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

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March 10, 2023

Abstract

Using newly constructed individual-level data based on the Bank of Korea's household debt database, we examine 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 the marginal propensity to consume (MPC) is 18 percent on average. The MPC monotonically decreases with the magnitude of anticipated income changes and the sensitivity of spending largely depends on the size relative to the individual's quarterly income. We also find a strong size effect regardless of liquidity constraints. When the predictable change in income is small, consumers tend to significantly deviate from consumption-smoothing behavior, implying a higher MPC. Theoretically, these empirical responses are justified by the welfare loss associated with the magnitude. The results have important implications for predicting consumption responses to government interventions.

JEL Classification: D12, E21, G51

Keywords: Anticipated income changes, Marginal Propensity to Consume, Heterogeneity

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[*]The views expressed herein are those of the authors and do not necessarily reflect the official views of the Bank of Korea. When reporting or citing this paper, the authors' names should always be explicitly stated.

[†]We are highly indebted to Sarah Zubairy, Yoon Jo, and Tatevik Sekhposyan for their constant guidance, support, and suggestion. We are also grateful to Chris Carroll, Adrien Auclert, Jonathan Meer, Andrew Barr, Dennis Jansen, Eunseong Ma, Choongryul Yang, and seminar and conference participants at TAMU, SNDE 2022, CEF 2022, WEAI 2022, and SETA 2022 for their helpful comments and feedback. All errors are our own.

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1 Introduction

Does household consumption respond to anticipated changes in income? If so, how do these responses depend on the magnitude of these changes? Which households are the most sensitive to these changes? These questions are crucial for evaluating the effectiveness of policies with predictable components and for understanding the macroeconomic implications on economic growth. Many policies — such as government transfers, tax rebates, and automatic stabilizers — have components that are highly predictable to households. The recent COVID-19-related stimulus packages have highlighted the need to analyze whether such policies stimulate consumption. One potential challenge for policymakers is determining the optimal level of payments for such programs. Existing policies target different income levels, and the size of the payments varies according to the individual. The 2001 federal income tax rebate program cost $38 billion with an average payment of US$500 per person. The 2008 and 2020 economic stimulus payments constituted a larger fraction of GDP and larger average individual payments.[1] Consumption constitutes almost two-thirds of the GDP in most countries, and estimating the extent to which household consumption would respond to predictable income changes of different magnitudes is critical to designing stabilization policies (Jappelli and Pistaferri, 2010).

A standard model of intertemporal allocation called the life-cycle permanent income hypothesis (LCPIH) suggests that agents are assumed to be rational and forward looking when making consumption decisions. Hence, the expected value of future income informs individuals' optimal current consumption choices. Indeed, consumption growth should be insensitive to future income changes if it is pre-announced or predictable, and if the spending response is independent of the shape and path of the anticipated 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 empirical and theoretical literature. Several studies have reported empirical evidence that rejects the LCPIH by demonstrating that household consumption *does* respond to anticipated income changes (Shea, 1995; Browning and Collado, 2001; Agarwal et al., 2007; Shapiro and Slemrod, 2009).[2] To rationalize this empirical finding, another strand of the literature emphasizes the role of liquidity constraints in the rational model (Baker et al., 2020; Johnson et al., 2006; Parker et al., 2013). We contribute to the growing literature on how the dynamics of the consumption path in response to an increase in anticipated income evolve over time, and whether consumption responses are related to variation in the size of income changes. We also scrutinize the role of the size of anticipated income changes over the liquidity channel, which is often captured as the main channel of excess sensitivity. To the best of our knowledge, few studies have evaluated how the

[1]The 2008 payments cost $96 billion dollars ($900 per individual) and constituted 0.7 percent of GDP. The $803 billion (4 percent of GDP) 2020 package involved $1,200 payments per individual, on average.

[2]Recent studies focus more on marginal propensity to consume (MPC) heterogeneity motivated by tax rebates and stimulus checks based on household survey data (Kaplan and Violante, 2014; Kueng, 2018; Coibion et al., 2020; Karger and Rajan, 2020).

magnitude of anticipated income changes affects individuals' MPC. The data sources they rely on have small samples and provide very limited information on household characteristics.[3]

In the first part of this paper, we examine how the MPC following income changes varies over time, and analyze whether there is any anticipation effect. We then explore how this consumption response is heterogeneous across individuals with different magnitudes in both absolute and relative terms. We consider the absolute size of predictable income changes as well as the size relative to an individual's total income and consumption expenditure and assess which factor has a greater influence on excess sensitivity. Lastly, we further exploit MPC heterogeneity by size distribution and explore the joint role of significant factors captured in prior studies including age, income, and liquidity.

To analyze the consumption path out of different magnitudes of anticipated income changes, we use de-identified individual-level data from a Bank of Korea (BOK) household debt database (household DB, hereafter) to construct a new panel data set for the period 2012–2016. We use this rich data set containing micro-level information (e.g. actual financial transactions in spending, income, debt, and other demographic features) to estimate individuals' quarterly debit and credit card expenditures after they make their final car loan payment — a natural experiment of an increase in discretionary individual income.[4] This experimental approach provides clearly identifiable income changes and overcomes empirical difficulties associated with examining consumption responses following anticipated income shocks.

A vast literature examines how anticipated income shocks affect consumption, yet their identification strategies may differ. Other studies have pursued similar exercises using different identification strategies on predictable income changes, for example on final mortgage payments (Scholnick, 2013), tax rebates (Agarwal et al., 2007; Shapiro and Slemrod, 2009), dividend payments from the Alaska Permanent Fund (Hsieh, 2003; Kueng, 2018), exhaustion of unemployment insurance benefits (Ganong and Noel, 2019), and stimulus checks (Coibion et al., 2020; Karger and Rajan, 2020). Our work is closely related to that of Stephens Jr (2008), who uses final car loan payments as a natural experiment approach. However, our data set has a much larger sample size and contains more detailed micro-level data.[5]

Our data set has at least five advantages over the data sources used in prior studies. First, our longitudinal panel data provides micro-level information along multiple dimensions. It contains the path of a specific debt, spending, income, credit information, and demographic characteristics at a quarterly frequency. This information allows us to conduct various micro-level analyses that could

[3] Scholnick (2013) uses a sample of 147 individuals to test whether the magnitude of predictable income changes following a household's final mortgage payment affects consumption smoothing, and finds that excess sensitivity is mainly driven by the magnitude.

[4] Research on the LCPIH constitutes an active strand of the literature and features natural experiments in macroeconomics (Fuchs-Schündeln and Hassan, 2016).

[5] Our newly constructed data provides detailed information related to debt structure such as quarterly payment amount, the duration of car loans, and the beginning and end dates of loan payments.

not be performed using existing macroeconomic data.

Second, this newly constructed data set is highly reliable, accurate, and nationally representative. Since it contains information collected from all individual accounts across all issuing banks in the country, it has more reliable underlying data than that used in other research.[6] Third, our data set provides accurate and timely information on the paths of spending and income changes. It uses actual financial transaction data on credit/debit card usage as well as the payment size and duration of debt recorded 2 months after the end of quarter.[7] Fourth, the data set has the same proportions of age, region, and credit rating as the total population, which makes it a well-represented sample.[8] Our final sample contains approximately 77,150 observations for individuals who anticipate a change in income. This large sample, which contains accurate, timely, and detailed micro-level information with more observations than in prior studies, is useful for examining the effects of anticipated income shocks on consumption-smoothing behavior.

Lastly, credit and debit card expenditure constitutes the majority of total consumption in the Korean economy — approximately 75 percent of total consumption on average during the sample period according to actual financial transaction data on consumption expenditure from the Credit Finance Association of Korea's annual report.[9] The growth rate of consumption in South Korea also increases proportionally with financial transactions; credit card expenditure is thus a useful proxy to capture the general trend of total consumption.

Our main empirical findings suggest that predictable income changes increase the MPC by approximately 18 percent on average. That is, consumption increases by 18 cents for each one dollar increase in predictable income. The spending response peaks in the quarter following the final payment (i.e. the quarter with predictable income changes) then returns sharply to zero with no anticipation effect prior to the change. This response is consistent with other studies that have identified a transitory increase in anticipated income changes (Shapiro and Slemrod, 2009; Kaplan and Violante, 2014; Coibion et al., 2020).[10] We then examine how the magnitude of anticipated income changes affects MPC heterogeneity. By estimating the standard parametric regression, we report the heterogeneity in spending responses at three different dimensions of magnitude — the absolute size of predictable income changes captured by final car loan payment (*FP*), payment size relative to quarterly income (*FP to Income*), and payment size relative to quarterly consumption (*FP to CCE* (credit card expenditure)).[11] We find that (i) consumption expenditure monotonically

[6]Previous studies using U.S. data often have limited access to all accounts.

[7]Our data set also mitigates potential problems associated with using survey data, including recall bias and measurement errors.

[8]The data represents about 2.4 percent of the total population, or around 1 million individuals.

[9]By way of comparison, approximately 10 percent of the U.S. population has no credit history. A higher percentage of consumption expenditure is transacted in cash in the U.S. than in South Korea, and is therefore hard to trace.

[10]Shapiro and Slemrod (2009) and Coibion et al. (2020) find that around 20 percent of predictable income changes (following tax rebates and fiscal stimulus payments, respectively) are spent on consumption in the U.S.

[11]Final payment (*FP*) represents the anticipated income changes following the final car loan payment

decreases with the size of the final payment in both absolute and relative terms and (ii) the payment size relative to income is the most significant factor affecting spending responses among the three classifications of magnitude.

We also document the role of liquidity constraints. To analyze how liquidity affects spending, we report conditional MPC heterogeneity on the payment size by three impacting factors including age, income, and liquidity. As our data has limited information on assets and/or wealth, we use proxy variables such as income and extra debt constraints. Intuitively, low-income households tend to hold low illiquid and liquid assets. In the presence of credit constraints (where individuals have limited access to credit), agents cannot borrow based on the prediction of an income increase. Therefore, income changes affect consumption levels, implying a high MPC.[12] Past research has also discussed poor and wealthy Hand-to-Mouth (HtM) households in which both groups exhibit high MPCs due to credit constraints; thus income is not an ideal proxy variable (Jappelli and Pistaferri, 2014; Kaplan et al., 2014). To address this issue, we consider another variable, mortgage debt status, which further limits agents' ability to borrow.[13] Notably, our analysis of joint distribution of the size and liquidity constraints suggests there is a strong size effect regardless of liquidity constraints. That is, MPC is higher only when the anticipated income increase is small for individuals (with or without binding liquidity constraints). Yet we do find that low-income individuals have higher MPCs conditional on the size variation. This indicates that MPC is higher for individuals with low payments than high payments regardless of their income. However, within the low-payment group, low-income individuals exhibit the highest MPCs, as predicted by conventional wisdom.

We report three additional robustness checks of our estimation results. First, we examine whether the size-dependent MPC still holds for an alternative grouping strategy. We consider five quintiles of relative size distribution instead of baseline terciles. We find that excess sensitivity has the greatest effect on the lowest quintile; MPC decreases monotonically as the relative size increases. Second, our main analysis of the path of consumption dynamics only considers the *average* response to anticipated income changes. To verify whether these dynamics have compositional effects at different magnitudes, we provide evidence on consumption dynamics by three distributional groups. Based on the results, we find that all three groups exhibit a peak response at the time of the income increase, which then decreases to an insignificant level after two quarters. Moreover, the dynamic changes are the most evident for the group with small payments. Third, as we convert the original currency (Korean won) using the mean value of exchange rates, we run the same regression on won to address any estimation bias resulting from the currency conversion. We also extend the analysis window to include two quarterly lags and four quarterly leads to provide more persistent results.

from the natural experiments.

[12] Low-income individuals tend to face a one-time provision of liquidity, which has been described as "one of the major determinants to generating high MPCs in macroeconomic models" (Coibion et al. (2020), p.12).

[13] We also considered other variables to capture liquidity constraints such as the mean value of the credit utilization rate, credit card consolidation loans, and default status. However, there are very few observations for those variables.

The second part of the paper documents relevant theoretical discussions behind the size-dependent MPC and provides evidence to inform policy implications. We discuss the welfare costs of deviating from optimal consumption decisions associated with different levels of magnitude of anticipated income changes. We also report why some standard models of intertemporal consumption choice or rational models may not exhibit size-dependent excess sensitivity, as we document in our empirical results. Finally, we conduct a policy experiment to investigate the implications of size-dependent MPC for government interventions involving transfers.

