0.14 in the first week and 0.25 in three months. A meta-analysis by Havranek and Sokolova (2020) shows that the mean MPC is 0.21, although they caution that the simple mean of the reported coefficients is not a reliable summary because of a publication bias.

The estimation results also show that the effects of the income shocks are short-lived. Coefficients γ_j^k are significant only for small k's. For the SCP shock, γ_j^k is significant only at $k = 0$, while it is significant up to $k = 4$ weeks for the income shock of bonus. As discussed in Online Appendix C, this result is robust when I use monthly frequency data, which shows that γ^k is significantly positive only for $k = 0$ month (i.e., the month of SCP). By contrast, the SCP effect lasts for around five weeks in Kubota, Onishi, and Toyama (2021) and Kaneda, Kubota, and Tanaka (2021), which use the same Mizuho bank account data and financial app data, respectively, for Japan. Baker et al. (2024) find that the 2020 CARES Act stimulus payments increase consumption for eight weeks in the U.S. using financial app data. Fagereng, Holm, and Natvik (2021) document even longer persistence for consumption responses to lottery prizes in Norway, which lasts for three years. Auclert, Rognlie and Straub (2023) find similar persistence from an Italian survey. I can consider several reasons for the transitory response in this study. Primarily, the number of SCP recipients in this study ($N = 5,282$) is considerably smaller than that of Kubota, Onishi, and Toyama (2021, $N = 2,832,537$), which decreases power in a test of a null hypothesis. Second, the COVID-19 pandemic dampened household consumption demand in 2020. In fact, I observe significantly negative γ^k for a large $k \geq 5$. Third, SCP recipients in this study are wealthier than those in previous studies, particularly because survey respondents are those who receive salary regularly. Individuals in Baker et al. (2024) consist primarily of lower- and middle-income households. However, no clear mechanism explains why this sample difference leads to different persistence.

Table 4 and Figure 2 provide a support for the parallel trend in consumption between individuals who differ in the timing of income shocks. Coefficient γ^k for negative k represents a consumption response before an income shock occurs, which is mostly insignificant.

Robustness Checks I check the robustness of the estimation results in various ways. First, I use an alternative measure of consumption for the dependent variable: cash withdrawals. The estimation results are shown in column (2) in Table 4 and the two right-hand panels of Figure 2. The on-impact responses of cash withdrawals to SCP and bonus shocks, γ_j^0, are positive and significantly different from zero. Specifically, the response of cash withdrawals to SCP payments, $\gamma_j^0 = 0.16$, is the same as the response of consumption. However, the response of cash withdrawals to bonus, $\gamma_j^0 = 0.05$, is considerably lower than the response of consumption, $\gamma_j^0 = 0.18$. In Online Appendix C, I use outflows excluding saving as the dependent variable, where I find that γ_j^0 to the bonus shock is significantly positive, although that to the SCP shock is insignificant.

Second, motivated by the local projection method developed by Jordà (2005), I run the following two-way fixed effect regression:

$$C_{it+k} = \alpha_i + \alpha_{tr} + \sum_j \gamma_j^k X_{ijt} + \omega W_{it} (+\beta C_{it-1}) + \varepsilon_{it}, \tag{2}$$

for multiple $k's$ ($k = -9, -8, \cdots, 9$) one by one, where X_{ijt} equals X_{ijt}^0 and W_{it} represents log wealth and income in period $t-1$. One benefit of using this method is that I can estimate the robustness of the estimation results by controlling consumption, wealth, and income in the previous period. For example, in the previous regression of equation (1), wealth at $t-1$ could not be controlled because it is positively correlated with the income shock at or before $t-1$ (i.e., X_{ijt}^k for $k \geq 1$), leading to a bias in the estimate of γ_j^k for $k \geq 1$. However, when using the local projection method, I can introduce wealth and C_{it-1}, which enables us to account for the effects of wealth and consumption smoothing. Figure 3 shows the consumption response to SCP and bonus, indicating the robustness of the previous estimation results. Namely, γ_j^0 is significantly positive at around 0.2. Further, it shows that controlling consumption in the previous period hardly changes the estimation results.

Online Appendix C provides further detailed estimation results. Online Appendix C provides further detailed estimation results. First, I use salary as the third type of income shock. While caution is necessary in interpreting the estimation results because salary is largely expected and persistent, I find the estimated coefficient γ_j^k for salary is 0.14, which is similar to 0.16 and 0.18 for SCP and bonus shocks, respectively. Second, I standardize variables associated with consumption and income shocks using their time means, so that coefficient γ_j^k conveys how much a 1% change in income relative to average income changes consumption, measured in percent. The estimation results reveal that on-impact γ_j^0 is significantly positive at 0.05 and 0.13 for SCP and bonus shocks, respectively, and that the effects of the income shocks are short-lived. Third, I run the regression separately for each type of income shock by using one of SCP, bonus, or salary incomes as X_{it}^k. The estimation results hardly change. Fourth, I estimate the consumption response to expected and unexpected income shocks. Because bonuses and salary are repeatedly paid, a considerable fraction of the income shocks are likely expected components. Specifically, I calculate expected and unexpected components when an income shock is positive. An expected shock is defined as an income shock in the latest period, whereas an unexpected shock is defined as the difference between the shock and the expected shock. I find that consumption responses to expected income shocks are similar to those to unexpected income shocks, which implies the possibility that households are irrational or tightly liquidity constrained. Fifth, I estimate the MPC by using different fixed effects or including week k dummy. Week k dummy is the variable that takes one for individual i in week t when an income shock occurs for individual i in week $t+k$. Sixth, I estimate the MPC using monthly frequency data rather than weekly. Because certain expenditure has a regular monthly pattern (e.g., utility bills are automatically withdrawn on the 10th of every month.), estimation on a weekly basis may generate spurious results. I confirm the robustness of the results to estimation on a monthly basis. For example, the on-impact response of consumption, γ^0, in response to SCP is 0.32, which is significant. Furthermore, I confirm that the response of consumption in the following month of SCP, γ^1, remains insignificant, indicating the transitory effects of SCP.

