Consumption Response to Anticipated Income Changes: Evidence from the Magnitude Effect*

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Abstract

Using newly constructed individual-level data from the Bank of Korea's household debt database, we study how consumers respond to anticipated income changes over time, and how their consumption responses vary depending on the magnitude of income changes. We find that consumption peaks in the quarter of anticipated income changes, with an average spending of 18 cents per dollar. Our results highlight significant size-dependent spending responses, indicating a notable deviation from consumption-smoothing behavior for smaller income changes. Notably, this pattern remains consistent regardless of liquidity constraints. These results have important implications for predicting consumption responses to government interventions.

JEL Classification: D12, E21, G51

Keywords: Anticipated income changes, Consumption, Heterogeneity

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1 Introduction

Do households adjust their consumption in response to anticipated income changes? If so, how do these adjustments vary with the magnitude of anticipated income changes, and which households are most responsive to such fluctuations? These questions are crucial to evaluate the effectiveness of policies with predictable components and to understand the macroeconomic implications on economic growth. Many policies such as government transfers, tax rebates, and automatic stabilizers, are designed with predictable elements that accommodate different income levels, adjusting payments based on individual attributes.[1] Determining the most effective payment amounts and assessing their economic impact continues to pose a significant challenge for policymakers.

The life-cycle permanent income hypothesis (LCPIH), a standard model of intertemporal allocation, suggests that agents base consumption decisions on expected future income, implying that consumption growth remains unaffected by predictable income changes (Jappelli and Pistaferri, 2010; Fuchs-Schündeln and Hassan, 2016). Violations of this theory, known as excess sensitivity, have inspired a large and growing literature, with numerous studies presenting empirical evidence that contradicts LCPIH by showing that household consumption does react to anticipated income changes (Agarwal, Liu and Souleles, 2007; Shapiro and Slemrod, 2009; Kueng, 2018; Coibion, Gorodnichenko and Weber, 2020).

In seeking to understand these deviations, the existing literature emphasizes the significance of liquidity constraints, suggesting that a lack of available resources can alter spending decisions ahead of expected income variations (Carroll, 1997; Parker et al., 2013; Kaplan and Violante, 2014; Baker et al., 2020). Another strand of literature highlights the importance of mental accounting in consumption-smoothing behavior, as highlighted by Baugh et al. (2021) and Graham and McDowall (2024), and further examines the role of spending on durable goods (Beraja and Zorzi, 2024). In contrast, Scholnick (2013) suggests that the magnitude of expected income changes might play a significant role in such deviations. Despite thorough exploration of these dynamics, investigations into how changes in the size of anticipated income affect consumption responses are limited, often restricted by the reliance on datasets with small sample sizes and a lack of details on household characteristics.[2]

[1]The 2001 tax rebate amounted to $38 billion, or $500 per person, whereas the 2008 and 2020 stimulus payments increased to $96 billion ($900 per person, 0.7 percent of GDP) and $803 billion ($1,200 per person, 4 percent of GDP), respectively, determined by eligibility based on income.

[2]Scholnick (2013) examines 147 individuals to study the impact of predictable income changes following

Our main contribution lies in analyzing the consumption response to anticipated changes in income of various magnitudes. First, we utilize a novel individual-level dataset to examine the variability in excess sensitivity across multiple dimensions. By employing detailed micro-level data and a substantially larger sample size than previous studies, we find that the spending sensitivity varies significantly depending on the magnitude of anticipated income changes. This variation remains consistent across individuals with different characteristics such as demographic features, income, and liquidity constraints. Second, we provide possible theoretical explanations for the observed heterogeneity in excess sensitivity. Within this framework, we quantify the welfare costs associated with deviations from optimal consumption decisions linked to different magnitudes of anticipated income changes. Lastly, we explore the policy implications of these magnitude effects by reassessing alternative fiscal policies in light of our findings.

The anticipated changes in income are examined within the context of a natural experiment, aligning with the methodologies of Stephens Jr (2008) and related studies.[3] In this setting, individuals expect an increase in discretionary income upon completing their final car loan payment. Auto loans follow a fixed repayment schedule with predetermined amounts over a set duration, leading to a rise in discretionary income once the final payment is made. Considering individuals are aware of both the amount and timing of the payment well in advance of the loan's completion, we argue that completing a long-term financial obligation is perceived as a predictable financial gain, similar to having more disposable income. Our empirical analysis reveals that anticipated income changes vary from minor to substantial, both in absolute and relative terms, among individuals of varying ages, income, and liquidity positions. This variation, in contrast to the typically fixed amount of a fiscal stimulus check, offers insights into a range of responses that are crucial to developing policies with anticipated components.

Our study employs longitudinal panel data sourced from the Bank of Korea's household debt database spanning from 2012 to 2016. This dataset includes de-identified data covering various factors such as income, credit activities, debt structure, consumption expenditure, and demographic

final mortgage payments on consumption-smoothing, finding that the magnitude mainly drives excess sensitivity. Beraja and Zorzi (2024) find that larger checks lead to lower spending, similar to our findings, and explore this through a model emphasizing durable spending and size-dependent adjustments.

[3] Other studies have pursued similar approaches, employing various identification strategies to examine predictable income changes. Examples include investigations into final mortgage payments (Scholnick, 2013), Alaska Permanent Fund (Hsieh, 2003; Kueng, 2018), and exhaustion of unemployment insurance benefits (Ganong and Noel, 2019).

details. Leveraging these comprehensive data sources, we aim to analyze variations in excess sensitivity, offering a methodological improvement over existing studies. First, it meticulously tracks loan details—start and end dates, payment amounts, and loan durations—allowing for clear identification of predictable income changes post-car loan repayment as a source of predictable increase in one's discretionary income. Next, it stands out for its high reliability, accuracy, and national representativeness. The data set uses a stratified random sample representing 2.4 percent of the total population, equivalent to one million individuals, ensuring proportional representation in various demographic groups to improve national coverage. Furthermore, consumption expenditure is measured through financial transactions from all issuing financial institutions within the country. This captures approximately 85 percent of total consumption, providing a reliable proxy for overall expenditure. Our analysis focuses on a subsample of nearly 70,000 observations of individuals expecting an increase in disposable income, and we find that the distribution of income and consumption patterns in our subsample closely mirrors that of the stratified sample.

We measure excess sensitivity by examining the dynamics of consumption over time and the variation in consumption responses to different magnitudes of anticipated income changes. To quantify consumption dynamics, we employ a basic estimation method that regresses consumption expenditure on distributed leads and lags linked to expected income changes following the final car loan payment. Recognizing that our data reflects spending rather than overall consumption, we refer to our estimated coefficients as measures of the marginal propensities to consume (MPC). We further investigate how the magnitude of anticipated income changes affects the heterogeneity of consumption responses using parametric regression analysis. In particular, we assess spending adjustments based on three measures: the absolute size of anticipated income changes following the final car loan payment, the payment size relative to quarterly income, and the payment size relative to typical quarterly consumption. This framework allows us to investigate how both absolute and relative income changes influence consumption adjustments.

Our main empirical findings show that, on average, people spend around 18 percent of their predictable income changes on consumption, aligning with the range observed in previous studies.[4] Consumption peaks in the quarter following the final car loan payment, which is the period of

[4]Numerous studies have found that the MPC out of predictable income changes, such as tax rebates and fiscal stimulus payments, ranges from 0.12 to 0.43 (Shapiro and Slemrod, 2009; Parker et al., 2013; Misra and Surico, 2014; Kueng, 2018; Coibion, Gorodnichenko and Weber, 2020). For further details on the literature review, refer to Appendix A.

expected increase in discretionary income. It then sharply declines to baseline levels, suggesting no anticipatory adjustments in consumption prior to the income shift. Our analysis also reveals the evidence behind the size-dependent MPC. Consumption expenditure consistently declines as the size of the anticipated income change increases, indicating that the MPC is influenced by both the absolute and relative magnitude of the income change. Individuals in the lowest tercile of the anticipated income change distribution exhibit the most significant consumption response, spending 76 cents for every dollar of the absolute change, compared to others experiencing predictable income changes. Notably, our results highlight that the relative size of the payment in relation to quarterly income is the most critical factor affecting spending behavior.

To explore the observed variability in excess sensitivity, we extend our analysis of size-dependent consumption responses across different distributions of key factors such as age, income, and liquidity. Due to limitations in our dataset, particularly the lack of detailed asset or wealth information, we use data on debt structures and rely on income and mortgage status as proxies for liquidity.[5] Our analysis of the joint distribution of size, age, income, and liquidity constraints reveals that size-dependent consumption responses persist throughout the distribution of these factors. In particular, MPCs are higher when expected income increases are relatively small, regardless of these variables. Lower-income individuals tend to exhibit higher MPCs within the same size distribution, consistent with conventional economic theory. More importantly, our findings indicate that the size effect outweighs the impact of liquidity constraints, with MPCs being highest when predictable income changes are small, irrespective of income level. This suggests that the magnitude of anticipated income fluctuations plays a more significant role in driving consumption adjustments than liquidity constraints alone.

We discuss these findings through the lens of consumption smoothing theories, showing how deviations from optimal smoothing help explain the heterogeneity in MPC and its sensitivity to the size of anticipated income changes. While traditional models predict persistent consumption responses to permanent income changes, our data reveals a sharp, one-time consumption spike following an income rise, suggesting behavioral influences. Specifically, income shocks perceived to be short to medium term are likely to generate different consumption responses than those assumed to be long term. When we consider short-lived income shocks, the consumption dynamics become

[5] Low-income individuals often encounter a one-time liquidity provision (Coibion, Gorodnichenko and Weber, 2020). Additionally, we introduce mortgage debt status as a variable that further restricts borrowing capacity, offering a more accurate measure of liquidity constraints based on available data.

closer to what we document in our estimation results.[6] The size-dependent response is tied to bounded rationality, where individuals are more likely to adjust consumption for larger income changes, as the utility gain from doing so is higher, while smaller changes result in lower welfare losses, reinforcing the idea that MPC varies with income magnitude.[7] The presence of monotonically increasing welfare costs with respect to magnitude supports our argument that MPC depends on the size of the anticipated income changes.