By revisiting the existing model on consumption-smoothing behavior, we find that the one-time sharp increase in consumption after the income change we observe (following a final car loan payment) cannot be explained using the standard model with rational agents. In most models, the consumption response persists as income shocks endure over a long time period, and constitutes a fraction of permanent income changes. One potential reason for this finding is that 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 closer to what we document in our estimation results.[14]

Another reason for our finding that consumption soon returns to normal could be related to bounded rationality: agents selectively become rational depending on the size of the income changes when adjusting their optimal consumption behavior.[15] We also discuss the welfare costs associated with magnitudes as another possible explanation for the size-dependent excess sensitivity. The utility gain from adjusting consumption is greater when the magnitude of the income change is large relative to the individual's income. Likewise, the welfare loss associated with not fully smoothing consumption is relatively low when the income change is small.[16] 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.

Lastly, our policy experiment exercise provides evidence of improvement in aggregate consumption growth when considering the magnitude effect and size-dependent heterogeneous MPC. Existing government interventions such as tax rebates or fiscal stimulus checks target households according to their reported income threshold. We argue that the types of anticipated income changes those policies generate share two characteristics with the income change caused by paying off a car loan we evaluate. First, both income changes are known in advance. Second, both constitute irregular income changes (Fuchs-Schündeln and Hassan, 2016). However, the persistence of income shocks triggered by fiscal stimulus packages is generally transitory, while income changes caused

[14]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.

[15]Browning and Collado (2001), Hsieh (2003), and Reis (2006) also present the bounded rationality affecting excess sensitivity depending on the size variation.

[16]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.

by repaying vehicle loans endure over a relatively long horizon. If anything, our approach prevails over the lower bound in the estimated MPCs as income shocks become more persistent.

To analyze the effectiveness of policies that vary in magnitude, we implement two policies: one targets the first income tercile with larger payments, while the other covers a higher fraction of the total population with a smaller average payment, implying a higher MPC for the latter group. When we consider the size effect associated with heterogeneous MPCs, we find that the aggregate growth in consumption increases from 0.47 percent under the first policy to 1.38 percent under the second, with a smaller payment size on average. This finding suggests that anticipated income changes generated by policies implemented with size variation will boost aggregate consumption in the short term.

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 5 presents several robustness analyses. Section 6 discusses the theoretical support, and Section 7 evaluates the policy implications of our findings. Section 8 concludes.

2 Data

2.1 Administrative Data

Our data comes from the BOK household debt database.[17] This database is a longitudinal quarterly panel of de-identified individual-level records from a major credit reporting agency 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.[18] The number of individuals with a credit history increased from 38 million to 44 million during the study period. According to the sampling results, approximately the same proportion of age, region, and credit rating groups were 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.[19] 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.[20] Our data set contains a larger number of observations with little measurement error or

[17]This database is constructed based on credit reports from the Korean Credit Bureau. It is similar to the U.S. Federal Reserve Bank of New York Consumer Credit panel.

[18]Approximately 1 million individuals aged 18+ engage in credit activities (i.e. use debit and/or credit cards.

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

[20]The most commonly used data to analyze consumption responses in the U.S. is the Panel Study of Income Dynamics and Consumption Expenditure Survey. However, such data sets have limited features

Table 1: Credit and Debit Card Usage out of Total Consumption

Year	2012	2013	2014	2015	2016
	0.72	0.71	0.73	0.77	0.84

Source: The Credit Finance Association of Korea

Notes: Table 1 represents the fraction of total consumption represented by credit and debit card usage across all issuing bank and financial institutions in South Korea, for the sample period from 2012 to 2016.

recall bias, which are potential problems associated with using survey data. It uses the actual financial transaction data across all issuing banks and financial institutions within the country. As the credit bureau automatically collects this data on a regular basis over many periods, it is highly accurate and timely. In addition, the consumption expenditure captured by financial transactions constitutes the majority of total consumption in South Korea. During the sample period, credit/debit card usage represents approximately 75 percent of total consumption, on average (see Table 1). Another important feature of this data set is that the utilization rate of credit/debit cards does not vary significantly by income level in South Korea.[21] 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.

We acknowledge that our data set suffers from at least three 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/debit card usage in South Korea minimizes the impact of this potential measurement error. A third concern about our data relates to the reporting of income and missing data. Credit bureaus collect income data based on the proof of income reported by each individual. Since higher-income individuals receive more advantageous interest rates and loan limits, consumers are motivated to submit proof of income, which improves the reliability of our data. We lack income information for only 2.4 percent of the total sample; for these individuals, we replace income with the estimated value based on past information including proof of income, card usage, and occupation.

and considerable measurement errors in income (Ni and Seol, 2014). Another strand of studies uses U.S. transaction data in a similar way, however it only has data on one restricted financial institution — JPMCI (Baker and Yannelis, 2017).

[21] Approximately 10 percent of the U.S. population is excluded from the sampling population because they have no credit history or simple inquiry. Moreover, low-income households in the U.S. tend to have a higher proportion of cash (rather than credit/debit card) transactions.

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).[22] 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

South Korea's average household debt per GDP ratio was 80–85 percent during the study period.[23] Mortgage debt accounts for the majority share of total household debt (54 percent), followed by credit card liability (17 percent), student loan (11 percent), and auto loans (9 percent). We focus on auto loans since they provide richer variation in terms of payment size among individuals with different income levels and other demographic characteristics. For each auto loan held by an individual, our panel data set includes information 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 car loan payment amount is CPI adjusted to year 2020 prices and converted from Korean won into US dollars using the mean exchange rates.[24] From 2012 to 2016, the mean value of the final car loan payment was $788 (minimum $89, maximum $5,660). In the distribution of final car loan payments (with more than 77,000 observations), more than half of the sample was under $1,000.

2.2.2 Sample Selection, Variables, and Descriptive Statistics

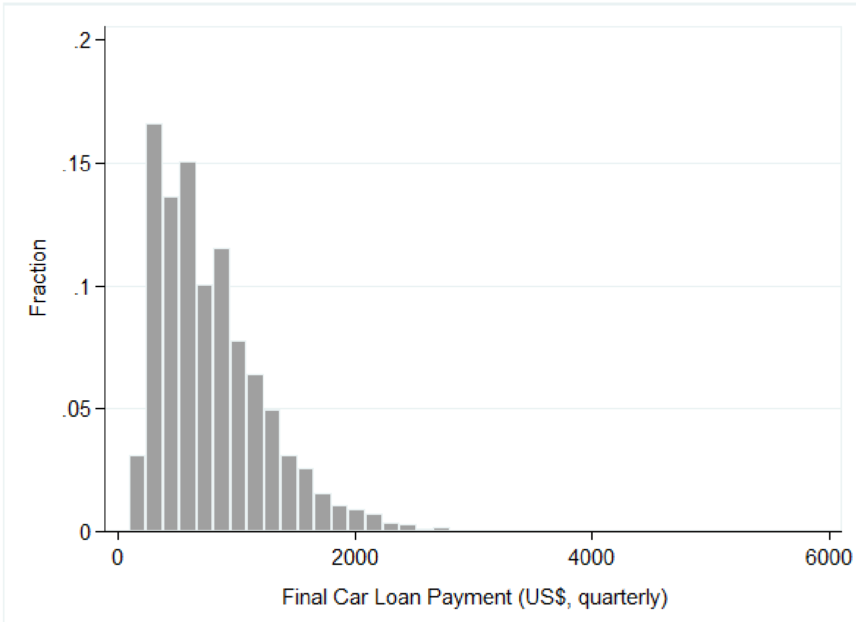
We restrict our final sample to individuals who have a regular car loan repayment for a fixed duration until maturity. We assume that consumers anticipate their changes in income for at least one quarter as car buyers receive multiple monthly notifications about the end date in advance. We exclude customers who pay off their loans early in a lump sum, because those individuals may roll over their existing loans that could be endogenously related to consumers' spending behavior. We only consider first-time car buyers because there is a chance that consumers who buy subsequent

[22] Various types of natural experiments have been used to test excess sensitivity. For instance, Scholnick (2013) considers the final mortgage payment. Johnson et al. (2006), Agarwal et al. (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 et al. (2020) and Karger and Rajan (2020) consider the COVID-19 economic impact payments.

[23] From 2012 to 2016, the real GDP per capita (in 2012 US dollars) was $29,388.

[24] To minimize currency conversion errors, we also report the results in the original currency in our robustness checks.

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.

cars may roll over and start a new loan after paying off their first loan, similarly to those who repay their loan early in a lump sum, which would lead to endogenously biased estimation results.[25] Multi-time car buyers may also exhibit different behaviors from first-time buyers that would affect our results, such as purchasing an additional vehicle or regularly changing cars. Lastly, we exclude the top and bottom 1 percent of the total distribution to avoid any outlier-biased results.

Table 2 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 measured using actual credit and debit card transactions per quarter across all issuing banks and financial institutions in the country.[26] Quarterly before-income data is collected by credit bureaus for tax reporting purposes and is based on the proof of income provided by each individual.

The final sample for our empirical analysis includes 77,148 observations. The summary statistics demonstrate that the mean value of the predictable income change is $788, quarterly income of $8,841, and consumption expenditure of $4,802. On average, this implies that the anticipated increase in discretionary income accounts for almost 10 percent of an individual's before-tax quarterly

[25]We plan to extend our final sample to include multi-time car buyers in future analysis.
[26]This data does not contain detailed information on the consumption category.

Table 2: 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. The credit card limit is based on 40 days of credit period. Credit grade is on a scale of 1 to 10, 1 being the highest (great), 10 being the lowest (poor).

income and 25 percent of their 2-quarter average consumption expenditure before the anticipated 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 40–59.

2.2.3 Representativeness

A challenge associated with empirical studies restricting their samples to individuals of a certain type (in our case, car buyers) is that they may not represent the broader population.[27] We provide two pieces of evidence that our sample is likely to be comparable to the overall population in South Korea.

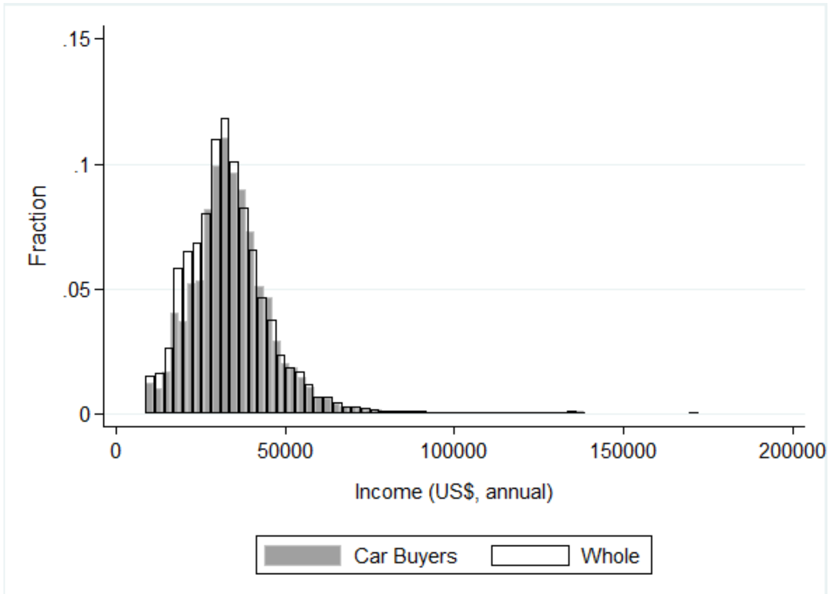
First, Figure 2a illustrates that the distribution of annual income in the car buyer group is very similar to that of the general population in the full sample represented in the BOK household debt database. Similar to the final car loan payment shown in Figure 1, the monetary amounts are converted into US dollars using year 2020 prices. The average annual income for the car buyer group is \$35,360 (\$8,840 per quarter). Though this group has a slightly smaller fraction of incomes under \$30,000 compared to the whole sample distribution, the sample itself represents the overall distribution well.[28] For the full sample distribution, we have 896,000 observations — 12 times more

[27] We restrict our samples to individuals who have historical credit activities and a good credit rating to qualify for car loans.