3.3 MPC Heterogeneity

A heterogeneity in the MPC can arise from two distinct sources: temporary circumstances and persistent characteristics, as emphasized in Jappelli and Pistaferri (2020), Gelman (2021), and Aguiar, Bils, and Boar (2023). Specifically, low wealth may be the consequence of bad luck (temporary adverse income shock) or impatience (persistent characteristics). Thus, even if low wealth is associated with a high MPC, its fundamental reason is unclear. To distinguish these two sources, I include both survey and time-varying transaction information in one equation and compare which factor matters. Specifically, individual i's characteristics obtained from the survey, such as time discount rate and risk aversion, can be linked to persistent characteristics, whereas the time-varying log wealth and liquidity constraint dummy can be linked to temporary circumstances.

To examine MPC heterogeneity, first, I divide data into groups and run the benchmark regression (1) for each group. Groups are classified based on the liquidity constraint dummy, log wealth, liquidity constraint (direct measure from the survey), age, risk aversion, and discount rate. Figure 4 depicts estimated coefficient γ^0 in each regression, suggesting that the liquidity constraint dummy and log wealth, both from the transaction data, have a clear association with γ^0. In other words, individuals with ample liquidity have a lower MPC. Other variables, all of which are based on the survey data, have a relatively weak association with γ^0; however, among them, the discount rate appears to be positively correlated with γ^0, suggesting that myopic individuals tend to have a higher MPC.

Next, I investigate MPC heterogeneity by running the following two-way fixed effect regression with cross terms:

$$C_{it} = \alpha_i + \alpha_{tr} + \sum_j \sum_{k=a}^{b} \gamma_j^k X_{ijt}^k + \sum_j \delta_j X_{ijt}^0 \times Z_{it} + \varepsilon_{it}, \tag{3}$$

where Z_{it} represents individual i's characteristics. The cross term of $X_{ijt}^0 \times Z_{it}$ captures how the on-impact MPC to j's income shock ($j \in$ SCP and bonus) depends on Z_{it}, where Z_{it} represents the vector of variables related to individual i's characteristics obtained from the survey and Mizuho Bank transaction data (log wealth and a liquidity constraint dummy in the previous period). I do not include income in the regression to avoid multicollinearity. Additionally, the non-cross terms of Z_{it} are excluded, as personal characteristics obtained from the survey—such as discount rate and risk aversion—are time invariant and embedded in individual fixed effects α_i. Moreover, liquidity measures, such as log wealth, are also excluded, because they are correlated with X_{ijt}^k for $k \geq 1$, which could generate a bias in the estimate of γ_j^k for $k \geq 1$. I use the unweighted average of discount rates of one week, one year, and ten years as the discount rate to save the number of regressors. In this regression, I explore heterogeneity in only the on-impact MPC (i.e., $k = 0$), not a dynamic path in heterogeneity, because of simplicity and short-lived income effects on consumption.

Table 5 presents the estimation results. To conserve space, I omit the coefficients of income shock X_{ijt}^k (i.e., γ_j^k), but focus on the cross terms (i.e., δ_j). In columns (1) to (4), I progressively introduce variables that are interacted with the income shock. In column (1), I use the liquidity constraint dummy, showing that δ_j is significantly positive for both SCP and bonus shocks. Recall that this liquidity constraint measure, following the definition of Kubota, Onishi, and Toyama (2021), takes the value of one if the individual's end-of-month wealth in the previous period is below their monthly income. The positive coefficient suggests that liquidity constrained individuals tend to exhibit a higher MPC than those who are not liquidity constrained. This finding is consistent with Kubota, Onishi, and Toyama's (2021) observations and numerous empirical studies.

Two measures of liquidity constraint—the liquidity constraint dummy and log wealth—are interacted with the income shock in column (2). The estimation results reveal that the cross-term coefficients of log wealth are significantly negative at the 10% level for both SCP and bonus shocks, whereas the liquidity constraint dummy is only significantly positive for bonus shocks. These two measures of liquidity constraint are highly correlated, as evidenced by the substantial increase in the standard error on the liquidity constraint dummy when log wealth is included, a finding also documented in Online Appendix B. The significantly negative coefficients on log wealth suggest that the balance of deposits, primarily comprising liquid demand deposits, plays a crucial role in determining the magnitude of the MPC. In contrast, the insignificant coefficient on the liquidity constraint dummy for the SCP payment may reflect the abnormal economic environment resulting from the COVID-19 pandemic.

Demographic variables obtained from the survey are incorporated in the regression, which is reported in column (3). The estimation results indicate that the cross-term coefficients of age are significantly positive for both SCP and bonus shocks, whereas those of log wealth are significantly negative. This suggests that elderly individuals tend to exhibit a higher MPC, aligning with a simple life cycle model where the elderly typically save less. It should be noted that aged individuals in this study are still under 60 years old and regular salary recipients, having greater wealth and income, which likely diminishes the cross-term coefficient with age unless liquidity measures are controlled. In this context, multivariate regression like this proves effective in isolating the age effect on the MPC. Furthermore, the table illustrates that the cross-term coefficients of the male dummy and education are insignificant.

In column (4), I further include risk-aversion and discount-rate measures obtained from the survey. The estimation results reveal that the cross-term coefficients related to risk aversion and discount rates are positive and significant when the income shock is a bonus, although they are insignificant when the income shock is SCP payments. This finding for the bonus implies that the MPC increases as individuals are more risk averse or myopic. It is intuitive to understand that myopic individuals have a higher MPC because they have a greater incentive to increase utility in the current period. A higher risk aversion increases the MPC, considering that such individuals dislike uncertainty about investment returns in the future and thus are inclined to consume today rather than save. However, it is worth noting that risk aversion may decrease, rather than increase, the MPC if it is combined with precautionary saving.