Our policy experiment provides evidence that accounting the magnitude effect and size-dependent heterogeneous MPCs can improve aggregate consumption growth. Existing government interventions, such as tax rebates or fiscal stimulus checks, typically allocate payments based on household income thresholds. These policies provide uniform payments within the same income brackets, making it difficult to evaluate the effects of varying payment sizes. A key advantage of our analysis is the availability of variations in the magnitudes of expected income changes across individuals with different characteristics.[8] To analyze the effectiveness of policies with varying payment sizes, we simulate two scenarios: one targets the lowest income tercile with larger payments, while the other distributes smaller average payments across a broader population, implying a higher MPC for the latter group. Our findings show that when accounting for the size effect and heterogeneous MPCs, aggregate consumption growth increases from 0.47 percent under the first policy to 1.38 percent under the second policy with a smaller payment size on average. These findings suggest that policies designed with size variation in anticipated income changes can effectively amplify short-term aggregate consumption growth.

The remainder of the paper proceeds as follows. Section 2 describes the institutional background and data. Section 3 explains our econometric methodology. Section 4 shows the estimation results, and Section 4.4 presents several robustness analyses. Section 5 discusses the theoretical support, and Section 6 evaluates the policy implications of our findings. Section 7 concludes.

[6]Based on the income change characteristics, car buyers in our sample have an average duration of a 3–5 year auto loan. Other types of debt have longer repayment periods; for example 30-year mortgages are common. We assume that because of this trait, some behavioral perceptions may affect consumption responses.

[7]Kueng (2018) presents a similar discussion of welfare loss, though they find that the Alaska Permanent Fund Dividend triggered high MPCs among high-income consumers.

[8]We argue that anticipated income changes from government transfers and the completion of car loans share two key traits: both are predictable and irregular (Fuchs-Schündeln and Hassan, 2016), though fiscal stimulus effects are more transitory. If anything, our approach prevails over the upper bound in the estimated MPCs as income shocks become more persistent.

2 Data and Descriptive Statistics

2.1 Data Source

Our data comes from the Bank of Korea (BOK) household debt database. This database is a longitudinal quarterly panel of de-identified individual-level records from a major credit bureau company in South Korea. The data is nationally representative as it uses stratified random sampling. The sample accounts for almost 2.4 percent of the population engaged in any type of credit activity. Based on the sampling results, approximately the same proportion of age, region, and credit rating groups was extracted. The data set also contains detailed micro-level information including annual income, consumption expenditure based on actual financial transactions, credit information, and demographic information such as age and region.[9] More importantly, this data set provides details of the path of specific debt including the type of debt, repayment size, and duration of each debt, which we use to identify anticipated income changes in our empirical analysis.

Our data set has several desirable features compared to other data sets used in previous research.[10] The dataset comprises financial transaction data from all major issuing banks and institutions nationwide. Collected automatically by the credit bureau over multiple periods, it ensures high accuracy and timeliness. It includes a larger number of observations with minimal measurement error or recall bias, which are common limitations of survey data. In addition, the consumption expenditure captured by financial transactions constitutes the majority of total consumption in South Korea. During the sample period, the average usage of credit and debit card usage represents approximately 75 percent of total consumption.[11] Another important feature of this data set is that the utilization rate of credit and debit cards does not vary significantly by income level in South Korea. Nonetheless, the growth rate of consumption increases proportionally with the growth of credit card usage. Hence, credit card expenditure is a useful proxy for total consumption in the economy.[12]

[9]Credit information includes the credit grade, credit card utilization rate, credit card liability, and default risk.

[10]Our dataset is similar to the NY Fed Consumer Credit Panel. In the U.S., consumption responses are often analyzed using the Panel Study of Income Dynamics and the Consumption Expenditure Survey, but these have limited features and income measurement errors(Ni and Seol, 2014). Other studies use U.S. transaction data, though typically from a single institution like JPMCI (Baker and Yannelis, 2017).

[11]The Credit Finance Association of Korea reports that credit and debit card usage out of total consumption had increased from 72 percent in 2012 to 84 percent in 2016.

[12]In contrast to the U.S., where approximately 10 percent of the population is excluded from sampling due

We acknowledge that our data set suffers from at least two disadvantages. First, it does not include information about assets or wealth. To address this limitation, we use variables such as quarterly income, the mean value of credit utilization rate, and extra debt constraints such as mortgage debt status to proxy for the role of liquidity. Second, our panel faces the challenge of tracing cash transactions. Given the missing information on cash outflows, our estimated values may be in the lower bound. However, the high rate of credit and debit card usage in South Korea minimizes the impact of this potential measurement error.

2.2 Institutional Background, Sample Selection, and Descriptive Statistics

The main aim of our empirical analysis is to estimate the consumption dynamics generated by anticipated income changes. To capture this dynamic, we consider the natural experiment of the anticipated increase in an individual's discretionary income after they make their final car loan payment, which is closely related to the identification in Stephens Jr (2008).[13] To this end, we construct a new panel data set by restricting our sample to individuals who hold auto loans (or car buyers) in the BOK database.

2.2.1 Auto Loans in South Korea

During the study period from 2012 to 2016, South Korea's average household debt-to-GDP ratio ranged between 80 and 85 percent.[14] Mortgage debt accounts for the majority share of total household debt (54 percent), followed by credit card liability (17 percent), student loans (11 percent), and auto loans (9 percent). We focus on auto loans, as they provide richer variation in terms of payment size between individuals with different income levels and other demographic

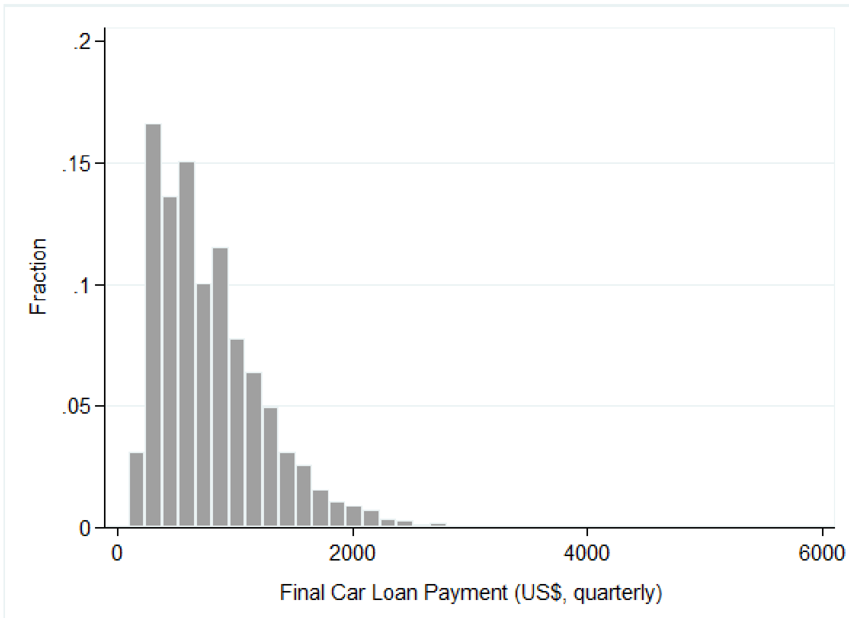
to a lack of credit history or minimal inquiries, our dataset includes active credit histories for the majority of the general population.

[13]Various types of natural experiments have been used to test excess sensitivity. For instance, Scholnick (2013) considers the final mortgage payment. Johnson, Parker and Souleles (2006), Agarwal, Liu and Souleles (2007), and Shapiro and Slemrod (2009) use tax rebates (e.g. the Economic Stimulus Act of 2008). In recent studies, Ganong and Noel (2019) reviews the exhaustion of unemployment insurance benefits, and Coibion, Gorodnichenko and Weber (2020) and Karger and Rajan (2020) consider the COVID-19 economic impact payments.

[14]The average real GDP per capita (in 2012 US dollars) was $29,388 compared to $58,021 in the U.S between 2012 and 2016.

characteristics. For each auto loan held by an individual, our panel data set includes information

Figure 1: Distribution of Final Car Loan Payment, 2012–2016



Notes: Figure 1 displays the distribution of quarterly final car loan payments in US dollars (CPI adjusted) with the base year of 2020. Each bin is $300 wide.

on the amount of the quarterly car loan repayments for each installment, the payment duration, and the beginning and end dates of the loan payments.

Figure 1 displays the distribution of quarterly final car loan payments in our final sample. The final amount of the car loan payment is the CPI adjusted for the prices in 2020 and converted from Korean won to US dollars using the mean exchange rates.[15] Between 2012 and 2016, the average value of the final car loan payment was $788, ranging from $89 to $5,660. In the distribution of final car loan payments, over half of the sample had payments below $1,000.

2.2.2 Sample Selection, Variables, and Descriptive Statistics

We restrict our final sample to individuals who have a regular car loan repayment for a fixed duration until maturity. We assume that consumers anticipate income changes at least one quarter ahead, as car buyers receive multiple monthly notifications about the loan's end date in advance.

[15] To reduce currency conversion errors, we present results in the original currency in our robustness checks (See Section 4.4).

Table 1: Descriptive Statistics

	Mean	Median	St.Dev.
Car Loans			
Quarterly payments	788	682	475
per quarterly before-tax income	9.91%	8.21%	6.61%
per quarterly total expenditures	25.27%	17.66%	24.40%
Quarterly expenditures			
Credit card expenditure (CCE)	4,802	4,091	3,247
Card utilization rate	27.39%	16.84%	58.80%
Quarterly before-tax Income	8,841	8,487	3,231
Card Holders' Characteristics			
Credit grade (scale 1 to 10)	3.30	3.00	2.06
Age between 40 and 59 (%)		56.51%	
Number of observations		77,148	

Notes: The unit is real US$ with the base year 2020. Credit grade is on a scale of 1 to 10, 1 being the highest (great), 10 being the lowest (poor).