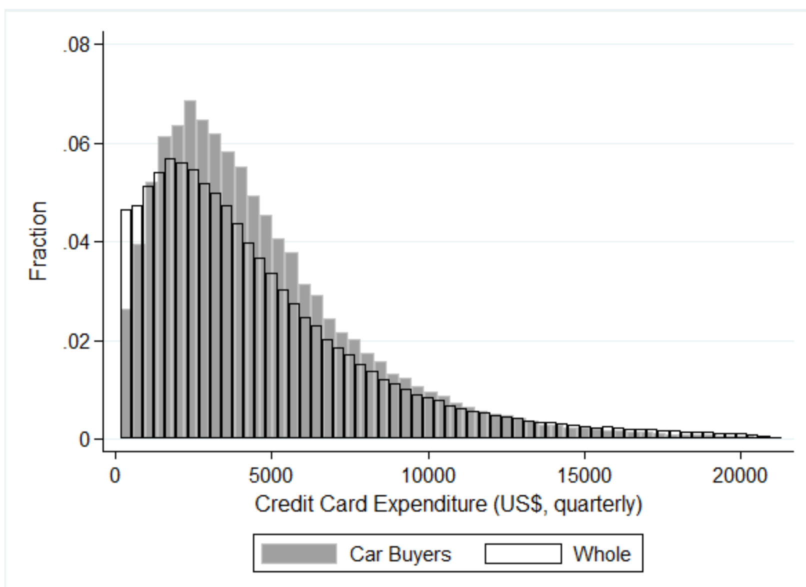
[28] The distribution of annual income for the car buyer group has a lower fraction of individuals with an

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).

than our final sample size.

Second, the distribution of consumption expenditure suggests a similar pattern as in Figure 2b. The mean value of quarterly credit and debit card expenditure for car buyers is $4,802. There is a smaller fraction of car buyers with expenditures below $3,000 per quarter, which makes the sample distribution a slightly right-skewed version of the full sample distribution. Although our final sample does not perfectly match the distribution of the whole population, the overall shape of the distribution and similar minimum and maximum values suggest it is likely to be representative of the total population. Beyond income and consumption distribution, we also show the distribution of the final payment size relative to income, final payment size relative to consumption, and age share in Appendix B.

3 Empirical Approach

A central implication of the LCPIH is that consumption responses should be insensitive to predictable income changes. In particular, if agents are assumed to be rational and forward looking, any foreseeable changes in income should result in zero consumption growth as individuals smooth their consumption over their lifetime. In this section, we examine whether our results empirically violate this standard theory and study the consumption dynamics related to a change in income.

To capture the changes in consumption associated with the anticipated income change, we first identify an increase in income that is foreseeable to consumers following Stephens Jr (2008).[29] In this natural experimental approach, we consider the quarter following the final car loan payment as an event in which individuals anticipate an increase in their discretionary income.[30] We assume that individuals anticipate this increase in discretionary income since they know the date of the final loan payment in advance, and are notified multiple times during the course of their repayments.

We combine a baseline identification strategy (natural experimental approach) with the newly constructed longitudinal panel data described in Section 2 to estimate how quarterly credit/debit card consumption expenditure varies over time in response to anticipated income changes. In the second part of our empirical analysis, we estimate how the magnitude of such anticipated income changes affects consumption dynamics. We consider three classifications of sizes: (i) the absolute size of the final payment, (ii) the size relative to the individual's quarterly income, and (iii) the

annual income under $30,000. However, the total distribution of the car buyer group has similar minimum and maximum values as the whole sample. This means we have car buyers with a medium to high income as well as a significant share of those with a lower income who need to purchase a car. In addition, the car buyer group has a smaller standard deviation of distribution relative to the whole sample.

[29] Scholnick (2013) similarly uses final mortgage payments and Stephens Jr (2008) uses final car payments to predict income increases. Other sources of anticipated income increases include the Alaska Permanent Fund Dividend, 2001 federal income tax rebates, and economic stimulus payments in 2008 and 2020 (Agarwal et al., 2007; Broda and Parker, 2014; Coibion et al., 2020; Hsieh, 2003; Johnson et al., 2006; Kueng, 2018; Misra and Surico, 2014).

[30] See Section 2.2.1 for more details.

size relative to the individual's quarterly consumption expenditure prior to the predictable income change. We then examine the relative importance across the three magnitudes by considering multi-variate regression analysis. Finally, we evaluate MPC heterogeneity by size distribution and compute the conditional MPC heterogeneity to examine the joint role of significant factors suggested in previous studies such as age, income, and liquidity.

3.1 Consumption Dynamics of Anticipated Income Changes

To verify whether our data exhibits excess sensitivity, we estimate how quarterly consumption expenditure responds to predictable income changes following final car loan payments.[31] For the baseline estimation, we first focus on the absolute size of the final car loan payment and examine how it affects consumption dynamics. We estimate the standard parametric regression, which is given by:[32]

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

where c_{it} is the dependent variable that measures changes in real consumption expenditure (i.e. changes in quarterly debit/credit card transactions) per quarter for individual i in period t. Our key independent variable, $FP_{i,t-s}$, denotes the US dollar amount of the final car loan payment made by individual i at time t. 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 $t = m$.[33] This lag term allows us to flexibly estimate the results around the event windows (before and after the event of predictable income changes, defined as the final car loan payment). The estimation result for leading periods represents the anticipation effects, and for lagging periods it illustrates delayed responses. Within the event window (n, m), we set $t = 0$ as the quarter following the final car loan payment; thus it indicates the first quarter with predictable income changes.

The coefficient term, β, measures the excess sensitivity of consumption expenditure from predictable income changes.[34] As in Agarwal et al. (2007) and Gross and Souleles (2002), we interpret the estimation result as an event study. At $t = 0$, the corresponding coefficient, β_0, measures the immediate response of changes in consumption after the final payment in US dollars. Monetary

[31] When the null hypothesis (where $\beta_s = 0$) is rejected, we consider this to be a violation of the LCPIH, and the estimation result exhibits excess sensitivity.

[32] In Scholnick (2013) and many others, the regression equation includes the squared term of anticipated income changes and examines whether this term is negative. The negative coefficient on the quadratic term implies a hump-shaped response. We include this term in our robustness analysis and find similar results (i.e. negative coefficient on the quadratic term).

[33] Following Agarwal et al. (2007), Scholnick (2013), and Kueng (2018), we allow for leads and lags to estimate the anticipation and delayed response effects.

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

amounts are CPI-adjusted values using the mean exchange rate in 2020. 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.[35]

We also control for time, region, and individual fixed effects that are captured by α_t, γ_i, and $Region_i$, respectively. x_{it} include control variables such as demographic characteristics (i.e. age, gender, region), changes in income other than final car loan payment, annual income level, and other characteristics related to credit information (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. The identifying assumption for the error term is that it is uncorrelated with the predictable income changes (i.e. $Cov[FP_{i,t-s}, \epsilon_{it}] = 0$).

3.2 Estimating the Magnitude Effect

One of the paper's main contributions is that it estimates how the magnitude (or size) of anticipated income changes affects the consumption response. For each estimation of our window of analysis, 4th quarter of 2012 to 4th quarter of 2016, we estimate the consumption response for three classifications of magnitude — the absolute value of income changes following the final car loan payment, the size of the final payment relative to the individual's quarterly income, and the size relative to the average value of their previous consumption expenditure.

The absolute size of the income change is measured by changes in income following the final car loan payment (FP) in US dollars (CPI adjusted). The measure of the relative size per quarterly income is defined as:

$$FP\ to\ Income_{it} = \frac{Final\ Car\ Loan\ Payment_{it}}{Quarterly\ Income_{it}}$$

where $Final\ car\ loan\ payment_{it}$ measures the absolute size of predictable income changes for individual i at time t. $Quarterly\ income_{it}$ is the quarterly before-tax income. Since this is the ratio of relative size to income, both payment and income variables may vary. To this end, there may be an endogenous relationship between the size of the car loan payment and income. In Section 4, we examine two further variables for total observations and show that there is no strong correlation between size variations and income; we still obtain a proportional income distribution from poor to rich given a fixed payment size.

Similarly, we consider the relative magnitude of the final car loan payment per quarterly consumption expenditure prior to the predictable income change. We measure the relative size per

[35] We estimate the excess sensitivity around the event from $t-1$ to $t+3$, taking the leading and lagging terms into account.

consumption as:

$$FP\ to\ CCE_{it} = \frac{Final\ Car\ Loan\ Payment_{it}}{Quarterly\ Credit\ Card\ Expenditure_{it}}$$

where $Quarterly\ credit\ card\ expenditure_{it}$ is the quarterly CCE prior to predictable income changes for individual i at time t. We consider the two-quarter average consumption expenditure captured by debit and credit card transactions prior to anticipated income changes. This ratio measures how the relative size of the final car loan payment in relation to an individual's usual consumption behavior affects excess sensitivity. Using the definitions above, we estimate the same parametric regression as shown in Equation (1), replacing $FP_{i,t}$ with $FP\ to\ Income$ and $FP\ to\ CCE$ to observe the relative magnitude effects. For each type of size, the coefficient term measures the average value of consumption change in response to a one-unit increase in anticipated income.[36]

We then estimate which type of size is the most explanatory variable that affects excess sensitivity. We modify our baseline specification to the multivariate regression analysis. Specifically, we consider the subset of three classifications at a time and test whether the level of statistical significance changes with the inclusion of an additional variable. The resulting multivariate regression estimates measure the relative importance of each variable among the three sizes and how one affects the others in terms of explanatory power.

3.3 Marginal Propensity to Consume 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 first examine the MPCs by the distribution of absolute and relative sizes. We assign individuals to one of three subgroups for each size classification — low (<25 percent, reference group), middle ($25--75$ percent), and high(>75 percent in the distribution).[37] 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 further explore how much of each variable matters conditional upon another.[38]

[36] 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.

[37] As a robustness check, we use an alternative grouping strategy of five quintiles.

[38] As we state in the Results section, we focus on the size relative to individual income, as this variable is the most important factor affecting excess sensitivity.

MPC Heterogeneity by Size Distribution.— Consumption response heterogeneity is estimated where the difference for each group is captured by 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 group D of size type y_{it}. For each estimation, we break down the variable of interest into three distributional subgroups so that the estimation results indicate the difference in excess sensitivity for each group. For instance, we analyze the MPC heterogeneity sorted by absolute size, for those with small to larger payment sizes. We perform similar exercises in which we sort by small vs. large relative payment size per income as well as per consumption.

Conditional MPC Heterogeneity.— We examine the MPC variation conditional on the payment size by three important factors suggested by 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. We also control for time, region, and individual fixed effects using the same control variables as those used in the baseline estimation. As we stratify three observable variables by tercile conditional on three distributional groups by size, we estimate the MPCs within nine (3×3) subgroups by construction.

To examine the conditional MPC heterogeneity across three factors, we first stratify individuals by age and relative size, then by income and relative size, and lastly by liquidity measure and relative size. Each coefficient term can be directly interpreted as a joint MPC distribution. For the liquidity measure, our data have limited information on assets and wealth, so we use the quarterly income level and extra debt constraint (i.e. mortgage debt status) as proxy variables as suggested in Fuchs-Schündeln and Hassan (2016).Individuals who have a low income or hold extra mortgage debt on top of their auto loan are highly likely to be liquidity constrained.[39]

[39] Although there is a discussion of wealthy Hand-to- Mouth (HtM) individuals who hold a sizable illiquid asset (or have a high income) but very low or no liquid assets, we assume income is still a good proxy to capture the liquidity constraints as this group is assumed to behave similarly to ”poor hand to mouth” (Kaplan et al., 2014). In addition, the estimation result for MPC heterogeneity for both types of proxies (income and extra debt constraints) suggests a similar pattern of consumption response.

4 Effects of Anticipated Income Changes

In this section, we present our main estimation results on how consumption responds to anticipated income changes. We first present the evidence on excess sensitivity and how consumption dynamics vary over time by including the lagging and leading terms in the standard parametric regression. We then show how this excess sensitivity depends on the type of magnitude considered. As discussed in Section 3, we describe the estimation results for three classifications of magnitude in both absolute and relative terms. Moreover, we provide evidence on which type of magnitudes best explain excess sensitivity. Lastly, we present the MPC heterogeneity by size distribution and conditional MPC heterogeneity, which depicts cross-sectional variations in age, income, and liquidity.