Column (4) also demonstrates that even after controlling for a variety of personal characteristics obtained from the survey, the cross-term coefficients of liquidity measures remain significant. This implies that temporary circumstances influence the MPC. However, persistent characteristics also play a role, as evidenced by the significant cross-term coefficients of age, risk aversion, and discount rates, particularly when the income shock is a bonus.

Magnitudes of Contribution to the MPC In the regression presented in Table 5, mainly the following five variables are significantly correlated with the MPC: the liquidity constraint dummy, log wealth, age, risk aversion (quantitative), and time discount rate (quantitative). I calculate how much these variables contribute to variations in the MPC based on the estimation result in the case of SCP and bonus income shocks reported in column (5). Because the coefficient of X^0_{it}, which corresponds to the MPC, is given by $\gamma^0 + \delta Z_{it}$ in equation (3), the magnitude of the contribution of each variable Z_{it} to the MPC can be calculated by the estimate of δ multiplied by the standard deviation of Z_{it} given by Tables 1 and 2.

The result is shown in Table 6. One standard deviation increase in log wealth decreases the MPC to SCP and bonus shocks by 0.15 and 0.04, respectively (i.e., 15 and 4 percentage points). This suggests that individuals with a wealth of 9.8 million JPY tend to consume 15,000 JPY and 4,000 JPY less in response to 100,000 JPY SCP and bonus payments, respectively, than individuals with a wealth of 1.3 million JPY. One standard deviation increase in age increases the MPC to SCP shocks by 0.074. That is, given that average individuals consume 20,000 JPY in response to 100,000 JPY of SCP payments, an individual 9.9 years older tends to consume 7,400 JPY more. One standard deviation increase in risk aversion and discount rate increases the MPC to bonus shocks by 0.020 and 0.053, respectively. That is, while the absolute risk aversion σ in this study ranges from -4.5 and 0.891, its increase by 0.637 is accompanied by a 2,000 JPY increase in consumption in response to bonus payments of 100,000 JPY. A more myopic individual who discounts the future by 19.9% more tends to consume 5,300 JPY more in response to bonus payments of 100,000 JPY. Considering that the estimated MPC is approximately

0.2 (i.e., 20%), the magnitudes of contribution are sizable.

Robustness Checks I again conduct various robustness checks. First, I use cash withdrawals as the dependent variable. Column (5) in Table 5 presents the estimation results. The cross-term coefficients on log wealth are significantly negative for both SCP and bonus shocks, suggesting the influence of temporary circumstances on the MPC again. Additionally, the cross-term coefficients on age and discount rates are significantly positive when the income shock is SCP payments, consistent with the results obtained when using consumption as the dependent variable. However, there are notable differences. When the income shock comes from a bonus, the coefficients on age, risk aversion, and discount rates become insignificant. In contrast, when the income shock is the SCP payment, the coefficient on discount rates becomes positive and significant. This indicates that myopic individuals tend to spend more in response to an income shock, though the nature of the income shock shifts from a bonus to the SCP. The reason for this difference is unclear, but it is important to consider that the SCP payment was distributed during the abnormal economic conditions of the COVID-19 pandemic, when online spending was preferred over cash transactions. This shift in consumer behavior may have heightened the sensitivity of discount rates to the use of cash. In Online Appendix C, I also show the estimation results when the dependent variable is outflows excluding saving, which demonstrates that the liquidity constraint dummy, risk aversion, and discount rates are significant when the income shock is a bonus, as I found before.

Second, I examine MPC heterogeneity using the local projection method, given by

$$C_{it+k} = \alpha_i + \alpha_{tr} + \sum_j \gamma_j^k X_{ijt} + \sum_j \delta_j^k X_{ijt} \times Z_{it} + \omega W_{it} + \varepsilon_{it}, \tag{4}$$

where δ_j^k represents how the MPC in week k after an income shock j depends on Z_{it}. By running the above regression for multiple $k's$, I can study dynamic dependence of the MPC on Z_{it}. Figure 5 shows the estimation results of δ^k, where the horizontal and vertical axes are k and t-value of δ^k, respectively, and the dashed line (± 1.96) indicates the 95% confidence intervals. Coefficient δ_j^k is transformed into t-values for readability. The figure indicates that the previous estimation results on heterogeneity is more or less robust. That is, the MPC tends to increase with age (for SCP), risk aversion (for both SCP and bonus), and discount rate (for bonus) when $k = 0$ or 1, whereas it tends to decrease with log wealth (for both SCP and bonus). Owing to the fact that the income shock effect is transitory, δ_j^k for positive $k's$ is mostly insignificant.

Online Appendix C.2 provides further detailed estimation results. First, I standardize variables associated with consumption and income shocks using their time means. The estimation results are robust to this change, in that cross-term coefficients associated with liquidity measures, risk aversion, and discount rates are significant when the income shock is a bonus. Second, I run the regression separately for each type of income shock by using one of SCP, bonus, or salary incomes as X_{it}^{k}, which also suggests the robustness of the results. Third, I run the regression without controlling for liquidity based on the transaction data. As expected, age becomes insignificant at the 5% level, although it is significant at the 10% level. Fourth, I run the regression for the income shock of salary. Fifth, I separate income shocks for bonus and salary, X_{it}^{0}, into expected and unexpected components (denoted by $X_{it,expected}^{0}$ and $X_{it,unexpected}^{0}$, respectively), and include the cross terms of $X_{it,expected}^{0} \times Z_{it}$ and $X_{it,unexpected}^{0} \times Z_{it}$ in the regression. I find that both expected and unexpected components of income shocks tend to yield positive coefficients on the cross terms with risk aversion and discount rate and negative coefficients on the cross term with log wealth. Sixth, I use more detailed explanatory variables, because the surveyed variables Z_t are not limited to those used in the previous analysis. Further, to save a number of regressors, I run univariate regression by using the cross term of X_{it}^{0} and one of the surveyed variables in separate regressions. Finally, I run the regression on a monthly basis, which shows that discount rate and liquidity (log wealth and/or liquidity constraint dummy) are significantly associated with the MPC.