We exclude consumers who repay their loans early in a lump sum, as they may roll over existing loans in a way that is endogenously linked to their spending behavior. Additionally, we focus on individuals with a single auto loan during the sample period to avoid endogeneity concerns arising from new loans taken for subsequent vehicle purchases. Multi-time car buyers may also exhibit distinct purchasing patterns, such as acquiring additional vehicles or frequently replacing cars, which could influence our results. Finally, we exclude the top and bottom one percent of the total distribution to mitigate potential bias from outliers.

Table 1 provides the descriptive statistics for the main variables, which include debt structure, consumption expenditure, income, and demographic information such as age, region, and credit information. The debt structure on auto loans captures the payment size, duration, and end date of the final car loan payment. Spending data is derived from actual credit and debit card transactions per quarter across all major issuing banks and financial institutions within the country.[16] Quarterly pre-tax income data is collected by credit bureaus for tax reporting purposes and is based on the proof of income provided by each individual.

Our final empirical analysis sample consists of 77,148 observations. Summary statistics show that the mean value of the predictable income change is $788, quarterly income of $8,841, and

[16]This dataset does not contain detailed information on the consumption category.

consumption expenditure of $4,802. On average, the anticipated increase in discretionary income represents nearly 10 percent of an individual's before-tax quarterly income and 25 percent of their two-quarter average consumption expenditure before the expected change. The credit card utilization rate is around 28 percent, and the sample exhibits a relatively good standing in their credit activities with an average credit rating of 3.30 on a scale from 1 (highest) to 10 (lowest). The majority of our final sample (56 percent) is aged from 40 to 59.

2.2.3 Representativeness

A challenge associated with empirical studies that restrict samples to specific groups (such as car buyers in our case) is the potential lack of representativeness of the broader population.[17] We provide two pieces of evidence suggesting that our sample is likely comparable to the overall population.

First, Figure 2a illustrates that the annual income distribution of car buyers closely aligns with that of the full sample in the database. The average annual income for car buyers is $35,360 comparable to the general population in the full sample. While this group has a slightly smaller fraction of individuals earning under $30,000 it still represents the overall distribution well.[18] The full sample consists of 896,000 observations — 12 times the size of our final sample.

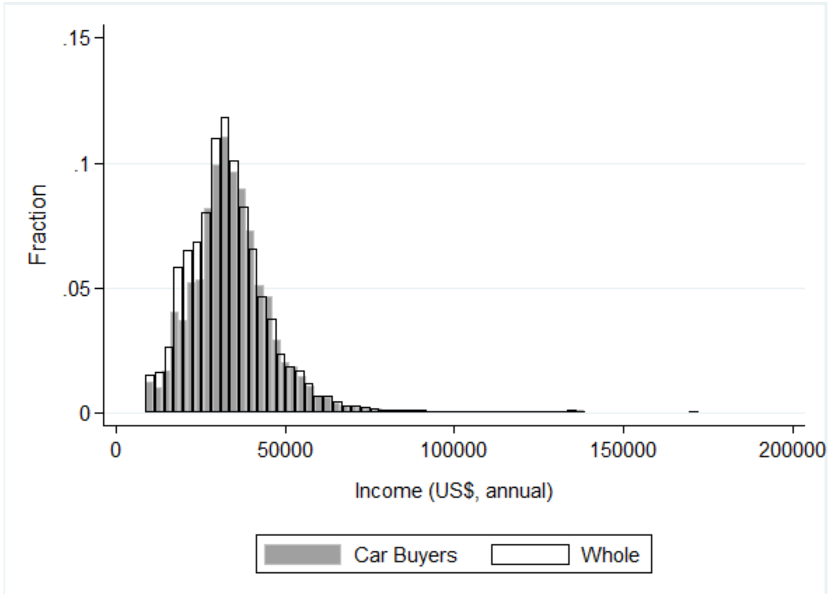
Second, the distribution of consumption expenditure suggests a similar pattern as shown in Figure 2b. The average quarterly credit and debit card expenditure for car buyers is $4,802. Although the proportion of individuals spending less than $3,000 per quarter is lower in this group, resulting in a slightly right-skewed distribution compared to the full sample, the overall shape and comparable minimum and maximum values suggest that it remains broadly representative of the general population. In addition to income and consumption distributions, Appendix B presents the distribution of final payment size relative to income and consumption, as well as the age distribution.

[17] Our sample is limited to individuals with a history of credit activity and a satisfactory credit rating, qualifying them for car loans.

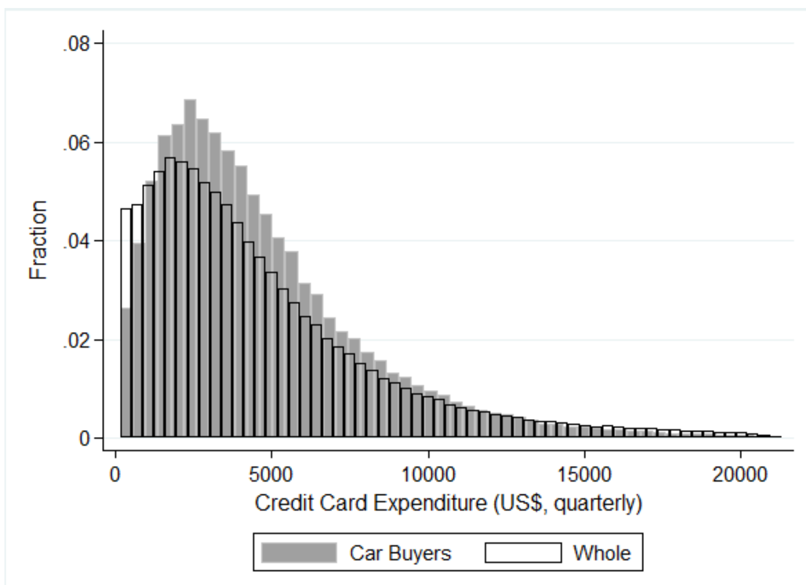
[18] The income distribution of car buyers has a lower proportion of individuals earning less than $30,000 annually but remains comparable in range to the overall sample, including both lower-income and middle- to high-income individuals. Additionally, the car buyer group shows lower income variability, as indicated by a smaller standard deviation compared to the full sample.

Figure 2: Representativeness: Income and Consumption

(a) Distribution of Annual Income



(b) Distribution of Credit Card Expenditure



Notes: Figure 2 shows the distribution of annual income and quarterly credit card expenditure in US dollars with the base year 2020. Each bin is $1,000 for income and $300 for consumption. The shaded bar indicates the distribution of the car buyers group, and the regular bar indicates the distribution of the whole sample (2012–2016).

3 Empirical Methodology

3.1 Consumption Dynamics of Anticipated Income Changes

To assess whether our data exhibits excess sensitivity following the final car loan payment, which reflects changes in anticipated income, we begin by estimating the standard parametric regression, which is given by:

$$\Delta c_{it} = \alpha_t + \gamma_i + Region_i + \sum_{s=n}^{m} \beta_s \cdot FP_{i,t-s} + \lambda' x_{it} + \epsilon_{it} \tag{1}$$

where c_{it} measures the real consumption expenditure captured by quarterly credit and debit card transactions per quarter for individual i in period t. $FP_{i,t-s}$ denotes the US dollar amount of the final car loan payment made by individual i at time t. The coefficient, β, measures the excess sensitivity of consumption expenditure to predictable income changes, and following Agarwal, Liu and Souleles (2007) and Gross and Souleles (2002), we interpret the estimation results within an event study framework.[19] The distributed lag term, s, represents the number of periods since the car loan was paid off for the event window from $t = n$ to $t = m$.[20] The estimation result for leading periods represents the anticipation effects, and for lagging periods it illustrates delayed responses. The marginal coefficient, β_s where $s \in \{1, 2, ...\}$, measures the additional effects depicted after the final payment. The sum of the marginal coefficients, $\sum_s \beta_s$, calculates the total cumulative changes in consumption responses after s quarters.

We also control for time, region, and individual fixed effects that are captured by α_t, γ_i, and $Region_i$, respectively. x_{it} includes control variables such as demographic characteristics (e.g., age, gender), changes in income other than final car loan payment, annual income level, and other credit-related characteristics (i.e., changes in credit card limits, credit card utilization rates, credit grades, and debt-to-income ratios). ϵ_{it} is an error term that measures the changes in consumption expenditure not explained by the final loan payment or control variables.

[19] Since we consider both consumption expenditure and the magnitude of predictable income changes in levels (i.e., US dollars, unit: 1\$), the coefficient term, β_s, can be interpreted as the MPC generated by a \$1 increase in predictable income.

[20] We allow for leads and lags to estimate the anticipation and delayed response effects following Agarwal, Liu and Souleles (2007), Scholnick (2013), and Kueng (2018).

3.2 Estimating the Magnitude Effect

3.2.1 Types of Sizes

We consider three classifications of sizes to estimate how the magnitude of such anticipated income changes affects consumption dynamics: (i) the absolute size of the final payment, (ii) the size relative to the individual's quarterly income, and (iii) the size relative to the individual's quarterly consumption expenditure prior to the predictable income change.

The absolute size of the anticipated income change is quantified as the change in discretionary income following the final car loan payment, expressed in US dollars and adjusted for CPI inflation. The measure of the relative size per before-tax quarterly income is defined as $FP\ to\ Income_{i,t} = Final\ Payment_{i,t}/Quarterly\ Income_{i,t}$. Since this measure represents the ratio of payment relative to income, both the payment amount and income levels may vary. Consequently, there may be some degree of endogeneity between the size of the car loan payment and income. In Section 4, we expand the analysis by examining additional variables and find no significant evidence of a strong correlation between variations in payment size and income.[21] Similarly, we consider the relative size of the final car loan payment to quarterly consumption expenditure prior to the predictable income change, capturing how the payment size relative to typical spending affects excess sensitivity. We measure the relative size per consumption as $FP\ to\ CCE_{i,t} = Final\ Payment_{i,t}/Quarterly\ CCE_{i,t}$ where $Quarterly\ CCE_{i,t}$ is the quarterly credit and debit card expenditure prior to predictable income changes for individual i at time t.