4.1 Effects of Anticipated income Changes on Consumption

We first report the evidence related to excess sensitivity, which is the violation of the permanent income hypothesis (PIH).[40] Table 3 presents the main estimation results of the average consumption response to the predictable income change following the final car loan payment (denoted FP). If the estimation result is greater than 0, this constitutes excess sensitivity. Moreover, the coefficient results could be directly interpreted as MPCs (the change in consumption expenditure in response to a $1 increase in payment) as both consumption and income changes are in dollars.

Columns (1) to (4) estimate the consumption responses under different specifications. Column (1) estimates the result without individual fixed effects and control variables: MPC equals 19 percent, which indicates that a $1 increase in payment raises consumption by 19 cents. The excess sensitivity reported in Column (1) may overestimate the estimation result, as changes in consumption may be related to factors other than changes in predictable income. Therefore, in Column (2) we add control variables that include demographic characteristics, changes in income other than the final car loan payment, annual income level, and other features related to credit information. Adding these control variables generates a smaller change in consumption (0.178), though there is a higher explanatory power captured by a rise in the R-squared term. In Column (3), we add individual fixed effects to Column (1), identifying the consumption response using only the variation in the final car loan payment at the individual level. The spending response then increases to 0.196; however, we observe a precise decrease in the R-squared term. Column (4) reports our main estimation results, which take into account all individual, time, and region fixed effects as well as control variables. The estimated result suggests that a $1 increase in predictable income boosts consumption by 17.7 cents, on average.[41]

[40] We test the null hypothesis $H_0 : \beta^{PIH} = 0$. The rejection of this hypothesis is considered excess sensitivity where consumption deviates from the optimal consumption choice under PIH out of anticipated income changes.

[41] Our MPC estimates are within the range of reported MPCs in previous studies. Agarwal et al. (2007), Johnson et al. (2006), and Misra and Surico (2014) find MPCs in the range of 0.20–0.40 after the receipt

Table 3: 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.

Table 3 reports the average effects of predictable income changes on consumption response at $t = 0$. We then exploit how consumption dynamics vary around the income change and examine whether there are any anticipation or delayed effects. Figure 3, Panel (a) displays the estimation results of the coefficient, β_s, which measures the marginal effects over time. Panel (b) indicates the cumulative effects over time.[42] In this estimation, we include one quarter of lead and three quarters of lags.[43] As a result, the estimates of one leading term indicate that there is no anticipation effect prior to the predictable income changes with 95 percent confidence intervals. We find that for highly predictable income changes where the payment is predetermined, individuals do not adjust their consumption significantly prior to the quarter with anticipated changes.

The point estimate of 0.18 at $t = 0$ in Panel (a) is statistically significant.[44] The marginal effect captured by the estimated coefficients, β_s, is highest in quarter zero. This means that an individual deviates from consumption smoothing most significantly in the quarter with anticipated

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 et al., 2020).

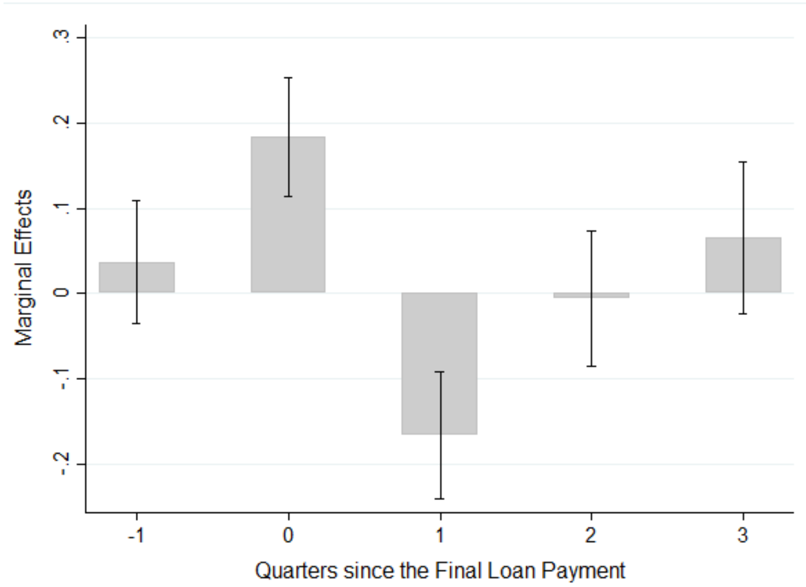
[42] In Appendix C, we also show how the income process evolves over time.

[43] We only consider one quarter of lead as the data frequency is on a quarterly basis. When we extend the lag terms to two quarters, we obtain similar estimation results.

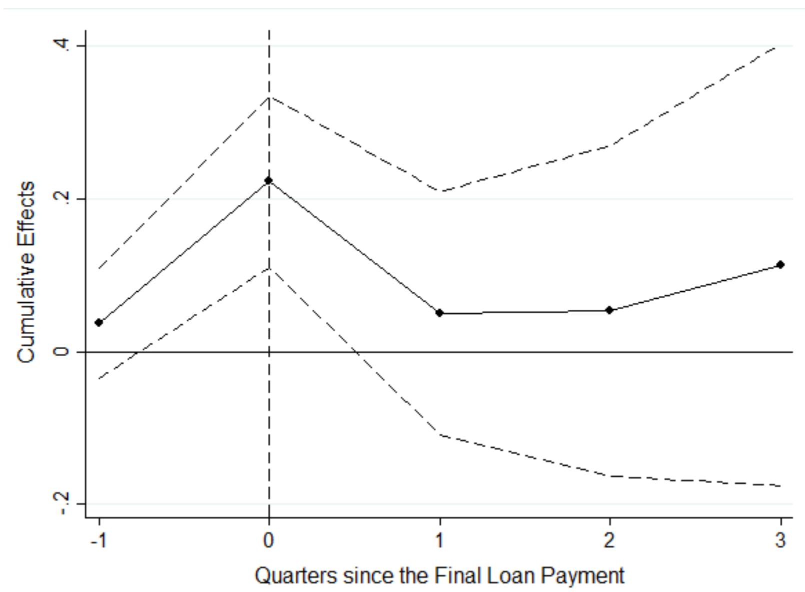
[44] In Figure 3 Panel (a), the point estimates of the regression coefficients are 0.04, 0.18, -0.17, -0.01, and 0.07 for the corresponding periods from $t-1, t, ...,$ up to $t+3$, respectively.

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 changes. At time $t+1$, the change in credit and debit card expenditure sharply decreases then gradually returns by the same amount from time $t+2$ to $t+3$ — two and three quarters after the income change, respectively. This effect is confirmed in Panel (b), which shows the cumulative effect on MPC of predictable changes captured by final payment. The point estimates of cumulative effects are 0.04, 0.22, 0.05, 0.04, and 0.11 for the corresponding periods from $t-1, t, ...,$ to $t+3$, respectively.

4.2 The Magnitude Effect on Consumption Response

One of our main interests is to examine how the magnitude of anticipated income changes affects consumption expenditure. We report the estimation results of average excess sensitivity out of absolute and relative payment sizes in this section. We also address how the size evolves over an income level and test whether those two variables are correlated with each other.

The Magnitude Effect on Excess Sensitivity.— Table 3 in Section 4.1 shows that there is a statistically significant excess sensitivity on average associated with anticipated income changes measured using the absolute level of payments. The main estimation result suggests that MPC is 0.17 (or 17 cents for every \$1 increase in payment). Appendix D Table D.1 reports similar results for both size relative to income and consumption. For the main estimation results, which control for all fixed effects and control variables, consumption increases by 1.43 units for every one-unit increase in relative size to income. Similarly, we find 0.58 unit changes in consumption for every one-unit increase in the size relative to consumption. The size relative to income exhibits the highest unit increase in consumption of the three ways to measure size.

We further explore the variation in size across three types of magnitudes (see Table 4). Each row represents the coefficient estimates of being in each subgroup (low (reference group), middle, and high) for each type of size.[45] As shown in Column (1), the excess sensitivity using absolute measures for all groups (from low to high) is statistically significant. This indicates that consumption increases significantly across all size distributions. We also find similar results for excess sensitivity using the size relative to income (Column (2)) and consumption (Column (3)). These estimated results suggest that there is evidence of excess sensitivity across all types of sizes on average as well as within size distributional groups.

Relative Importance across Magnitudes.— We next present the relative importance of three types of sizes by considering multivariate regression analysis. Columns (4) to (6) in Table 4 report the estimation results for the subset of three types of magnitudes. Column (4) includes both *FP* and *FP to Income*. As a result, the reference group has the largest coefficient (0.879), which is statistically significant. This column also indicates that the significance of *FP* response is dominated by *FP to Income*. This means that the predictable income changes relative to one's quarterly income

[45] Each group's heterogeneity is explained in detail in Section 4.3.

Table 4: 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.

is a more important factor affecting excess sensitivity than the absolute size of income changes (*FP*). Similarly, Column (5) considers *FP* and *FP to CCE*. When both variables are considered, we lose some significance on the result related to *FP to CCE*, meaning that *FP* dominates *FP to CCE*. Lastly, Column (6) indicates the relationship between *FP to Income* and *FP to CCE*. In this case, the results indicate that the estimates of *FP to Income* are statistically significant over *FP to CCE*. In summary, the payment size relative to one's quarterly income has the greatest influence on excess sensitivity, followed by the absolute payment size and the payment size relative to one's 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 we control for variables including income level, changes in income other than the final loan payment, and debt-to-income ratios in our regression analysis, payment size can be related to the amount of a consumer's down payment or preferences regarding car value. For instance, affluent consumers may pay a large down payment to ensure smaller repayments, and wealthy (impoverished) households are more likely to purchase a luxury (compact) car, leading to higher (lower) payments, on average. To address this issue, we examine how the size variation changes with the level of an individual's quarterly income. Figure 4, Panel (a) presents the relationship between the payment size (in $100 US dollars) and quarterly income (in $1,000).[46] 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 (in both absolute and relative terms), our sample contains individuals with different levels of income. In addition, there is no strong correlation between the payment size and quarterly income, with a correlation coefficient value equal to 0.2.

4.3 Marginal Propensity to Consume Heterogeneity

4.3.1 MPC Heterogeneity by Distribution

In this subsection, we show MPC heterogeneity by the distribution of different types of magnitudes. The consumption response is estimated based on Equation (2), where $\mathbb{1}(y_{it} = D)$ is an indicator function for variable $y_{it} \in \{FP,\ FP\ to\ Income,\ FP\ to\ CCE\}$ of distributional group $D \in \{Low, Middle, High\}$. In Table 4, we present the group heterogeneity across the three magnitudes listed above. In Columns (1) to (6), the first row represents the excess sensitivity for the reference group (bottom 25 percent of the size distribution) and the following rows indicate the values for the middle (25–75 percent) and high (top 25 percent) groups.

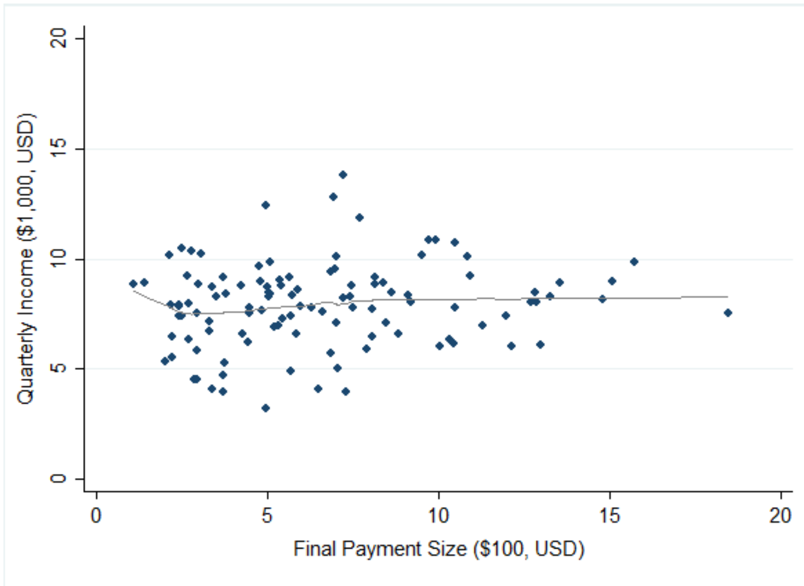
MPC Heterogeneity in Absolute Magnitudes.— The estimation results shown in Column (1) indicate how quarterly consumption expenditures respond to the absolute payment size. The low group has the cut-off value of the payment size at $421 per quarter, while the medium and high groups have $680 and $1,040, respectively. The reference group (first row, Column (1)) exhibits the highest excess sensitivity: a $1 increase in income yields a 75 cent boost in consumption. The second and third rows indicate the estimates for the middle and high groups. The middle group has estimated values of 0.20 (that is, less than 0.558 compared to the reference group's estimate). Similarly, the high group has an excess sensitivity of 0.14, implying the lowest MPC.[47] Overall, we find that MPC monotonically decreases by absolute size, and that there is a large group heterogeneity across size distributions.