Discussions The main takeaway from this heterogeneity analysis is as follows. First, both persistent characteristics and temporary circumstances are important to explain MPC heterogeneity, particularly in response to the bonus income shock. On the one hand, individuals' persistent characteristics, specifically risk aversion and time discount rates, are associated with the MPC. On the other hand, the MPC is associated with individuals' time-varying financial situations, namely whether they are wealthy or liquidity constrained. In this regard, this study is consistent with Jappelli and Pistaferri (2020) and Gelman (2021).

Second, many personal characteristics are not strong predictors of MPC heterogeneity. Neither gender nor education seems to matter for the MPC. As detailed in Online Appendix C, I find that even the direct measure of the liquidity constraint—obtained from the survey by asking whether respondents can pay the same amount of their household income by withdrawing their savings, selling their assets, or borrowing from financial institutions, friends, or relatives—is insignificant. An exception is age, which appears to influence the MPC positively. Consequently, the R squared in the regression of heterogeneity is far below one, and a large fraction of MPC heterogeneity remains unexplained, which echoes the findings by Lewis, Melcangi, and Pilossoph (2021).

Last but not least, it should be noted that no significance does not mean that personal characteristics have no importance as the source of MPC heterogeneity. Particularly, the number of individuals may be insufficient and the observation period from 2019 to 2022 may be too short to have time-series variations in log wealth or the liquidity constraint dummy. Meanwhile, we should also be aware that the estimation results may be subject to the multiple testing problem. As the number of tests increases, it becomes more likely that the null hypothesis will be rejected at some point, even if the null hypothesis is correct.

4 Concluding Remarks

In this study, I analyzed the sources of heterogeneity in the magnitude of the MPC by combining transaction data from one of Japan's megabanks and survey data of its bank account holders. The first remaining issue is the endogenous nature of personal characteristics. In this study, I analyzed personal characteristics obtained through the survey, such as time discount rates, as if they were exogenous. However, these individual characteristics are not only generic, but can also be acquired and changed, and responses to the survey may also be affected by the short-term economic environment. Second, various factors other than those considered in this study may contribute to the heterogeneity in the MPC. Consequently, it is too early to draw conclusions about the magnitude or relative magnitude of the two factors, temporary circumstances and persistent characteristics. It is necessary to continue the survey to examine how surveyed personal characteristics change or to conduct randomized controlled trials to examine how the MPC changes when individuals' environments are randomly changed.

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Table 1: Descriptive Statistics of the Transaction Data as of 2020

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Amount of consumption	5,282	4,489,489	5,377,928	1,834,046	3,321,536	5,515,031
Amount of outflows exc saving	5,282	9,167,932	18,885,658	2,956,058	5,282,236	9,074,235
Amount of cash withdrawals	5,282	1,784,225	2,191,529	463,000	1,241,605	2,396,922
Amount of saving	5,282	568,710	2,163,784	0	0	242,202.8
Amount of direct debit	5,282	2,253,895	2,112,501	712,794	1,798,334	3,183,422
Amount of card payments in direct debit	5,282	1,122,584	1,378,400	48,746.2	697,003	1,698,958
Amount of debit card payments	5,282	5,349	58,961	0	0	0
Amount of transfers	5,282	1,577,331	4,267,977	0	226,100	1,460,169
SCP dummy	5,282	0.466	0.506	0	0	1
Amount of SCP	5,282	113,877	150,529	0	0	200,000
Amount of bonus	5,282	734,883	968,250	0	354,749	1,207,858
Amount of salary	5,282	3,391,207	2,744,588	1,706,816	3,067,808	4,507,992
Log wealth	5,237	7.201	1.987	5.938	7.373	8.719
Log income	5,237	7.798	1.922	7.765	8.324	8.701
Liquidity constraint dummy	5,237	0.186	0.336	0	0	0.231
Age	5,237	48.185	9.906	40.923	49.923	55.923

Note: The table provides a summary of actual transactions in 2020 for the individuals who answered the survey. The monetary unit is Japanese yen. Consumption equals the sum of card payments in direct debit, debit card payments, transfers, and cash withdrawals. Saving represents outflows associated with repayments, securities, and installments. Wealth and income are expressed as the mean of the log of one plus total deposits and annual income, respectively, in thousand yen. The SCP dummy takes one if an individual receives an SCP payment. The liquidity constraint dummy takes one if the end-of-month wealth is below the annual income divided by 12. I do not report the maximum or minimum values to maintain anonymity.

Table 2: Descriptive Statistics of the Survey Data

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Male	5,248	0.645	0.479	0.000	0.000	1.000	1.000	1.000
Own house	5,282	0.679	0.467	0	0	1	1	1
Education	5,282	4.543	1.214	1	4	5	5	7
Risk aversion	5,282	0.693	0.637	−4.500	0.784	0.879	0.891	0.891
Discount rate 1 week	5,214	2.311	11.529	0.001	0.010	0.100	1.000	100.000
Discont rate 1 year	5,188	7.653	21.005	0.001	0.100	1.000	10.000	100.000
Discount rate 10 years	5,079	29.441	40.745	0.001	1.000	10.000	10.000	100.000
Liquidity constraint	5,156	1.369	0.712	1.000	1.000	1.000	2.000	4.000
Risk aversion A (direct)	5,255	3.152	1.136	1.000	2.000	3.000	4.000	5.000
Risk aversion B (direct)	5,208	3.206	1.089	1.000	2.000	3.000	4.000	5.000
Discount rate (direct, inverse)	5,164	2.754	0.760	1.000	2.000	3.000	3.000	4.000
Inflation perception	5,123	8.525	7.597	−5.000	5.000	10.000	10.000	50.000
Inflation expectation	5,001	8.138	8.878	−5.000	5.000	5.000	10.000	50.000
Wage increase expectation	4,958	0.975	6.282	−5.000	0.000	0.000	1.000	50.000
Fiscal debt concern (inverse)	5,282	2.257	1.209	1	1	2	3	5
Discount rate	5,073	13.063	19.591	0.001	0.400	3.700	10.000	100.000