Using the definitions above, we re-estimate the parametric regression as in Equation (1), substituting $FP_{i,t}$ with $FP\ to\ Income_{i,t}$ and $FP\ to\ CCE_{i,t}$ to assess the effects of relative magnitudes on consumption dynamics. For each type of size, the coefficient measures the average value of consumption change in response to a one-unit increase in anticipated income. Note that for the absolute size, the coefficient of parametric regression, β_s, measures the MPC corresponding to a \$1 increase in income. For relative sizes, the coefficient term measures consumption unit increase in response to a one-unit income increase in relative terms.

[21] We observe that the income distribution remains proportional across various income groups, even with a fixed payment size. For instance, individuals in the bottom tercile may include both lower-income individuals who make smaller payments due to purchasing compact cars and higher-income individuals whose larger down payments result in relatively small remaining payments.

3.2.2 MPC Heterogeneity

Another central question we address in this paper is the heterogeneous consumption responses by size and other observable individual characteristics. To provide further evidence of MPC heterogeneity, we examine the MPCs by the distribution of absolute and relative sizes. We assign individuals to one of three subgroups for each size classification — low (below 25 percent, reference group), middle (between 25 and 75 percent), and high (above 75 percent) in the distribution.[22] This measure combines the cross-distribution variation in the three types of sizes and within-size variation by distribution. We then use other variables such as age, income, and liquidity to explore further how much of each variable matters conditional upon another.

MPC Heterogeneity by Size Distribution.— Consumption response heterogeneity is estimated by capturing the difference for each group using an indicator function, $\mathbb{1}(y_{it} = D)$. The parametric regression equation is given by:

$$\Delta c_{it} = \alpha_t + \gamma_i + Region_i + \sum_{D} \beta_D \cdot FP_{it} \times \mathbb{1}(y_{it} \in D) + \lambda' x_{it} + \epsilon_{it} \tag{2}$$

where $y_{it} \in \{FP,\ FP\ to\ Income,\ FP\ to\ CCE\}$ is the variable of interest for each distributional group $D \in \{Low,\ Middle,\ High\}$. The coefficient term, β_D, measures the change in consumption for each size-based group D in y_{it}. For each estimation, we analyze MPC heterogeneity by absolute payment size and similarly classify observations into subgroups by relative payment size based on income and consumption.

Conditional MPC Heterogeneity.— We examine MPC variation based on payment size, conditioning on three key factors identified in previous studies: age, income, and liquidity. The specification of the conditional consumption response is given by:

$$\Delta c_{it} = \alpha_t + \gamma_i + Region_i + \sum_{D_z} \beta_{D_z} \cdot FP_{it} \times \mathbb{1}(z_{it} \in D_z) + \sum \delta_{D_z} \times \mathbb{1}(z_{it} \in D_z) + \lambda' x_{it} + \epsilon_{it} \tag{3}$$

where $z_{it} \in \{Age,\ Income,\ Liquidity\}$ is three observable factors for each tercile D_z of variable z conditional on the payment size. The coefficient term β_{D_z} represents our key parameter of interest, assessing whether the respective variable systematically affects the consumption response to car loan repayment size FP_{it}. We control for time, region, and individual fixed effects using the same

[22] In Section 4.4, we use an alternative grouping strategy based on five quintiles as a robustness check.

set of variables as in the baseline estimation.

To examine conditional MPC heterogeneity across three key factors—age, income, and liquidity—we first stratify individuals by relative size within each factor, resulting in nine (3×3) subgroups. Each coefficient term represents a joint MPC distribution, allowing for a direct interpretation of how consumption responses vary across these dimensions. Given data limitations on assets and wealth, we use quarterly income and extra debt constraints, such as mortgage debt status, as proxies for liquidity constraints, following Fuchs-Schündeln and Hassan (2016). Specifically, individuals with low income or additional mortgage debt alongside their auto loan are likely to be liquidity-constrained.[23]

4 Effects of Anticipated Income Changes

This section presents our main estimation results on consumption responses to anticipated income changes, highlighting excess sensitivity and its variation over time. As discussed in Section 3, we evaluate three magnitude classifications in absolute and relative terms to determine which best explains the observed patterns. Additionally, we examine MPC heterogeneity by size distribution and conditional factors such as age, income, and liquidity.

4.1 Effects of Anticipated income Changes on Consumption

We begin by presenting evidence of excess sensitivity. Table 2 presents the main estimation results on the average consumption response to the predictable income changes following the final car loan payment. Columns (1) to (4) present the consumption responses under different specifications. Column (1) reports results without individual fixed effects and control variables, yielding an MPC of 19 percent. However, this estimate may be overstated, as consumption changes could be related to factors other than predictable income. To address this, Column (2) introduces control variables such as demographic characteristics, changes in income other than the final car loan payment, annual income level, and credit-related features. With these controls, the estimated MPC declines to 0.178, while the explanatory power improves, as reflected in a higher R-squared value. In Column (3), individual fixed effects are added to Column (1), isolating the consumption response

[23]While some research discusses wealthy hand-to-mouth individuals who hold substantial illiquid assets but have limited liquid funds, we assume income remains a reasonable proxy for liquidity constraints, as this group behaves similarly to "poor hand-to-mouth" individuals (Kaplan, Violante and Weidner, 2014).

Table 2: Consumption Response to Anticipated Income Changes

Dep. Var: Δc_{it}	(1)	(2)	(3)	(4)
FP	0.190***	0.178***	0.196***	0.177***
	(0.032)	(0.032)	(0.034)	(0.033)
Constant	0.237	0.219	0.266	0.393*
	(0.152)	(0.156)	(0.167)	(0.218)
Control Variables	No	Yes	No	Yes
Time and Region FE	Yes	Yes	Yes	Yes
Individual FE	No	No	Yes	Yes
R-squared	0.003	0.028	0.003	0.059
Observations	77,148	77,148	77,148	77,148

Notes: FP indicates the final car loan payment level. Control variables include the changes in income, annual income level, the changes in credit card limits, credit card utilization rates, credit grades, debt to income ratios, and age dummies (30-39, 40-49, 50-59, 60-69, and 70+). Considering the measurement errors, observations with final payments greater than 1.5 are excluded from the sample. Robust standard errors in parentheses are clustered at the individual level. *, **, *** represent the significance level at 10%, 5%, and 1%, respectively.

to variations in the final car loan payment at the individual level. This adjustment raises the spending response to 0.196 but leads to a slight decrease in the R-squared term. Finally, Column (4) presents our main estimation results, incorporating individual, time, and region fixed effects along with control variables. The estimated result suggests that a $1 increase in predictable income boosts consumption by 17.7 cents, on average.[24]

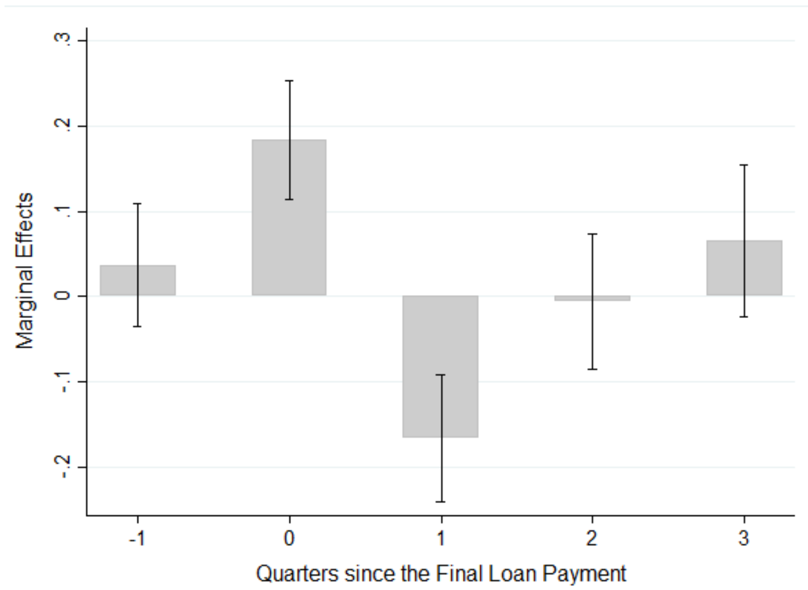
We then exploit how consumption dynamics evolve around the income change, investigating potential anticipation or delayed effects. Figure 3 presents these results, with Panel (a) showing the estimated coefficients β_s for marginal effects over time and Panel (b) depicting cumulative effects.[25] The lead term estimates indicate no significant anticipation effect prior to the predictable

[24] Our MPC estimates are within the range of reported MPCs in previous studies. Agarwal, Liu and Souleles (2007), Johnson, Parker and Souleles (2006), and Misra and Surico (2014) find MPCs in the range of 0.20–0.40 after the receipt of 2001 federal income tax rebates ($500). Broda and Parker (2014) and Parker (1999) report that MPC ranged from 0.10 to 0.30 in response to the 2008 economic stimulus payment ($900). Scholnick (2013) finds a slightly higher MPC of 0.40 associated with final mortgage payments ($627). Lastly, recent studies on the 2020 economic stimulus payments ($1,200) show that MPC was 0.25–0.40 (Baker and Yannelis, 2017; Coibion, Gorodnichenko and Weber, 2020).