[46]To clearly depict the relationship between payment size and income, we stratify our sample to 1,100 observations. Appendix E, Figure E.1 shows the scatter plot for the full sample during the study period. Although the data becomes noisy, we still observe no strong correlation between the relative size of the car loan payments and quarterly income.

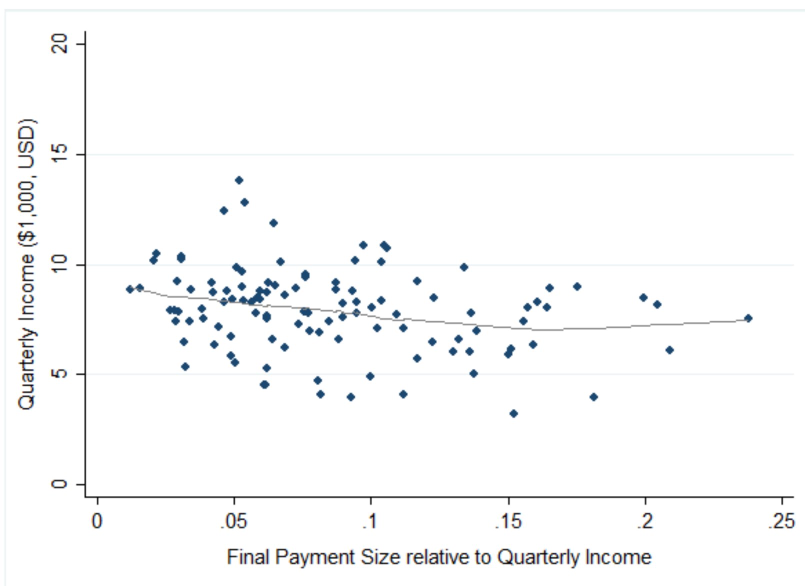
[47]These results suggest that we have group heterogeneity in excess sensitivity. For the final payment size, the difference between the reference group and the other two (middle and high) is large, while the group heterogeneity between the middle and high groups is relatively small.

Figure 4: Distribution of Final Car Loan Payment, 2012–2016

(a) Quarterly Income and Final Payment Size



(b) Quarterly Income and Relative Final Payment Size



Notes: Figure 4, Panel (a) plots the payment size (per $100) and Panel (b) for the relative size ratio against quarterly income. The solid line indicates the fitted line for two variables in each panel.

MPC Heterogeneity in Relative Magnitudes.— Columns (2) and (3) report the estimation results for excess sensitivity over *FP to Income* and *FP to CCE*. For the size relative to income, the reference group has a cut-off value of 5 percent, followed by 8 and 13 percent for the middle and high groups, respectively. Similarly, the size relative to consumption expenditure has a cut-off value at 10, 17, and 31 percent for each tercile. Similar to the estimation result for the absolute size, relative size in both income and consumption have monotonically decreasing excess sensitivity with significant heterogeneity across size variations. The estimate of coefficients for the *FP to CCE* for the reference group is relatively small (0.321) compared to the other magnitudes, though the monotonic relationship still holds. These results suggest the key finding of our paper: when the size of the payment relative to quarterly income is small, individuals deviate significantly from consumption-smoothing behavior. When the payment size accounts for a larger fraction of individual income, the tendency to smooth consumption due to an anticipated income change increases.

In summary, we find that (i) there is excess sensitivity, that is, consumption responds to anticipated income changes following the final car loan payment, (ii) the payment size relative to income is the most prominent of the three types of sizes, (iii) MPC decreases monotonically with size, and (iv) the spending responses are heterogeneous across variations in size.

4.3.2 Conditional Marginal Propensity to Consume

Our main estimation results on excess sensitivity suggest that there is heterogeneity in spending responses for consumers with different magnitudes of anticipated income changes. Previous research has demonstrated that liquidity constraints have played a significant role in explaining excess sensitivity, though it has often overlooked how MPC varies with the size of the income change. 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 et al., 2014; Fuchs-Schündeln and Hassan, 2016).[48] The mechanism behind these earlier findings suggests that when households are liquidity constrained, changes in income are most likely to be spent on consumption due to a lack of liquid income sources. To determine whether the MPC of different magnitudes still holds under binding liquidity constraints, we document the conditional MPC heterogeneity of the relative payment size over three significant factors commonly captured in the existing literature: age, income, and liquidity. We focus on the payment size relative to income along different dimensions as this is the most important variable among the three magnitudes.[49]

[48]Prior studies also argue that younger households tend to be liquidity constrained. However, our analysis focuses on illiquidity related to income level rather than demographic characteristics.

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

Age and Income.— In Figure 5, we show the conditional MPC heterogeneity. Panel (a) displays the distribution of MPC across different age groups and the size relative to income. Our results indicate that MPC is higher when the relative size is small, regardless of age. This result shows that age is not the main factor affecting the MPC. 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) displays the conditional MPC due to income and relative size. As we have no strong correlation between the payment size and income, this conditional MPC estimates the dimension along these two variables.[50] We find that the MPC increases by more when the payment size accounts for a smaller fraction of an individual's quarterly income for all income groups. That is, the MPC is higher for the low FP to Income group than for the medium to high relative size groups, regardless of income level. In addition, the MPC is highest for the lowest relative size and low-income individuals. This finding suggests that there is a strong size effect even in the presence of liquidity constraints (captured by low-income individuals). Panel (d) indicates the population share, income, and size relative to income. As shown in the figure, the distribution of the population share is centered on the middle-income group.

The Role of Liquidity Constraints.— Recent studies, including Kaplan et al. (2014), suggest that households may be wealthy (or have a high income) but still be liquidity constrained. For instance, from 1989 to 2010 around 30 percent of U.S. households were "wealthy hand to mouth households." This means that income level may not adequately explain the role of liquidity. Furthermore, our data set does not contain information on asset holdings of wealth. Therefore, we consider another variable, extra debt constraint (captured by a mortgage debt status), which limits individuals' borrowing ability along with age and income variables.

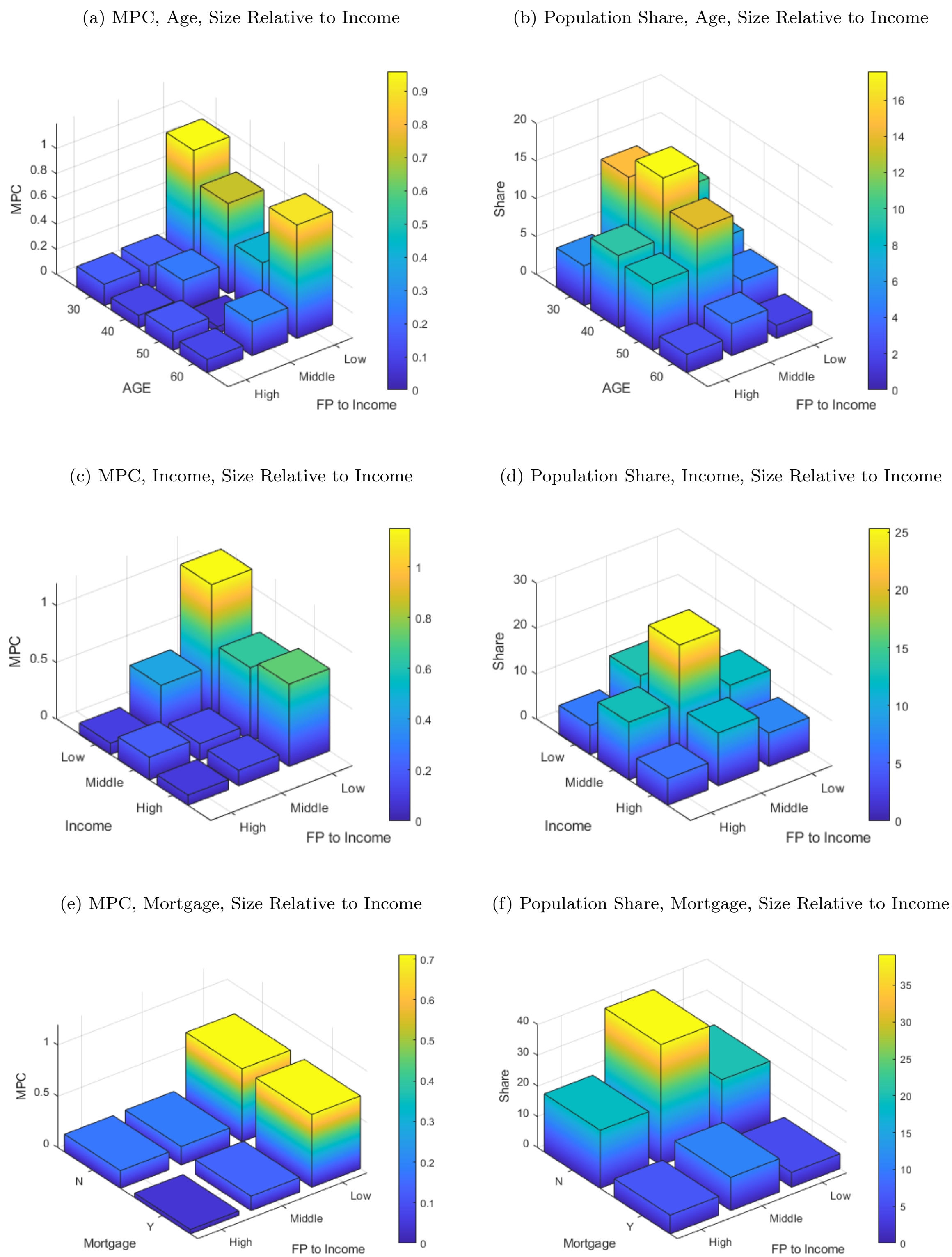
Panel (e) of Figure 5 displays the conditional MPC distribution of being affected by this extra credit constraint. We find that there is a sizable MPC response with low size regardless of mortgage debt status. This result suggests that there is a strong size effect regardless of the liquidity channel affecting consumption-smoothing behavior. Panel (f) presents the population share, mortgage status, and relative size. We find that most of the individuals in our sample do not have both auto loan and mortgage debt simultaneously. We also consider other variables such as the high rate of credit utilization, use of credit card consolidation loans, late credit card payments, high level of unused credit lines, and high default risk to capture liquidity. However, the number of observations on those variables in our sample data is too limited to generate a meaningful result.

Figure 6 displays the MPC sorted by the relative size tercile, conditional on the same level of income with 95 percent confidence interval bands.[51] Similar to Figure 5, the MPC is highest for individuals in the lowest relative size tercile across all three income groups (from low to high). Nevertheless, the differences in MPC between the low and high relative size groups (within each

[50] See Figure 4 for more details.

[51] This figure is a two-dimensional view of Figure 5, Panel (c). Figure 6 illustrates the statistical significance level of differences across income groups.