Note: The male dummy takes one for male and zero for female. The own house dummy takes one if an individual owns a house and zero otherwise. The discount rate in the last row is the unweighted average of discount rates for one week, one year, and ten years. See Section 2.1 and Appendix A for details.

Table 3: Cross Sectional Relationships between Wealth/Income (Transaction Data) and Personal Characteristics (Survey)

	Dependent variables		
	(1)	(2)	(3)
	Log wealth	Log wealth	Log income
Explanatory variables			
(Intercept)	3.0181***	1.418***	6.1931***
	(0.251)	(0.275)	(0.262)
Age	0.0289***	0.0239***	0.0193***
	(0.003)	(0.003)	(0.004)
Male	-0.021	-0.1984**	0.687***
	(0.066)	(0.065)	(0.071)
Education	0.3786***	0.3518***	0.1037***
	(0.027)	(0.026)	(0.027)
Discount rate 1 week (quant)	0.0049	0.0042	0.0028
	(0.0037)	(0.0037)	(0.0032)
Discount rate 1 year (quant)	-0.0043**	-0.0038	-0.0017
	(0.0021)	(0.0020)	(0.0020)
Discount rate 10 years (quant)	-0.0025**	-0.0022**	-0.0008
	(0.0008)	(0.0008)	(0.0008)
Discount rate (direct, inverse)	0.327***	0.3221***	0.019
	(0.041)	(0.040)	(0.041)
Risk aversion (quant)	0.057	0.056	0.005
	(0.047)	(0.047)	(0.044)
Risk aversion A (direct)	0.0714**	0.0816**	-0.040
	(0.036)	(0.035)	(0.036)
Risk aversion B (direct)	0.023	0.028	-0.020
	(0.037)	(0.036)	(0.038)
Inflation perception	-0.0171***	-0.0132**	-0.0153**
	(0.005)	(0.005)	(0.005)
Inflation expectation	-0.001	-0.001	0.001
	(0.004)	(0.004)	(0.004)
Wage increase expectation	-0.009	-0.008	-0.005
	(0.005)	(0.005)	(0.006)
Log income		0.2584***	
		(0.019)	
No. of observations	4,424	4,424	4,424
R^2	0.099	0.163	0.053

Note: Figures in parentheses indicate standard errors clustered at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: MPC Estimation Results

	(1)		(2)	
Dependent variable	Consumption		Cash withdrawals	
Income shock	SCP	Bonus	SCP	Bonus
Explanatory variables				
Income^{-9}	-0.022	0.001	-0.0275***	0.000
	(0.043)	(0.005)	(0.005)	(0.002)
Income^{-8}	-0.022	-0.007*	-0.0236***	-0.003**
	(0.068)	(0.004)	(0.008)	(0.001)
Income^{-7}	-0.007	-0.008**	-0.010	0.000
	(0.043)	(0.004)	(0.011)	(0.001)
Income^{-6}	-0.016	-0.0138***	0.009	-0.0027**
	(0.030)	(0.003)	(0.015)	(0.001)
Income^{-5}	-0.0858***	-0.001	-0.002	-0.001
	(0.018)	(0.004)	(0.012)	(0.001)
Income^{-4}	0.042	-0.006	-0.0176*	-0.0041***
	(0.067)	(0.004)	(0.011)	(0.002)
Income^{-3}	-0.0797***	-0.0136***	-0.010	-0.0032***
	(0.016)	(0.003)	(0.009)	(0.001)
Income^{-2}	-0.019	-0.0072**	0.002	0.001
	(0.043)	(0.003)	(0.011)	(0.001)
Income^{-1}		-0.003		0.003
		(0.005)		(0.002)
Income	0.1668***	0.1842***	0.1636***	0.052***
	(0.023)	(0.019)	(0.016)	(0.004)
Income^{1}	0.017	0.0754***	0.0696***	0.0253***
	(0.019)	(0.017)	(0.012)	(0.003)
Income^{2}	-0.023	0.0304***	0.0201*	0.016***
	(0.022)	(0.005)	(0.010)	(0.002)
Income^{3}	-0.012	0.0116*	0.002	0.0059***
	(0.041)	(0.007)	(0.008)	(0.002)
Income^{4}	0.006	0.0152**	0.006	0.002
	(0.031)	(0.007)	(0.009)	(0.002)
Income^{5}	-0.0672***	0.002	-0.003	0.000
	(0.018)	(0.004)	(0.009)	(0.002)
Income^{6}	-0.045	0.004	-0.012	0.002
	(0.028)	(0.005)	(0.015)	(0.002)
Income^{7}	-0.0812***	0.012	-0.0193***	0.003
	(0.017)	(0.008)	(0.006)	(0.002)
Income^{8}	-0.019	0.0092*	-0.0136**	0.000
	(0.029)	(0.005)	(0.007)	(0.001)
Income^{9}	-0.0618***	0.002	-0.0226***	-0.0042***
	(0.022)	(0.005)	(0.006)	(0.001)
Fixed effects	individual, week*prefecture			
No. of observations	974,298		974,298	
No. of individuals	5,239		5,239	
R^2	0.048		0.054	