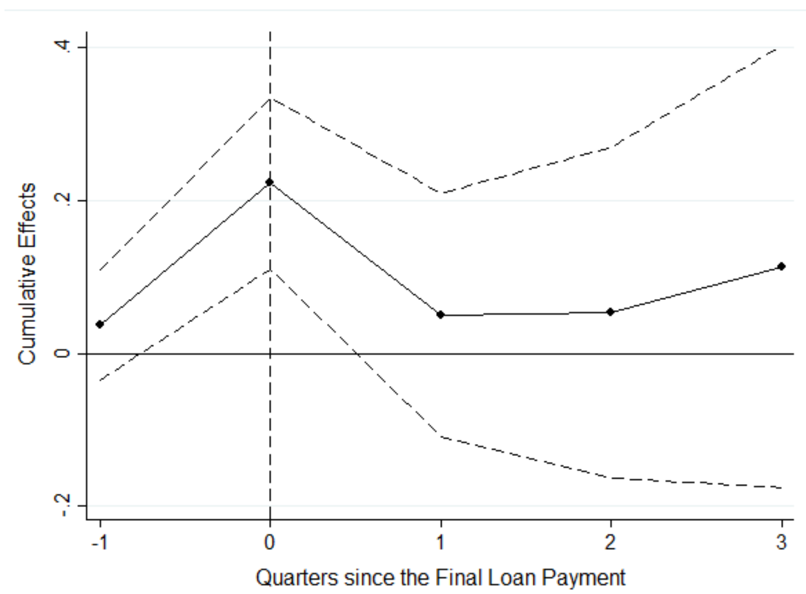
[25] In Appendix C, we illustrate how the income process evolves over time. Figure C.1 shows that income stabilizes at a higher level after the final car loan payment.

Figure 3: Consumption Response by Time

(a) Marginal Effects on Marginal Propensity to Consume



(b) Cumulative Effects on Marginal Propensity to Consume



Notes: Figure 3 Panel (a) illustrates leads and lags of the regression coefficients estimated by the standard parametric regression equation (Equation 1). Panel (b) displays the cumulative effect on consumption response following the final car loan payment over time. Bars and lines show the estimated coefficients and 95 percent confidence intervals, respectively. Standard errors are clustered at the individual level.

income change with 95 percent confidence intervals.[26] At $t = 0$, the point estimate of 0.18 in Panel (a) is statistically significant, indicating the largest deviation from consumption smoothing occurs in the quarter of the income change.[27] At $t + 1$, consumption response declines sharply before gradually returning to previous levels at $t + 2$. Panel (b) confirms this pattern, showing cumulative MPC effects of 0.04, 0.22, 0.05, 0.04, and 0.11 for periods $t - 1$ through $t + 3$, respectively.

4.2 The Magnitude Effect on Consumption Response

The Magnitude Effect on Excess Sensitivity.— Our baseline estimation of excess sensitivity reported in Table 2, is based on absolute payment size.[28] We further analyze variation across three types of magnitudes. Table 3 reports coefficient estimates for each subgroup across different size measures. In Columns (1) to (6), the first row reports excess sensitivity for the reference group (bottom 25 percent of the size distribution), while the subsequent rows present values for the middle (25–75 percent) and high (top 25 percent) groups. Column (1) shows that excess sensitivity is statistically significant across all groups using absolute measures. The low group exhibits the highest excess sensitivity, where a \$1 income increase leads to a 75-cent rise in consumption. In contrast, the middle group has an estimated MPC of 0.20—0.558 lower than the reference group—while the high group has the lowest MPC at 0.14.[29] Overall, MPC declines monotonically with absolute size, highlighting significant heterogeneity across size distributions.

Similar results are observed when measuring size relative to income (Column 2) and consumption (Column 3). The MPC for payment size relative to income is comparable in magnitude to that of absolute size, whereas size relative to consumption shows a slightly smaller consumption response. However, the MPC still follows a monotonically decreasing pattern. These findings suggest evidence of excess sensitivity both across all size categories on average and within different size distribution groups.

[26] Given the quarterly data frequency, we include only one-quarter lead. Extending lag terms to two quarters in our robustness analysis yields similar results.

[27] In Figure 3 Panel (a), the point estimates of the regression coefficients are 0.04, 0.18, -0.17, -0.01, and 0.07 for the corresponding periods from $t - 1, t, ...,$ up to $t + 3$, respectively.

[28] Appendix D, Table D.1 provides similar evidence of excess sensitivity for payment size relative to income and consumption.

[29] These results indicate group heterogeneity in excess sensitivity, with a large difference between the reference and other groups, while the middle and high groups show relatively small variation.

Table 3: The Effect on Consumption by Absolute and Relative Magnitudes

Dep. Var: Δc_{it}	(1)	(2)	(3)	(4)	(5)	(6)
FP (reference group)	0.758***	0.712***	0.321***	0.863***	0.761***	0.712***
	(0.156)	(0.158)	(0.066)	(0.169)	(0.156)	(0.158)
FP * $\mathbb{1}$ (FP=Middle)	-0.558***			-0.308	-0.502***	
	(0.164)			(0.218)	(0.170)	
FP * $\mathbb{1}$ (FP=High)	-0.614***			-0.343	-0.492***	
	(0.160)			(0.229)	(0.182)	
FP * $\mathbb{1}$ (FP to Income=Middle)		-0.540***		-0.378*		-0.474***
		(0.165)		(0.217)		(0.173)
FP * $\mathbb{1}$ (FP to Income=High)		-0.565***		-0.378*		-0.417**
		(0.163)		(0.228)		(0.192)
FP* $\mathbb{1}$ (FP to CCE=Middle)			-0.184**		-0.129	-0.144
			(0.075)		(0.092)	(0.100)
FP* $\mathbb{1}$ (FP to CCE=High)			-0.225		-0.172	-0.199
			(0.153)		(0.169)	(0.177)
Constant	0.390*	0.396*	0.393*	0.393*	0.392*	0.396*
	(0.218)	(0.218)	(0.218)	(0.218)	(0.218)	(0.218)
R-squared	0.059	0.059	0.059	0.059	0.059	0.059
N	77,148	77,148	77,148	77,148	77,148	77,148

Notes: FP, FP to Income, and FP to CCE indicate the absolute size of final car loan payment, final payment to quarterly before-tax income ratio, and final payment to quarterly consumption expenditure ratio, respectively. The reference group is defined as the bottom 25 percent of size distribution. Control variables include the changes in income, annual income level, the changes in credit card limits, credit card utilization rates, credit grades, debt to income ratios, and age dummies (30-39, 40-49, 50-59, 60-69, and 70+). Considering the measurement errors, observations with final payments greater than 1.5 are excluded from the sample. Robust standard errors in parentheses are clustered at the individual level. *, **, *** represent the significance level at 10%, 5%, and 1%, respectively.

Relative Importance across Magnitudes.— We next assess the relative importance of the three size measures using multivariate regression analysis. Columns (4) to (6) in Table 3 report estimates for different magnitude combinations. Column (4) includes absolute payment size and its relative size to quarterly income, with the reference group showing the largest significant coefficient (0.863). The result indicates that relative size outweighs the absolute measure, suggesting a stronger role in driving excess sensitivity. Similarly, Columns (5) and (6) consider the combinations of absolute size with relative size to consumption, and relative size to income with relative size to consumption, respectively. Overall, payment size relative to quarterly income exerts the most significant influence on excess sensitivity, followed by absolute payment size and then payment size relative to usual consumption expenditure.

Payment Size and Quarterly Income.— One concern that arises from considering an effect in relative terms is a possible correlation between the payment size and income. Although our regression analysis controls for variables such as income level, income changes other than the final loan payment, and debt-to-income ratios, payment size may still be influenced by the consumer's initial down payment or preferences for vehicle value.[30] To address this issue, we examine how the size variation changes with the level of an individual's quarterly income. In Appendix E, Figure E.1, Panel (a) presents the relationship between the payment size (in $100 US dollars) and quarterly income (in $1,000).[31] Panel (b) displays the relationship between the size relative to income ratio and quarterly income. Both figures illustrate that the payment size does not depend on income level. Within each size distribution, both in absolute and relative terms, our sample includes individuals across various income levels. Moreover, the correlation between payment size and quarterly income is weak, with a correlation coefficient of 0.2.

4.3 Conditional MPC Heterogeneity

Our main estimation results suggest heterogeneity in spending responses based on the magnitude of anticipated income changes. While previous research highlights liquidity constraints as a key driver of excess sensitivity, it has often overlooked how consumption responses vary with the size of income changes.[32] To assess whether MPC across different magnitudes remains consistent, we examine its conditional heterogeneity across three key factors commonly captured in the literature: age, income, and liquidity. We primarily focus on the payment size relative to income, as it is the most significant determinant among the three measures.[33]

Age and Income.— Figure 4 illustrates the conditional MPC heterogeneity. Panel (a) displays the distribution of MPC across age groups and the payment size relative to income. Our results indicate that MPC is higher when the relative size is small regardless of age, suggesting that age is

[30]For instance, high-income consumers may opt for a larger down payment to reduce subsequent loan repayments, while wealthier (lower-income) households are more likely to purchase luxury (compact) vehicles, resulting in systematically higher (lower) payment amounts on average.

[31]To better capture the relationship between payment size and income, we stratify our sample to 1,100 observations of each bins.

[32]These studies assume that the deviation in consumption smoothing is due to liquidity constraints or illiquidity, since households with few liquid assets and/or a low income are more likely to be liquidity constrained (Kaplan, Violante and Weidner, 2014; Fuchs-Schündeln and Hassan, 2016).

[33]In Appendix F, we also report the conditional MPC heterogeneity across absolute payment size, age, and income.

not the primary driver of MPC variation. In Panel (b), we also show the population share of being in each subgroup, and find that the share is mostly concentrated among the 30–50 age group. Panel (c) presents the conditional MPC based on income and relative payment size. Since there is no strong correlation between payment size and income, this conditional MPC estimates the dimension of these two variables. We find that the MPC increases more when the payment constitutes a smaller fraction of an individual's quarterly income across all income levels. Specifically, the MPC is highest for individuals in the lowest relative size and low-income group, indicating a strong size effect even when liquidity constraints (as reflected by low income) are present. Panel (d) illustrates the distribution of population share by income and relative size. The data show that most individuals are centered on the middle-income group.