Figure 5: 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

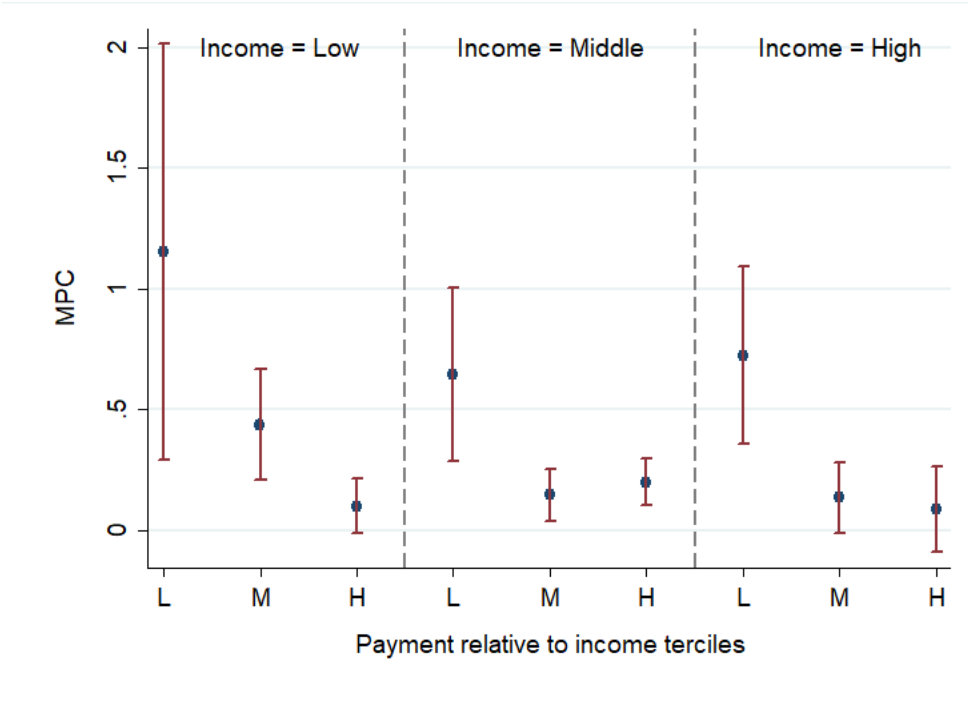
(d) Population Share, Income, Size Relative to Income

(e) MPC, Mortgage, Size Relative to Income

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

Notes: Figure 5 shows the conditional MPC heterogeneity (and population share) among age, income, and payment size relative to income.

Figure 6: MPC by income given the relative size to income (FP to Income)



Notes: Figure 6 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.

income level) are highly statistically significant, implying strong evidence of size effect across all income distributions.

In Appendix E, Figure F.2 provides an additional scope on the MPC sorted by income groups given the relative payment size, which confirms our previous finding of the largest excess sensitivity for the lowest relative size. By testing the difference between the two groups (high-income group conditional on the low relative size and low-income group conditional on the high relative size), we find that the two groups are statistically different from each other at the 1 percent level of significance (F-statistic = 7.11). More importantly, the excess sensitivity for the low-income group tends to be higher given the relative size.

In other words, among income terciles, low-income individuals, who tend to be liquidity constrained, spend the most of their predictable income changes conditional on the same relative size. This result highlights an important implication that we have a higher MPC for low-income households, which is also consistent with conventional wisdom. However, the role of liquidity constraint on excess sensitivity is dominated by the relative size of payment to income. This means that the heterogeneity in excess sensitivity may be explained by households with low liquidity, but this only holds under identical relative size to income.

5 Robustness Checks

In this section, we conduct three robustness analyses to verify the validity of our main estimation results. First, we examine how excess sensitivity varies when analyzing the effects based on an alternative grouping strategy. Second, we further exploit consumption dynamic heterogeneity, rather than the average consumption path over time documented in our paper. Lastly, we report the estimation results in the original currency (i.e., Korean won) with an extended analysis window and alternative regression specifications to avoid any bias caused by currency conversion using the mean exchange rate.

Consumption Responses by Alternative Grouping.— In the baseline estimation, we divide size variations into three subgroups. In our robustness analysis, we exploit the size-dependent MPCs in relative terms, closely following Kueng (2018).[52] We assign individuals to five quintiles (each quintile represents 20 percent of the relative size distribution) and examine how the consumption responds to predictable income changes for the narrowly defined group. We assess group heterogeneity by regressing:

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

where y_{it} is the variable of interest. An indicator function, $\mathbb{1}(y_{it} \in q_y)$, equals 1 if individual i's FP to Income ratio is in 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 observed y, which is $FP\ to\ Income$.

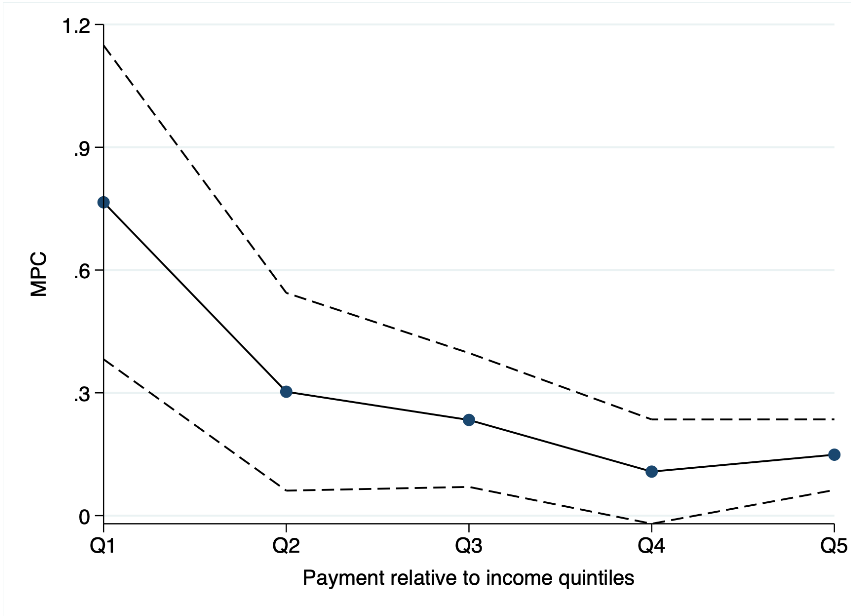
Figure 7 plots the coefficient, β_{q_y}, that measures the excess sensitivity for individual i's observed size relative to income in the qth quintile. We find that the coefficients of spending response decrease monotonically with relative payment size even with five subgroups. The lowest point estimate, 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.[53] By contrast, individuals for whom the payment size accounts for only a small fraction of their quarterly income spend most of their predicted extra income (point estimate is 0.85). With confidence interval bands at 95 percent, the monotonic decline in slope by relative size is highly statistically significant.

Heterogeneity in Consumption Dynamics.— Our main analysis of the consumption path (out of anticipated income changes) over time captures the average effects around the event window.

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

[53] The point estimate for each quintile from Q1 to Q5 is as follows: 0.85, 0.35, 0.20, 0.12, and 0.11.

Figure 7: Effects by Payment Size Relative to Income (FP to Income) Quintiles



Notes: Figure 7 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.

In particular, we find that consumption response peaks with the arrival of predictable changes then sharply returns to zero in cumulative effects. 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 different distributional groups broken down by relative size. Appendix G reports the consumption dynamics by payment size relative to income group (low, middle, high). The marginal and cumulative effects on MPC with distributional size groups are displayed in Figures G.1 and G.2, respectively. We find similar patterns for all three groups as shown in our main findings. That is, excess sensitivity is highest when individuals face an increase in anticipated income; individuals then sharply decrease their consumption expenditure in the quarter following the income change. The high level of excess sensitivity largely comes from the group with the small relative size. We also document the consumption path by income level and find that high-income individuals have insignificant responses over all time horizons, implying that it is the *size* of predictable income changes that affects consumption responses.

Results in Original Currency.— Another challenge associated with our empirical analysis is the conversion of different currencies into US dollars for ease of comparison. We convert our data from Korean won (original currency in data, CPI adjusted) into US dollars using the mean exchange rate during the sample period. This may bias the estimation result if there are any measurement errors or if we consider a fixed-year exchange rate instead of taking an average value of exchange rates. To address this issue, we apply the same estimation analogy to the original data with no currency conversion. In Appendix G, Table G.1 documents the excess sensitivity of the anticipated income changes. Our results using the original currency are also consistent with our main estimation results; the value of excess sensitivity is 0.177 in both cases after controlling for time, region, and individual fixed effects with the same control variables. In addition, we extend our analysis with alternative specifications of the independent variable. We consider the log difference of consumption expenditure instead of the level of change in spending. Consumption growth increases by 0.35 percent in response to an anticipated 1 percent increase in income. We also allow for a larger number of observations (double our baseline final sample) with extended event windows (1–2 quarterly lags and 3–4 quarterly leads) to check on the persistence of estimation result. As a result, the marginal effect in consumption response consistently peaks in the quarter following the final payment.

6 Theoretical Discussion

A standard model of intertemporal allocation in consumption suggests that the consumption response to predetermined or highly predictable income changes should be zero. In this model, agents are assumed to be rational and forward looking when making the optimal consumption decision. Today's consumption choice depends on the expected value of future income changes; therefore, predictable income changes should not affect cause consumption to increase or decrease (i.e., the implied MPC for anticipated income changes should be close to zero).[54] Our empirical results strongly reject this theory: we find that predictable income changes trigger a significant deviation from consumption-smoothing behavior. Consumption responses also vary according to the size of anticipated income changes and peak with the arrival of income changes and then sharply return to zero the following quarter.

According to one strand of research on excess sensitivity, 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 et al., 1997; Johnson et al., 2006; Parker, 2017; Coibion et al., 2020).[55] When liquidity is constrained, consumers are either unable or unwilling to increase their consumption prior to the anticipated income changes. This one-time provision of liquidity therefore causes individuals to react intensively to income changes.

While liquidity constraints can help reconcile the empirical rejection of the standard theory, significant excess sensitivity can often be found even among unconstrained individuals. Our empirical analysis also reveals the effects of liquidity constraints on excess sensitivity. We find a sizable MPC even among individuals who do not have access to credit markets to smooth their consumption. More importantly, the sensitivity of spending largely depends on the magnitude of the predicted

[54] In Appendix H, we include the basic theoretical assumption under the PIH.

[55] Low-income households tend to hold low levels of illiquid and liquid assets or wealth (Kaplan et al., 2014).

income changes. 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.

The mechanisms underlying the magnitude effect and one-time peak response in consumption dynamics have been under-examined in the literature. We seek to fill this gap by revisiting the standard models of consumption and discussing why they cannot generate the one-time peak consumption dynamics. We also discuss two other potential explanations of the magnitude effect — bounded rationality and the welfare costs of deviating optimal consumption choices at different sizes of predetermined income changes.

Standard Models of Consumption.— We consider a standard life-cycle model with borrowing constraints following Carroll (1997). An individual's optimal consumption behavior is obtained from a well-defined intertemporal optimization condition. Each individual's maximization problem at time t is given by:

$$\max_{\{c_t\}_{t=\tau}^{T}} E_t \sum_{t=\tau}^{T} \beta^t u\left(c_t\right) \tag{5}$$

subject to

$$m_t = m_{t-1} + r a_{t-1} + e^{y_t} - d_t - c_t \tag{6}$$

$$a_t = a_{t-1} + d_t \tag{7}$$

$$y_t = p_t + \tau_t + \epsilon_t^T \tag{8}$$

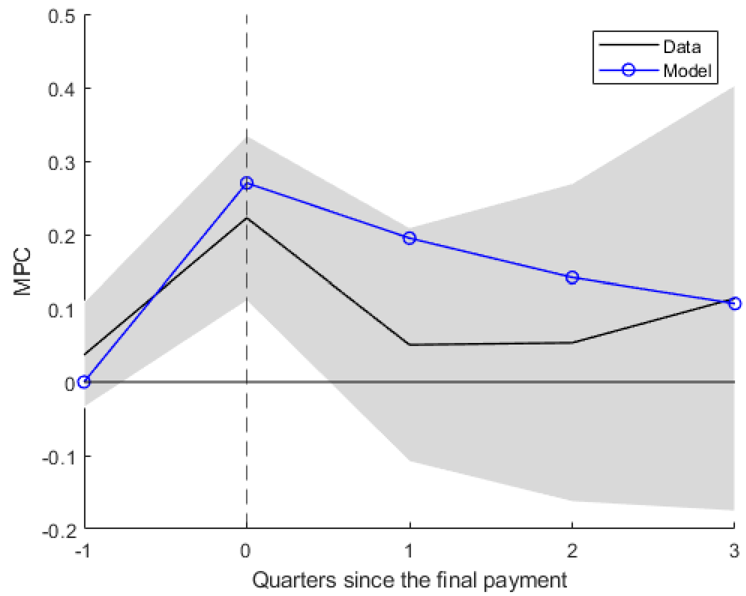
$$p_t = \rho p_{t-1} + \epsilon_t^P \tag{9}$$

$$m_t \geq 0 \quad \forall t = \tau, ..., T \tag{10}$$

where β is the stochastic discount factor and c_t is consumption. m_t and a_t are liquid and illiquid assets, respectively. y_t is labor income and d_t is deposits to illiquid assets. τ_t is deterministic income component at age t. ρ is parameter value for persistence of income. ϵ_t^T is transitory income shock and ϵ_t^P is permanent income shocks. For this simple model, we consider the utility function where $u(c_t) = c_t^{1-\gamma}/(1-\gamma)$. The calibrated parameter values we consider are as follows: $\gamma = 1.2,\ \beta = 0.9,\ \rho = 0.9,\ \sigma_T = \sigma_P = 0.1$, and $r = 0.05$.