Note: Consumption (dependent variable) equals the sum of card payments in direct debit, debit card payments, transfers, and cash withdrawals. Figures in parentheses indicate standard errors clustered at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Estimation Results of MPC Heterogeneity

	(1)		(2)	
Dependent variable	Consumption		Consumption	
Income shock	SCP	Bonus	SCP	Bonus
Variables interacted with the income shock				
Bank transaction data				
Liquidity constraint dummy	0.1224**	0.2297***	-0.0889	0.1513***
	(0.049)	(0.036)	(0.072)	(0.046)
Log wealth			-0.0673***	-0.0221*
			(0.017)	(0.013)
Fixed effects	individual, week*prefecture			
No. of observations	974,298		974,298	
No. of individuals	5,239		5,239	
R^2	0.049		0.049	

	(3)		(4)		(5)	
Dependent variable	Consumption		Consumption		Cash withdrawals	
Income shock	SCP	Bonus	SCP	Bonus	SCP	Bonus
Variables interacted with the income shock						
Bank transaction data						
Liquidity constraint dummy	-0.089	0.1508***	-0.094	0.159***	0.054	0.0494***
	(0.071)	(0.047)	(0.071)	(0.047)	(0.057)	(0.015)
Log wealth	-0.0747***	-0.025**	-0.0763***	-0.0204*	-0.0307**	-0.0197***
	(0.016)	(0.011)	(0.017)	(0.012)	(0.013)	(0.002)
Survey data						
Age	0.0078***	0.003**	0.0075***	0.0024*	0.0072***	0.0005
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.0004)
Male	0.017	-0.074	-0.002	-0.066	0.040	-0.005
	(0.056)	(0.080)	(0.057)	(0.075)	(0.037)	(0.007)
Education	0.012	-0.019	0.014	-0.022	0.009	-0.0066*
	(0.016)	(0.014)	(0.017)	(0.014)	(0.012)	(0.004)
Risk aversion (quant)			-0.042	0.031**	-0.046	0.007
			(0.037)	(0.013)	(0.030)	(0.005)
Discount rate (quant)			0.0008	0.0027**	0.0016**	-0.00003
			(0.0009)	(0.0011)	(0.0007)	(0.00019)
Fixed effects	individual, week*prefecture					
No. of observations	967,940		930,554		930,554	
No. of individuals	5,205		5,004		5,004	
R^2	0.049		0.049		0.056	

Note: Figures in parentheses indicate standard errors clustered at the individual level. To conserve space, I show only the coefficients of cross terms with income shock X_{ijt}^k. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Magnitudes of Contribution to the MPC

	SCP	Bonus
Liquidity constraint dummy	–	0.053
Log wealth	−0.152	−0.041
Age	0.074	0.024
Risk aversion (quant)	–	0.020
Discount rate (quant)	–	0.053

Note: The magnitude of the contribution of each variable to the MPC is calculated by the cross-term coefficient (obtained from column (4) in Table 5) multiplied by its standard deviation.

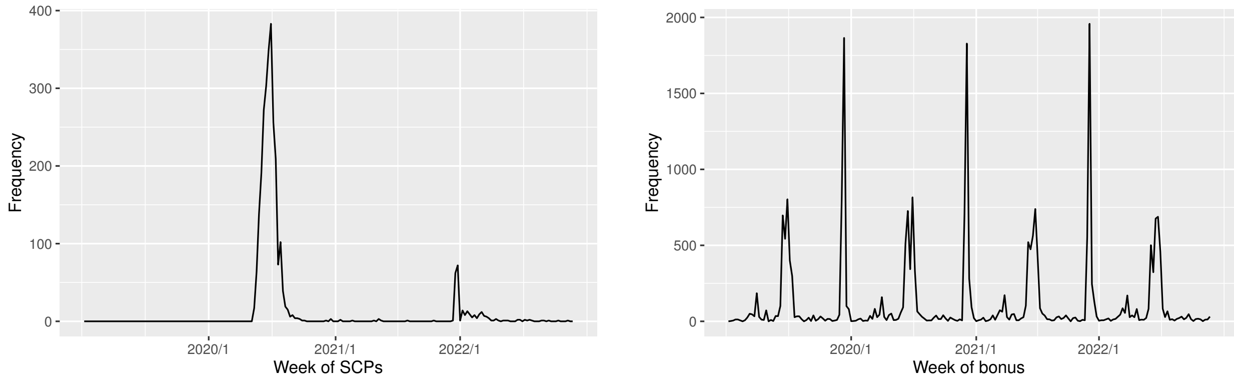

Figure 1: Timing of Income Shocks: SCP (left) and Bonus (right)