The Role of Liquidity Constraints.— Recent studies, such as Kaplan, Violante and Weidner (2014), suggest that households may be wealthy or have high incomes while still facing liquidity constraints.[34] This implies that income level alone may not adequately explain the role of liquidity. Moreover, our data set lacks information on asset holdings of wealth. To address this, we incorporate an alternative measure – extra debt constraint – proxied by mortgage debt status, which restricts individuals' borrowing ability alongside age and income variables.[35] Panel (e) of Figure 4 presents the impact of extra credit constraints on conditional MPC. Our findings indicate a sizable and significant MPC response among individuals with small payment sizes, irrespective of mortgage debt status. Although Panel (f) shows that only a small fraction of individuals hold both auto loans and mortgage debt simultaneously, the strong MPC response suggests that payment size is a key determinant of consumption behavior, independent of liquidity constraints.

Figure 5 further presents the MPC distribution by relative size tercile, conditional on a fixed income level, with 95 percent confidence interval bands.[36] Consistent with Figure 4, individuals in the lowest relative size tercile exhibit the highest MPC across all three income groups. Moreover, the differences in MPC between the low and high relative size groups within each income level are highly

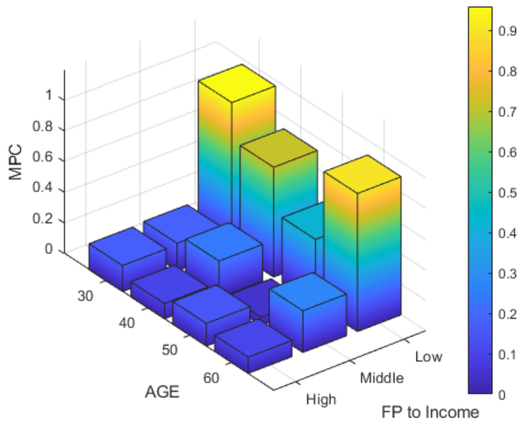
[34]For instance, approximately 30 percent of U.S. households were classified as wealthy hand to mouth households between 1989 and 2010.

[35]We extend our analysis to other liquidity-related factors, including high credit utilization rates, credit card consolidation loans, late credit card payments, high levels of unused credit lines, and high default risk. However, the limited number of observations for these variables in our sample prevents robust statistical inference.

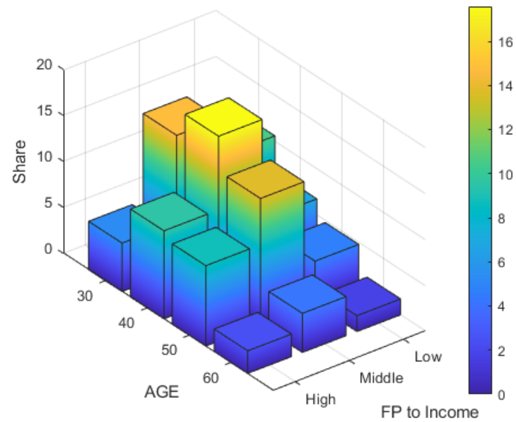
[36]This figure provides a two-dimensional representation of Figure 4, Panel (c), highlighting the statistical significance of differences across income groups.

Figure 4: Heterogeneous consumption responses

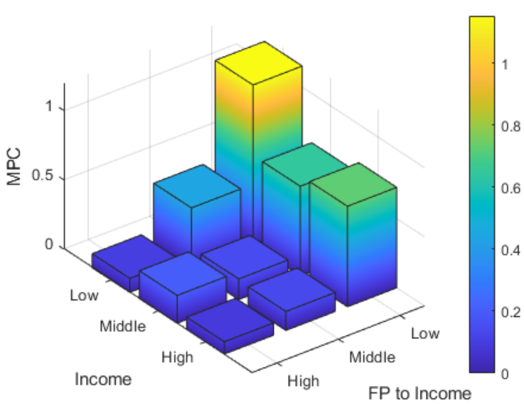
(a) MPC, Age, Size Relative to Income



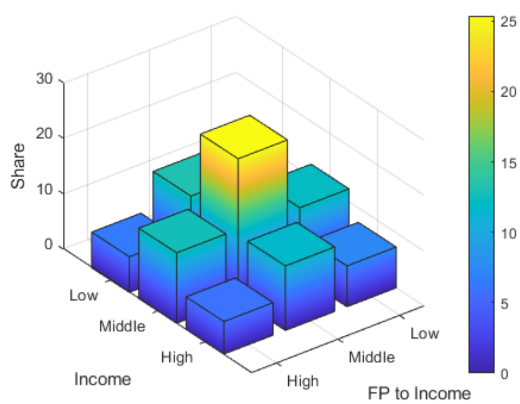
(b) Population Share, Age, Size Relative to Income



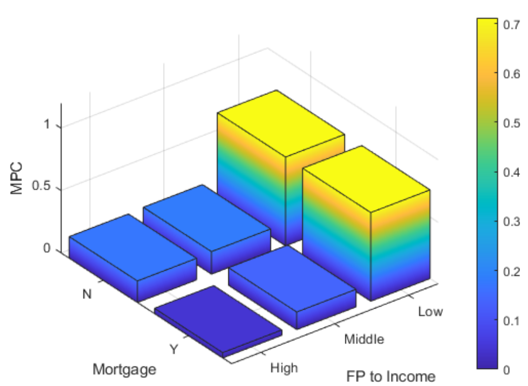
(c) MPC, Income, Size Relative to Income



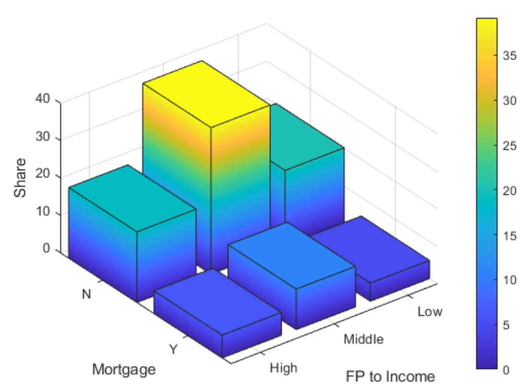
(d) Population Share, Income, Size Relative to Income



(e) MPC, Mortgage, Size Relative to Income

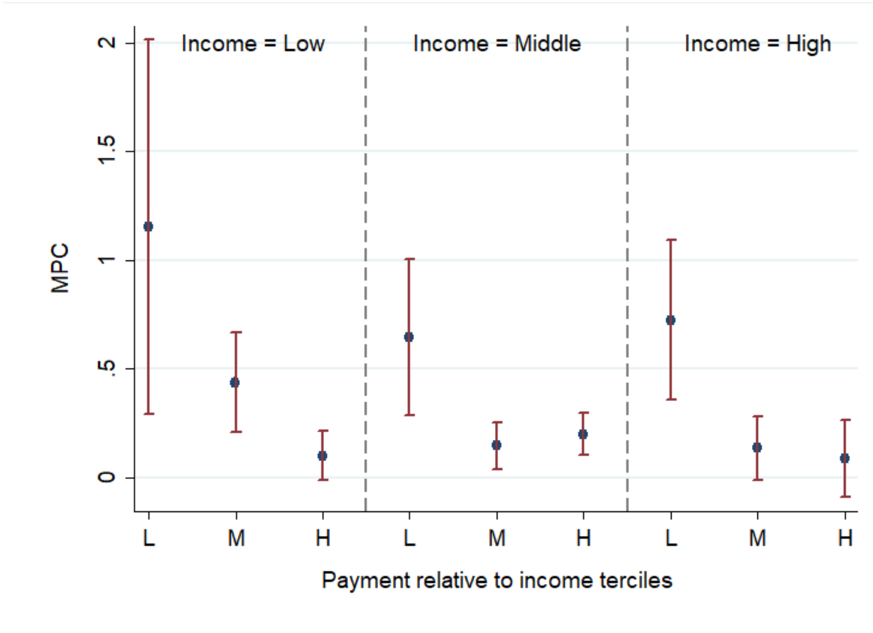


(f) Population Share, Mortgage, Size Relative to Income



Notes: Figure 4 shows the conditional MPC heterogeneity (and population share) among age, income, and payment size relative to income.

Figure 5: MPC by income given the relative size to income (FP to Income)



Notes: Figure 5 displays the spending responses of the final payment size relative to quarterly income terciles based on income level (low, middle, high). Bars and lines show the estimated coefficients and 95 percent confidence intervals, respectively. Standard errors are clustered at the individual level.

statistically significant, providing strong evidence of a size effect across the income distribution. Appendix F, Figure F.2, provides additional insights into the MPC distribution across income groups conditional on relative size, reinforcing our earlier finding that excess sensitivity is highest for the smallest relative size. A statistical comparison between high-income individuals with low relative size and low-income individuals with high relative size reveals a significant difference at the 1 percent level (F-statistic = 7.11), indicating that MPC remains significantly larger even for high-income consumers when they fall within the low-size distribution. More importantly, excess sensitivity remains more pronounced among low-income individuals, who are more likely to be liquidity-constrained, after controlling for relative size. This suggests that, within income terciles, low-income individuals exhibit the highest propensity to spend predictable income changes when the relative payment size is held constant. This finding underscores a key implication: while MPC tends to be higher for low-income households, aligning with conventional economic wisdom, the dominant factor influencing excess sensitivity is the relative size of the payment to income. Thus, while liquidity constraints contribute to heterogeneity in excess sensitivity, their impact is contingent on an equivalent relative payment size across households.

4.4 Robustness Checks

We conduct three robustness checks to validate our main results. First, we test excess sensitivity using an alternative grouping strategy. Second, we examine heterogeneity in consumption dynamics beyond the average trajectory. Lastly, we re-estimate results in the original currency (Korean won), using an extended analysis window and alternative regression specifications to address potential estimation biases.