In Figure 8, we show the result of consumption response of data versus model where the shock lasts for nine quarters. As shown in the figure, the one-time peak response is slightly captured though the model cannot fully capture the one-time sharp increase in consumption with persistent income shocks. In the standard models of consumption, consumption proportionally increases with the increase in permanent income changes. As the income shocks persist over time, the increase in consumption response also becomes persistent. This indicates that the empirical finding we document in our main results cannot be generated by this model. One view that explains the reason why the standard model fails to match the empirical result is therefore related to individuals'

Figure 8: Consumption Response in Data versus Model



perceived shocks. In particular, the car loan payment lasts for three to five years on average. Theoretically, the change of income following the final car loan payment alters the permanent income to a higher level though agents may take this income shocks as short to medium-term income changes with myopia.

Bounded Rationality and Welfare Cost.— One potential reason to reject the PIH is the bounded rationality of size variations in predetermined income changes. In standard consumption models, individuals are assumed to be fully rational when making optimal consumption decisions. When this assumption is violated or not fully binding, excess sensitivity in response to different levels of income shocks may occur. Bounded rationality suggests that agents selectively become rational; especially to the large amount of income changes; to recompute the optimal consumption path (Browning and Collado, 2001; Hsieh, 2003; Scholnick, 2013). In other words, individuals with bounded rationality will (not) adjust consumption optimally to large (small) amount of income changes as the utility of not doing so is large (small). Conversely, Reis (2006) revisits the expectation formation model and find that the slow consumption adjustment to anticipated income shocks and excess smoothness puzzles can be reconciled by inattentive consumers. In addition, agents who have small adjustment costs in planning may remain inattentive in between updating information, and therefore, deviate further from the consumption-smoothing behavior.

Another explanation supporting our empirical findings on the relative magnitude effects on consumption — that is, when the size of the anticipated income change as a fraction of current income is low, spending increases by more — is that the welfare loss from not fully smoothing consumption is relatively low when the anticipated increase in income is small relative to overall income. In other words, deviating from the optimal consumption choice is less costly for individuals who have a small payment size relative to their current income. Closely following Fuchs-Schündeln and Hassan (2016) and Kueng (2018), we calculate welfare loss based on a sufficient statics 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:

$$Welfare\ loss\ (c_i^{deviate}, c_i^{pih}) \approx \frac{\delta}{2} \cdot \sum_t \zeta_t \left(\frac{c_t^{deviate} - c_t^{pih}}{c_t^{pih}} \right)^2 \tag{11}$$

where δ captures the curvature of the utility function. ζ_t is the utility weight function where $\zeta_t = \gamma^t \frac{\partial u(c_t^{pih})}{\partial c} c_t^{pih} / \sum_i \gamma^n \frac{\partial u(c_n^{pih})}{\partial c} c_n^{pih} = \frac{\gamma^t u(c_t^{pih})}{U(c^{pih})}$ as we assume the utility function $u(c) = c^{1-\delta}/(1-\delta)$.[56] We set the standard value of $\delta = 2$ considered in the literature. After considering the envelope theorem, equation 11 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.

7 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.[57] Since we use the estimated values based on our final 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 concern associated with constructing such a policy experiment is the type of income changes in fiscal policy, including tax rebates or fiscal stimulus checks relative to those generated by repaying a vehicle loan. We argue that those income sources share two common characteristics. First, both types of income changes are either announced in advance or predetermined to consumers.

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

[57] 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.

Consumers thus have advance information on the size and arrival time of payments.[58] Second, unique government interventions including stimulus packages and repaying certain types of loans are considered irregular income changes (Fuchs-Schündeln and Hassan, 2016). Such income changes contrast with regular income changes such as tax refunds that happen repeatedly over the course of an individual's life.

These two types of income shocks also differ in other ways including persistence, target distribution, and payment size. The persistence of income shocks generated by fiscal stimulus packages is relatively transitory, while the income changes following a final vehicle loan payment persist for longer. If anything, our approach prevails over the upper bound in the estimated MPCs as income shocks become more persistent, and the consumption response is stronger for permanent income shocks. In addition, many fiscal policies target households by income level, while our empirical sample covers a more generalized population across all income groups. The estimated MPCs out of low-income relative to all income groups are reported to be high when agents are liquidity constrained, though our evidence on the liquidity channel provides moderately mixed evidence on this. 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 \$500–1,200.[59] The mean payment size is comparable to some extent to our payment size — \$800, with a cut-off point of \$421 for the first quintile and \$1,040 for the fourth quintile.

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.[60] 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 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:

$$MPC_j = \sum_i \frac{\overbrace{\beta_i \tau_i(j)}^{MPC_i \,\times\, \Delta\ \text{income}_i(j)}}{\underbrace{T}_{\text{Total transfers}}} \tag{12}$$

[58]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.

[59]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.

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

Table 5: 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.

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.[61] 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:

$$g(C)_j = \frac{\sum_i \beta_i \tau_i(j)}{\sum_i c_i} \tag{13}$$

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.[62] 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 5 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

[61] 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.

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

under this policy is therefore higher than that of the first policy.[63] 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.

8 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 decreases. 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, the role of binding liquidity constraints has often been emphasized as the main mechanism to understand 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

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

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.

References

Agarwal, Sumit, Chunlin Liu, and Nicholas S Souleles. “The reaction of consumer spending and debt to tax rebates—evidence from consumer credit data.” *Journal of political Economy* 115 (2007): 986–1019.

Baker, Scott R, Robert A Farrokhnia, Steffen Meyer, Michaela Pagel, and Constantine Yannelis. Income, liquidity, and the consumption response to the 2020 economic stimulus payments. Technical report, National Bureau of Economic Research, 2020.

Baker, Scott R and Constantine Yannelis. “Income changes and consumption: Evidence from the 2013 federal government shutdown.” *Review of Economic Dynamics* 23 (2017): 99–124.

Broda, Christian and Jonathan A Parker. “The economic stimulus payments of 2008 and the aggregate demand for consumption.” *Journal of Monetary Economics* 68 (2014): S20–S36.

Browning, Martin and M Dolores Collado. “The response of expenditures to anticipated income changes: panel data estimates.” *American Economic Review* 91 (2001): 681–692.

Carroll, Christopher D. “Buffer-stock saving and the life cycle/permanent income hypothesis.” *The Quarterly journal of economics* 112 (1997): 1–55.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber. How Did US Consumers Use Their Stimulus Payments? Technical report, National Bureau of Economic Research, 2020.

Fuchs-Schündeln, Nicola and Tarek Alexander Hassan. “Natural experiments in macroeconomics.” *Handbook of macroeconomics.* . Volume 2 . Elsevier, 2016. 923–1012.

Ganong, Peter and Pascal Noel. “Consumer spending during unemployment: Positive and normative implications.” *American Economic Review* 109 (2019): 2383–2424.

Garcia, René, Annamaria Lusardi, and Serena Ng. “Excess sensitivity and asymmetries in consumption: an empirical investigation.” *Journal of Money, Credit, and Banking* (1997): 154–176.

Gross, David B and Nicholas S Souleles. “Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data.” *The Quarterly journal of economics* 117 (2002): 149–185.

Hsieh, Chang-Tai. “Do consumers react to anticipated income changes? Evidence from the Alaska permanent fund.” *American Economic Review* 93 (2003): 397–405.

Jappelli, Tullio and Luigi Pistaferri. “The consumption response to income changes.” *Annual Review of Economics* 2 (2010): 479–506.

Jappelli, Tullio and Luigi Pistaferri. "Fiscal policy and MPC heterogeneity." *American Economic Journal: Macroeconomics* 6 (2014): 107–36.

Johnson, David S, Jonathan A Parker, and Nicholas S Souleles. "Household expenditure and the income tax rebates of 2001." *American Economic Review* 96 (2006): 1589–1610.

Kaplan, Greg and Giovanni L Violante. "A model of the consumption response to fiscal stimulus payments." *Econometrica* 82 (2014): 1199–1239.

Kaplan, Greg, Giovanni L Violante, and Justin Weidner. The wealthy hand-to-mouth. Technical report, National Bureau of Economic Research, 2014.

Karger, Ezra and Aastha Rajan. "Heterogeneity in the marginal propensity to consume: evidence from Covid-19 stimulus payments." (2020).

Kueng, Lorenz. "Excess sensitivity of high-income consumers." *The Quarterly Journal of Economics* 133 (2018): 1693–1751.

Meghir, Costas and Luigi Pistaferri. "Earnings, consumption and life cycle choices." *Handbook of labor economics.* . Volume 4 . Elsevier, 2011. 773–854.

Misra, Kanishka and Paolo Surico. "Consumption, income changes, and heterogeneity: Evidence from two fiscal stimulus programs." *American Economic Journal: Macroeconomics* 6 (2014): 84–106.

Ni, Shawn and Youn Seol. "New evidence on excess sensitivity of household consumption." *Journal of Monetary Economics* 63 (2014): 80–94.

Pagel, Michaela. "Expectations-based reference-dependent life-cycle consumption." *The Review of Economic Studies* 84 (2017): 885–934.

Parker, Jonathan A. "The reaction of household consumption to predictable changes in social security taxes." *American Economic Review* 89 (1999): 959–973.

Parker, Jonathan A. "Why don't households smooth consumption? Evidence from a $25 million experiment." *American Economic Journal: Macroeconomics* 9 (2017): 153–83.

Parker, Jonathan A, Nicholas S Souleles, David S Johnson, and Robert McClelland. "Consumer spending and the economic stimulus payments of 2008." *American Economic Review* 103 (2013): 2530–53.

Reis, Ricardo. "Inattentive consumers." *Journal of monetary Economics* 53 (2006): 1761–1800.

Scholnick, Barry. "Consumption smoothing after the final mortgage payment: testing the magnitude hypothesis." *Review of Economics and Statistics* 95 (2013): 1444–1449.

Shapiro, Matthew D and Joel Slemrod. "Did the 2008 tax rebates stimulate spending?." *American Economic Review* 99 (2009): 374–79.

Shea, John. "Myopia, liquidity constraints, and aggregate consumption: a simple test." *Journal of money, credit and banking* 27 (1995): 798–805.

Stephens Jr, Melvin. "The consumption response to predictable changes in discretionary income: Evidence from the repayment of vehicle loans." *The Review of Economics and Statistics* 90 (2008): 241–252.