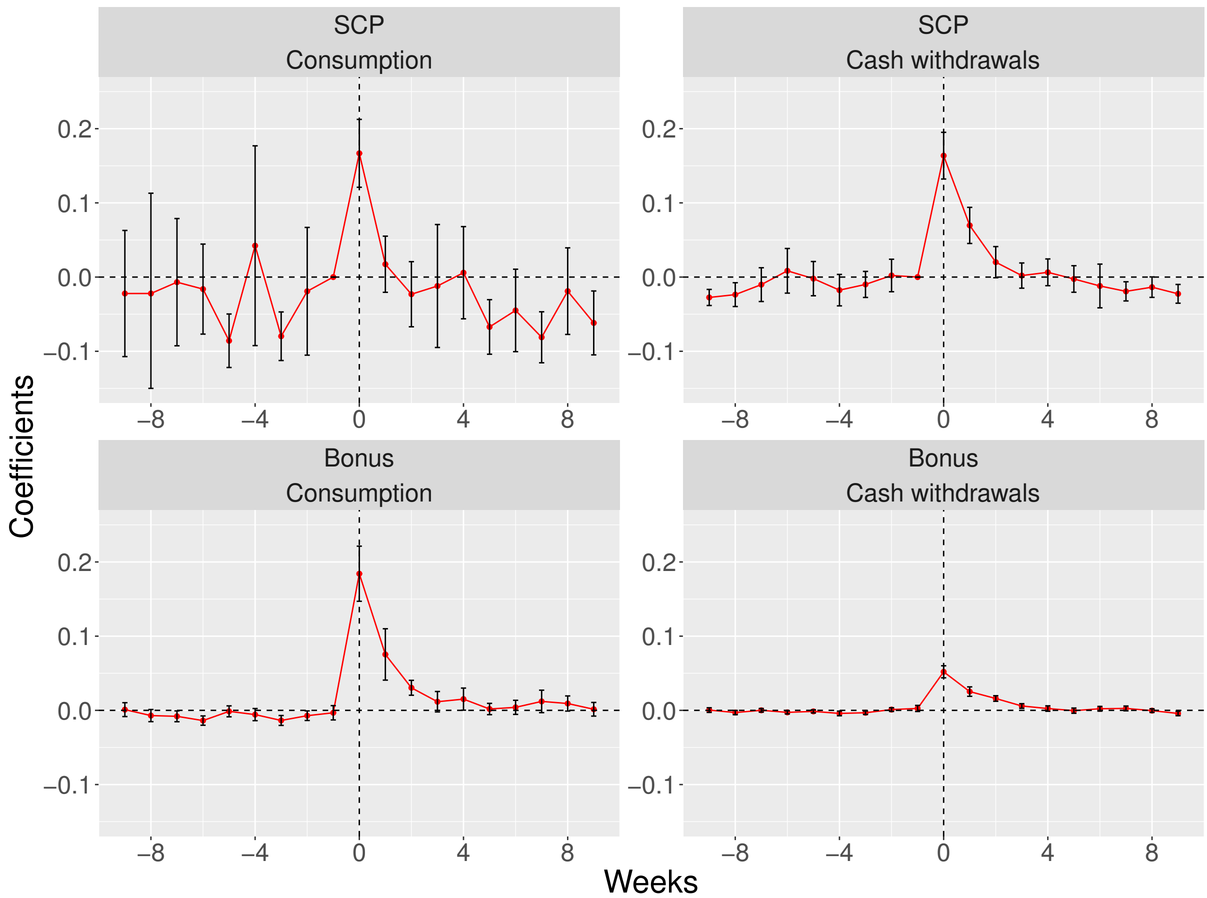

Figure 2: Consumption Responses to Income Shocks

Note: The figure shows estimated coefficients γ^k for $k = -9, -8, \cdots, 8, 9$, which suggests consumption responses in week $|k|$ before/after income shocks. Bars indicate 95% confidence intervals.

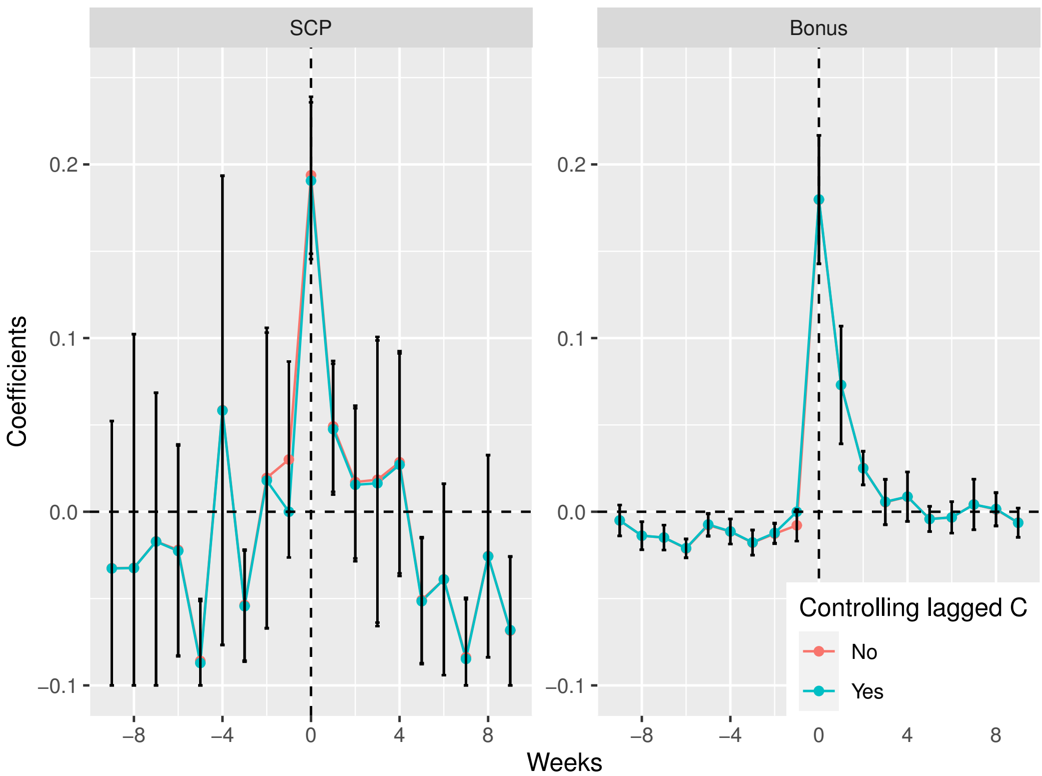

Figure 3: Consumption Responses to Income Shocks Based on Local Projection

Note: The figure shows estimated coefficients γ^k for $k = -9, -8, \cdots, 8, 9$, which suggests consumption responses in week $|k|$ before/after income shocks. Bars indicate 95% confidence intervals.