Consumption Responses by Alternative Grouping.— In the baseline estimation, we classify size variations into three subgroups. For robustness, we extend the analysis to examine size-dependent MPCs in relative terms, following the methodology of Kueng (2018).[37] To refine this analysis, we divide individuals into five quintiles, each representing 20 percent of the relative size distribution, and analyze how consumption responds to predictable income changes within these narrowly defined groups. We assess heterogeneity across groups by estimating the following regression:

$$\Delta c_{it} = \alpha_t + \gamma_i + Region_i + \sum_{q_y} \beta_{q_y} \cdot FP_{it} \times \mathbb{1}(y_{it} \in q_y) + \sum_{q_y} \gamma_{q_y} \times \mathbb{1}(y_{it} \in q_y) + \lambda' x_{it} + \epsilon_{it} \tag{4}$$

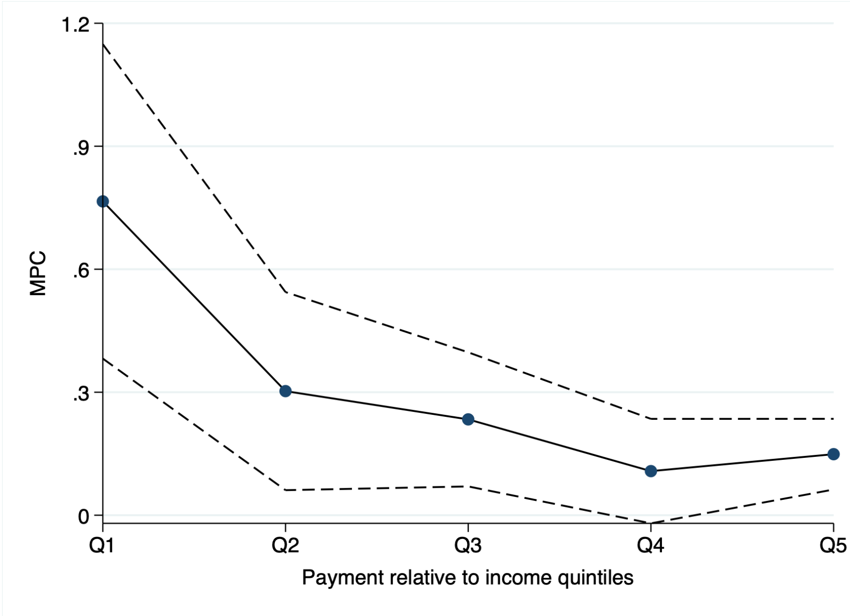
where y_{it} is the variable of interest. The indicator function, $\mathbb{1}(y_{it} \in q_y)$, equals 1 if individual i's payment-to-income ratio falls within the qth quintile, and 0 otherwise. We decompose the average effects on excess sensitivity into five quintiles, where $Q1$ denotes the lowest 20 percent and $Q5$ the highest 20 percent group in the distribution. The coefficient, β_{q_y}, measures how consumption expenditure responds to a one-unit increase in y which is the observed payment-to-income ratio.

Figure 6 plots the coefficient, β_{q_y}, that measures the excess sensitivity for individual i's observed size relative to income in the qth quintile. We find that the coefficients of spending response decrease monotonically with relative payment size even with five subgroups. The lowest point estimate, 0.11, for the highest quintile (Q5) indicates that individuals who have a large payment relative to their quarterly income tend to smooth consumption more optimally, and therefore reveal a low excess sensitivity.[38] In contrast, individuals for whom the payment size accounts for only a small fraction of their quarterly income spend most of their predicted extra income, with a point estimate of 0.85. The monotonic decline in MPC across relative size categories remains highly statistically

[37] Kueng (2018) examines spending heterogeneity based on individuals' liquid assets, income, and the size of income changes following the Alaska permanent fund dividend.

[38] The point estimates of spending responses to anticipated income changes by payment-to-income ratio quintiles (Q1 to Q5) are 0.85, 0.35, 0.20, 0.12, and 0.11, respectively.

Figure 6: Effects by Payment Size Relative to Income (FP to Income) Quintiles



Notes: Figure 6 plots the regression coefficients estimated by five quintiles of the final payment size relative to quarterly income ratio. The dashed lines represent 95 percent confidence intervals.

significant, as indicated by the 95 percent confidence interval bands.

Heterogeneity in Consumption Dynamics.— Our analysis of consumption responses to anticipated income changes shows that spending peaks upon the income change and quickly returns to zero in cumulative effects on average. To verify whether this finding still holds with different magnitudes of income change, we apply the same estimation analysis used in the main result to three distributional groups categorized by relative size.

Appendix G examines consumption dynamics across income groups classified by payment size relative to income (low, middle, and high). Figures G.1 and G.2 depict the marginal and cumulative effects on MPC across these distributional size groups. The findings are consistent with our main results: excess sensitivity is most pronounced when individuals experience an anticipated income increase, followed by a sharp decline in consumption expenditure in the subsequent quarter. This effect is particularly strong among individuals with the smallest relative payment size. Furthermore, an analysis of consumption patterns by income level reveals that high-income individuals exhibit insignificant responses across all time horizons, suggesting that the *size* of predictable income changes, rather than income level itself, is the primary driver of consumption adjustments.

Results in Original Currency.— Another challenge is converting Korean won to U.S. dollars for comparability, as using the sample-period mean exchange rate may introduce bias. To address this, we replicate our estimation using the original currency. Appendix G, Table G.1, reports the excess sensitivity of anticipated income changes, showing that the results remain consistent with our main estimation. Specifically, after controlling for time, region, and individual fixed effects, the excess sensitivity estimate remains 0.177 in both cases. Additionally, we extend our analysis by considering alternative specifications of the independent variable, using the log difference of consumption expenditure instead of the level of change in spending. The results show that a 1 percent anticipated income increase leads to a 0.35 percent rise in consumption growth. Additionally, we double the sample size and extend event windows (2 quarterly lags and 4 quarterly leads) to assess the persistence of the estimated effects.[39] The results confirm that the marginal consumption response consistently peaks in the quarter following the final payment.

5 Theoretical Discussion

In the standard intertemporal consumption model, rational agents optimize consumption based on expected future income, implying a near-zero MPC for predictable income changes. Our empirical results strongly reject this theory: we find that predictable income changes trigger a significant deviation from consumption-smoothing behavior. Moreover, consumption responses vary with the magnitude of anticipated income changes, peaking at the time of income receipt and rapidly returning to zero in the subsequent quarter.

One strand of research on excess sensitivity suggests that low-income individuals are much more likely to significantly increase their consumption if they anticipate a boost in income because they are more likely to be liquidity constrained (Garcia, Lusardi and Ng, 1997; Johnson, Parker and Souleles, 2006; Parker, 2017; Coibion, Gorodnichenko and Weber, 2020).[40] While liquidity constraints explain some deviations from standard consumption theory, excess sensitivity persists even among those with credit access. Our findings show that spending sensitivity is driven more by the magnitude of anticipated income changes than liquidity constraints, making relative size the dom-

[39] See Figure G.4 in Appendix G.

[40] Low-income households tend to hold low levels of illiquid and liquid assets or wealth (Kaplan, Violante and Weidner, 2014). Meghir and Pistaferri (2011) and Pagel (2017) provide other perspectives on consumption responses and emphasize the importance of risk aversion and the life-cycle effects as potential mechanisms of excess sensitivity.

inant factor.[41] Despite its significance, the magnitude effect and the one-time peak consumption response have been largely overlooked in the literature. To address this gap, we reassess standard models to better understand this peak and explore the role of bounded rationality.

Standard Models of Consumption.— In standard consumption models, consumption increases proportionally with permanent income changes, and as income shocks persist over time, so does the corresponding consumption response. This implies that the empirical patterns documented in our main results cannot be fully explained by these models. A key explanation for this discrepancy lies in how individuals perceive income shocks. While the completion of a car loan, which typically spans three to five years, theoretically results in a permanent increase in disposable income, individuals may interpret this change differently. Instead of viewing it as a lasting income shift, they may perceive it as a short- to medium-term fluctuation. This myopic behavior suggests that individuals may not fully adjust their long-term consumption plans in response to predictable changes in disposable income, deviating from the assumptions of forward-looking, optimizing agents in standard models.

In addition, this perception-driven behavior may be amplified by liquidity constraints or precautionary savings motives. If individuals interpret the freed-up income as transitory rather than permanent, they may allocate it toward immediate consumption rather than smoothing it over time. This deviation from standard consumption-smoothing behavior emphasizes the limitations of conventional models in capturing real-world responses to anticipated income changes and highlights the need for alternative frameworks that incorporate factors such as myopia, liquidity constraints, and mental accounting in household decision-making.

Bounded Rationality and Welfare Cost.— Bounded rationality implies that agents selectively apply rational decision-making, particularly in response to large income changes, when recomputing their optimal consumption path (Browning and Collado, 2001; Hsieh, 2003; Scholnick, 2013). In other words, individuals exhibiting bounded rationality are more likely to adjust consumption optimally in response to large income changes but may not do so for small changes, as the utility cost of not adjusting is lower in the latter case.