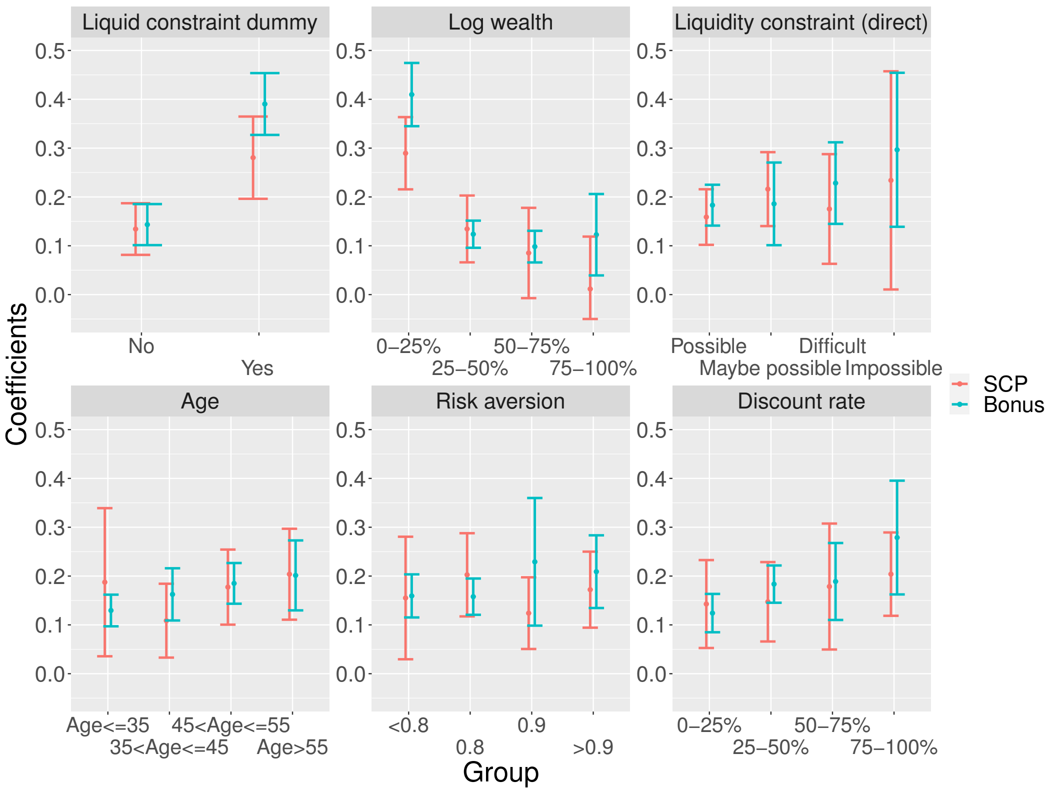

Figure 4: Consumption Responses to Income Shocks by Groups

Note: The figure shows estimated coefficient γ^0. Bars indicate 95% confidence intervals. I divide data into two groups according to the variable shown as the title of each panel.

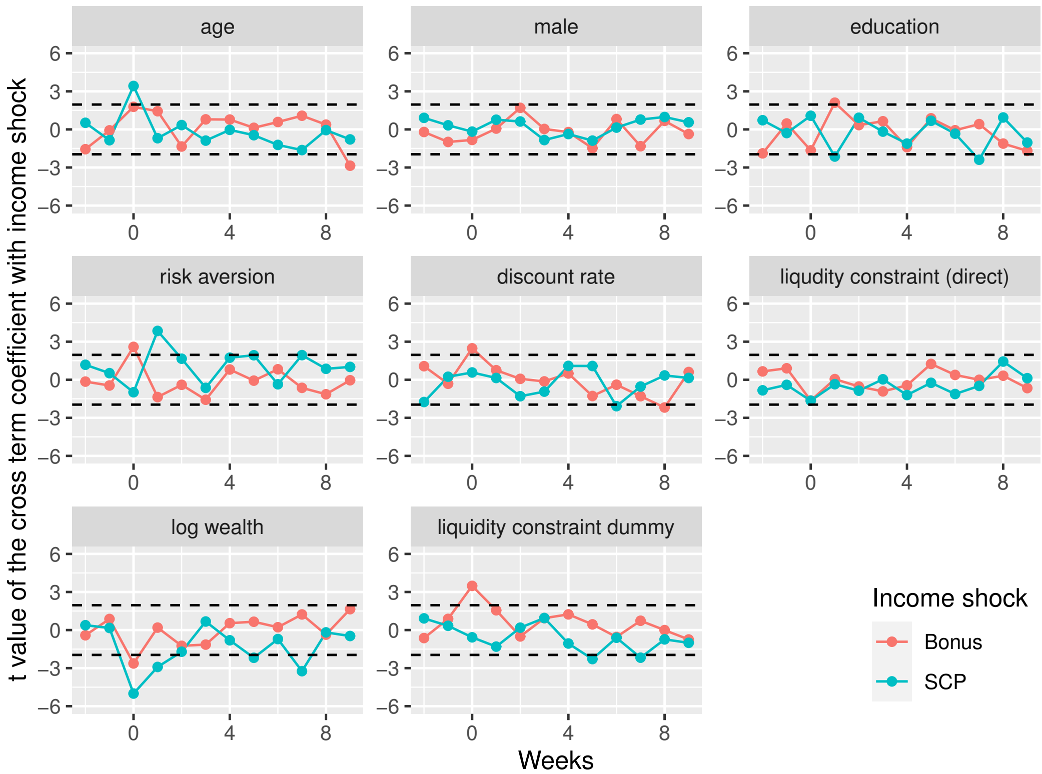

Figure 5: Consumption Response Heterogeneity: t-values of Cross Term Coefficients Based on Local Projection

Note: The figure shows the t-values of estimated coefficients δ^k (cross-term coefficients with income shocks) for $k = -2, -1, \cdots, 8, 9$. The dashed line indicate 95% confidence intervals.