To further support the concept of bounded rationality, we quantify the welfare costs and demon-

[41] Our analysis partially highlights the role of liquidity constraints in excess sensitivity. While low-income individuals exhibit the largest spending adjustments to anticipated income changes within the same size group, this effect only holds conditional on the size distribution.

strate that individuals with small anticipated income changes incur relatively lower costs when deviating from the optimal consumption choice. Building on the methodology of Fuchs-Schündeln and Hassan (2016) and Kueng (2018), we compute welfare losses using a sufficient statistics approach. The potential loss of not fully smoothing consumption could be calculated as the difference in the utility of optimizing the decision and the deviation behavior as follows:

$$Welfare\ loss\ (c_i^{deviate}, c_i^{pih}) \approx \frac{\delta}{2} \cdot \sum_t \zeta_t \left(\frac{c_t^{deviate} - c_t^{pih}}{c_t^{pih}} \right)^2 \tag{5}$$

where δ captures the curvature of the utility function. The term ζ_t denotes the utility weight function, given by $\zeta_t = \gamma^t \frac{\partial u(c_t^{pih})}{\partial c} c_t^{pih} / \sum_i \gamma^n \frac{\partial u(c_n^{pih})}{\partial c} c_n^{pih} = \frac{\gamma^t u(c_t^{pih})}{U(c^{pih})}$ under the assumption that the utility function is specified as $u(c) = c^{1-\delta}/(1-\delta)$.[42] We set the standard value of $\delta = 2$ considered in the literature. After considering the envelope theorem, Equation 5 becomes $\delta/2 \cdot \left((1 - MPC) \cdot FP_i/c_i^{pih}\right)^2$ where FP_i/c_i^{pih} is the final car loan payment relative to individual's average consumption (or permanent income). As a result, we find a monotonically increasing welfare loss associated with the size of income changes with the corresponding values of 0.13, 0.61, and 2.4 percent for three income terciles, respectively. This indicates that individuals with small payment size relative to income incur lower costs from deviating from their optimal consumption smoothing behavior.

6 Policy Implications of the Magnitude Effect

In this section, we examine the implications of the magnitude effect of anticipated income changes for existing fiscal policies. The prediction of our estimation result suggests that (i) consumers do respond to anticipated income changes (even when they are announced in advance) and (ii) the MPC is higher when the size of the income change is small in both absolute and relative terms. To access the effectiveness of government interventions, we consider two stimulus designs and show that our estimated MPCs with different magnitudes of income changes can be used to calculate aggregate consumption growth.[43] Since we use the estimated values based on our final

[42] In Appendix H, we describe a detailed derivation for the welfare loss statistics.

[43] Our policy experiment closely follows the analysis conducted in Jappelli and Pistaferri (2014). The main difference that we make in this paper comes from the role of magnitude effects in evaluating the effectiveness of existing policies.

sample distribution, it is also worth emphasizing that the purpose of our policy experiment is to exemplify the qualitative direction of existing policies with the magnitude effect rather than generate an exact quantitative comparison.

One challenge in designing such a policy experiment is the nature of income changes in fiscal policy such as stimulus checks compared to those from repaying a vehicle loan. We argue these income sources share two common traits. First, both are either announced in advance or predetermined to consumers. Consumers thus have advance information on the size and arrival time of payments.[44] Second, unique government interventions including stimulus packages and repaying certain types of loans are considered irregular income changes. Such income changes contrast with regular income changes such as tax refunds that happen repeatedly over the course of an individual's life.

These income shocks also differ in other ways including persistence, target distribution, and payment size. Fiscal stimulus effects tend to be transitory, while income changes from completing a vehicle loan payment persist longer. If anything, our approach represents an upper bound on estimated MPCs, as more persistent income shocks tend to elicit stronger consumption responses. In addition, many fiscal policies target low-income households, whereas our sample includes a broader income range. With this higher coverage of income distribution, our final sample exhibits advantages for evaluating the effectiveness of policies, such as the capacity to analyze the consumption path across the total population. Lastly, the size of historical government policies varies from $500 to $1,200, with an average of $800.[45] This is comparable to our payment size, which ranges from $421 to $1,040.

We consider two policies in which the government transfer was equivalent to 1 percent of national disposable income (or GDP). By construction, this accounts for $3 million in our sample economy.[46] We then consider two scenarios of MPCs combined with different levels of transfer payments distributed among individuals to compute the aggregate MPC and aggregate consumption growth rate. The first case considers the homogeneous MPC, which equals 0.25 (the average of

[44] For fiscal policies, there are implementation lags after the initial announcement is made to households. We assume that the income changes followed by such policies are foreseeable to consumers before the actual payment is received with an initial announcement.

[45] The 2001 income tax rebates targeted individuals with more than US$6,000 with an average payment of $500 per individual. The 2008 and 2020 economic stimulus payments targeted incomes below $75,000 with average payments of $900 and $1,200 per person, respectively.

[46] This is defined as the sum of each individual's disposable income in the final sample used in our main estimation.

the MPC for the low-income tercile). The second case is the heterogeneous MPC, which is the estimated MPC in our main analysis of different magnitudes. To compute the aggregate MPC for policy experiment j for $j \in \{1, 2\}$, we calculate:

$$MPC_j = \sum_i \frac{\overbrace{\beta_i \tau_i(j)}^{MPC_i \times \Delta \text{ income}_i(j)}}{\underbrace{T}_{\text{Total transfers}}} \tag{6}$$

where β_i is the MPC for individual i computed using sample data and $\tau_i(j)$ is the transfer amount received by individual i for policy experiment j.[47] T is total revenue recurred by the government; this is equal to $T = 0.01 \times \sum_i y_i$, where y_i is disposable income. In addition, the aggregate consumption growth for policy experiment j is computed as:

$$g(C)_j = \frac{\sum_i \beta_i \tau_i(j)}{\sum_i c_i} \tag{7}$$

where $g(C)_j$ denotes aggregate consumption growth for policy experiment j and c_i is the consumption expenditure for individual i.

Our first policy experiment targets the first income tercile (the bottom 25 percent of the income distribution) in the total sample population.[48] In this policy, the income cut-off value is $28,150 and the transfer payment is $1,420, which is distributed equally among individuals who receive the payments. Table 4 reports the effect of the government transfer program under two policy experiments with the homogeneous and heterogeneous MPC. When we consider heterogeneous MPC separately from homogeneous MPC, the aggregate MPC and consumption growth increase slightly from 0.24 to 0.25 and from 0.45 percent to 0.47 percent, respectively. The difference in the two cases is marginal, which may be because the payment size accounts for a relatively larger share of quarterly income.

In the second policy, we target the first and second income terciles. As this policy covers a larger proportion of the total sample population, the mean payment size per individual is smaller given the same total cost for the government. The transfer payments are equally distributed to up to 75 percent of income distribution with an average payment of $470. The income cut-off

[47]The transfer payment received by individual i in policy experiment j is equal to $\tau_i(j) = T/d^j \times \mathbb{1}(i \in t^j)$, where d^j is the total number of transfer recipients for policy j and $\mathbb{1}(i \in t^j)$ is an indicator function of the status of the transfer recipient.

[48]The tercile distribution follows the main estimation strategy used in our empirical analysis.

Table 4: Effect of Government Transfers on Consumption Response

Policy Transfer: 1 percent of GDP	Aggregate MPC	Aggregate Consumption Growth
Homogeneous MPC		
Transfer to 1st bottom income tercile	0.24	0.45%
Heterogeneous MPC		
Transfer to 1st bottom income tercile	0.25	0.47%
Transfer to 1st and 2nd bottom income tercile	0.73	1.38%

Notes: In our first policy experiment, we distribute transfers to bottom income tercile only. In the second policy experiment, we consider both first and second income terciles in our final sample population.

under this policy is therefore higher than that of the first policy.[49] The payment size relative to income decreases for both income terciles, implying a higher MPC from the anticipated income changes. This prediction is confirmed in our experimental results, where the second policy with heterogeneous MPC exhibits a significantly higher aggregate MPC (0.73). In addition, the policy with relatively smaller payments boosts overall consumption growth by 1.38 percent.

7 Concluding Remarks

The foundation of understanding how household consumption responds to anticipated income shocks begins with the implication of the PIH, where consumption growth is independent of the shape and path of anticipated income changes. Violation of this theory, excess sensitivity, has been frequently documented in the literature, although the importance of how variation in the size of income changes affects the consumption response has been less studied. Using newly constructed longitudinal panel data with micro-level information from the BOK household debt database, we contribute to the literature by studying how consumption dynamics vary with the magnitude of predictable income changes.

We evaluate the natural experiment of predetermined income shocks in the quarter following the final car loan payment. The average MPC generated by the final payment is about 18 percent; the consumption expenditure peaks with the arrival of the income change and then sharply de-

[49] The income cut-off for the second policy is $40,800; the average income level is $35,364 for the total sample.

creases. There is also a large group heterogeneity in spending in response to both the absolute and relative size of income changes. The MPC monotonically decreases in all three types of magnitudes that we consider: the absolute payment size, the payment size relative to income, and the payment size relative to consumption. Qualitatively, this result implies that the smaller magnitude of anticipated income changes results in a significant deviation in consumption-smoothing behavior or optimal consumption decisions. We highlight that the relative size of income plays a predominant role in explaining spending sensitivity. Nevertheless, binding liquidity constraints are often been emphasized as the main mechanism underlying excess sensitivity. In this paper, we consider three factors — age, income, and extra debt constraints — to analyze the effect of liquidity on MPC heterogeneity. Our main estimation results on conditional MPC with size variations suggest that there is a strong size (or magnitude) effect even for individuals who are liquidity-constrained.

Our theoretical discussion features the potential mechanism behind the size-dependent MPC generated by anticipated income changes. By revisiting the standard model with rational agents, we document that the one-time sharp increase in consumption dynamics caused by anticipated income changes cannot be explained with permanent income shocks. Taking the bounded rationality, the MPC significantly increases for a small payment size as agents selectively become rational subject to the size of income changes when making their optimal consumption decisions. Similarly, the negligible welfare cost of not fully smoothing consumption out of a small payment size can be considered another potential mechanism behind our empirical findings.

Our results have important policy implications for evaluating the effectiveness of the fiscal policy. In a policy experiment designed to highlight the qualitative implications of implementing various fiscal policies, we document that a government transfer program (equivalent to 1 percent of GDP) distributed equally among the bottom first and second terciles of the income distribution in our sample economy can boost aggregate consumption growth by 1.38 percent. The difference in growth is 0.91 percent when we compare this policy to one that targets the bottom income tercile with larger individual payments. With broader coverage of the total population, the average payment size (in both absolute and relative terms) decreases, implying a higher MPC.

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