Appendix

A Literature Review

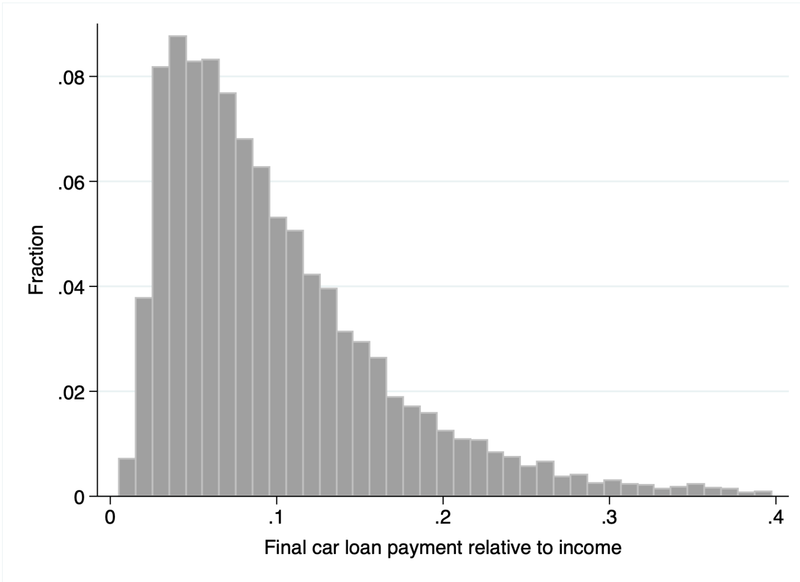
Table A.1: Overview of Marginal Propensity to Consume using Natural Experiments

Study	Experiment (USD)	Data	MPC (out of 1)	Liquidity constraint	Size
Agarwal et al. (2007)	2001 Federal income tax rebates ($500)	Credit card accounts; 2000 - 2002	0.40	Based on credit limit, utilization rate, and age	No
Johnson et al. (2006)	2001 Federal income tax rebates ($500)	CEX interview survey; 2000 - 2002	0.20 - 0.40	Based on age, income, and liquid assets	No
Misra and Surico (2014)	2001 Federal income tax rebates ($500) & 2008 Economic stimulus payments ($900)	CEX interview survey; 2000 - 2002 & 2007 - 2008	0.43 (2001) & 0.16 (2008)	Based on high income and high mortgage debt	No
Broda and Parker (2014)	2008 Economic stimulus payments ($900)	Scanner data; 2007 - 2009	0.10	Availability of easily accessible funds	No
Parker et al. (2013)	2008 Economic stimulus payments ($900)	CEX interview survey; 2007 - 2008	0.12 - 0.30	Based on age, income, and liquid assets	No
Scholnick (2013)	Last mortgage payment ($627)	Credit card accounts; 2004 - 2006	0.40	Based on liquid assets	Yes
Kueng (2018)	Alaska permanent fund ($1650)	Credit card accounts; 2010 - 2014	0.25	Based on income and liquid assets	Yes
Baker et al. (2020)	2020 Economic stimulus payments ($1200)	Transaction level data; 2016-2020	0.25 - 0.40	Based on income and liquid assets	No
Coibion et al. (2020)	2021 Economic stimulus payments ($1200)	Scanner data; 2018 - 2020	0.40	Based on income and liquid assets	No

Notes: Table A.1 reports the overview of marginal propensity to consume (MPC) in response to an anticipated income increase based on natural experiments for each studies. Each experiment has a corresponding amount in US dollars which indicates the average amount received at an individual level. For 2020 Economic stimulus payments, we only list studies that examine the first time payment made to households.

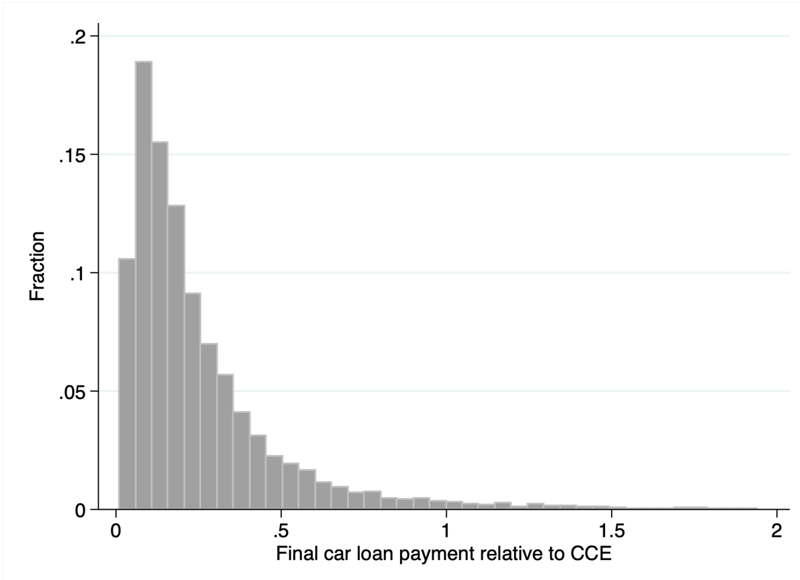
B Distribution of Sample

Figure B.1: Distribution of payment size relative to income, 2012-2016



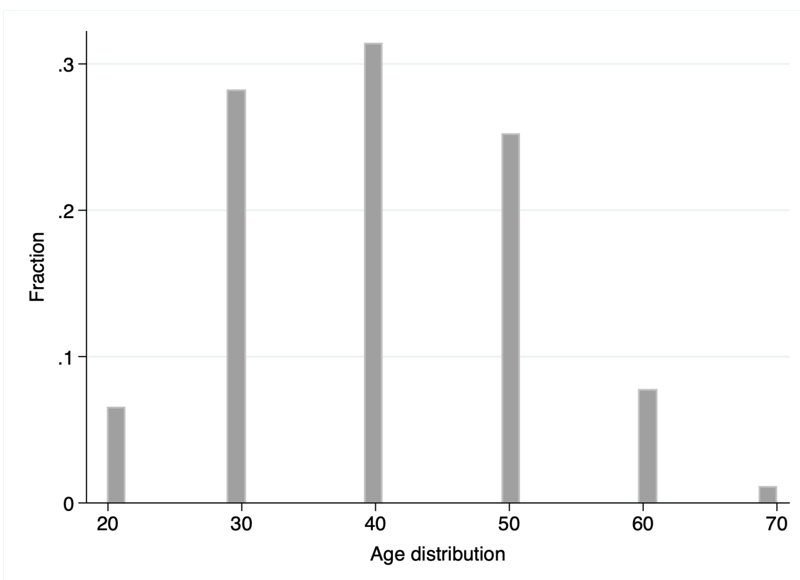
Notes: Figure B.1 plots the distribution of the final car loan payment size relative to income ratio for sample period from 2012 to 2016.

Figure B.2: Distribution of payment size relative to consumption, 2012-2016



Notes: Figure B.2 plots the distribution of the final car loan payment size relative to consumption expenditure ratio for sample period from 2012 to 2016.

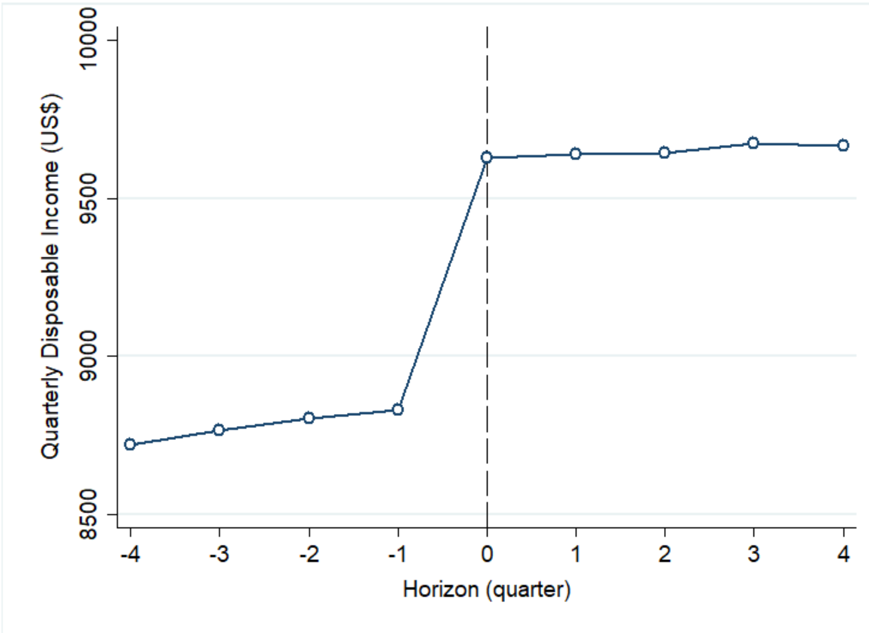
Figure B.3: Distribution of age, 2012-2016



Notes: Figure B.3 plots the distribution of age groups (from 20 to 70) for sample period from 2012 to 2016.

C Income process

Figure C.1: Income dynamics



Notes: Figure C.1 plots the quarterly income dynamics for final sample distribution. Dotted line indicates the event time ($t = 0$) where individuals have increase in income following the final car loan payment in $t - 1$ quarter.

D Marginal Propensity to Consume by Relative Magnitudes

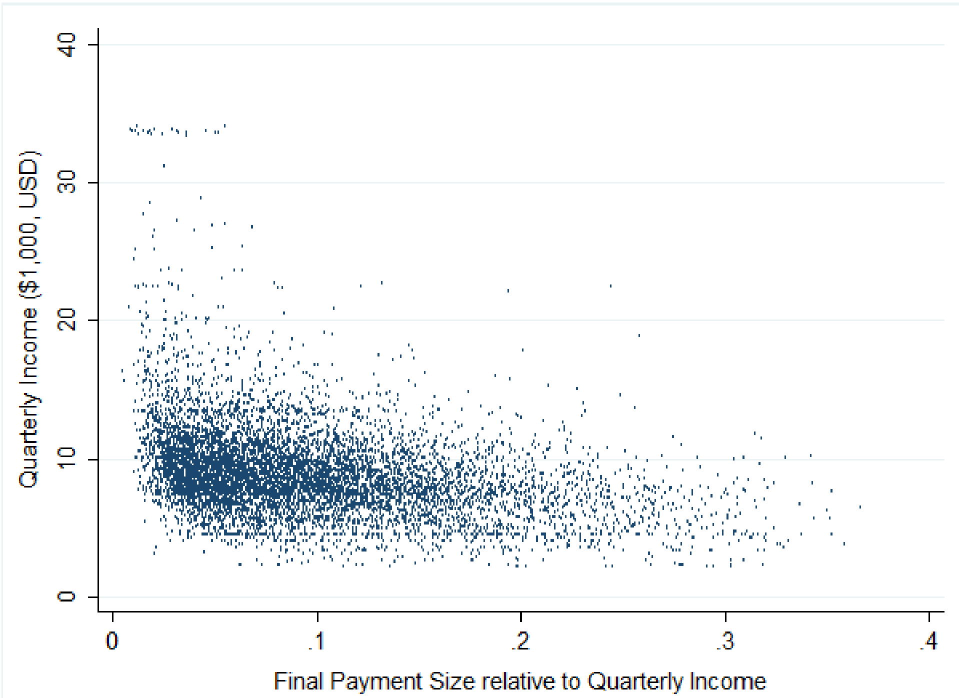
Table D.1: Consumption Response by Relative Magnitudes

Dep. Var: Δc_{it}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FP to Income	1.609***	1.422***	1.626***	1.426***				
	(0.243)	(0.241)	(0.255)	(0.246)				
FP to CCE					0.690***	0.675***	0.658***	0.580***
					(0.053)	(0.052)	(0.057)	(0.055)
Constant	-0.202	-0.216	-0.391**	-0.224	-0.202	-0.205	-0.389**	-0.216
	(0.146)	(0.150)	(0.166)	(0.227)	(0.146)	(0.150)	(0.166)	(0.227)
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes
Time, Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	No	Yes	Yes	No	No	Yes	Yes
R-squared	0.003	0.028	0.003	0.059	0.004	0.029	0.004	0.064
Observations	77,148	77,148	77,148	77,148	77,148	77,148	77,148	77,148

Notes: FP to Income and FP to CCE indicate the final payment size relative to income and consumption, respectively. 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+). Robust standard errors in parentheses are clustered at the individual level. *, **, *** represent the significance level at 10%, 5%, and 1%, respectively.

E Consumption Response by Relative Magnitudes

Figure E.1: Relative Payment Size and Quarterly Income



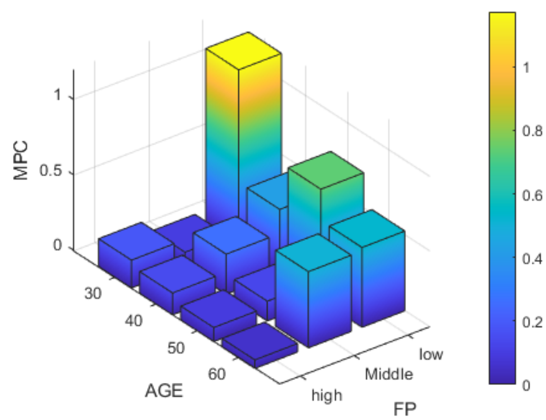
Notes: Figure E.1 plots the relative size ratio against quarterly income for the full sample. The solid line indicates the fitted line for two variables in each panel.

F Conditional MPC Heterogeneity by Absolute Payment Size

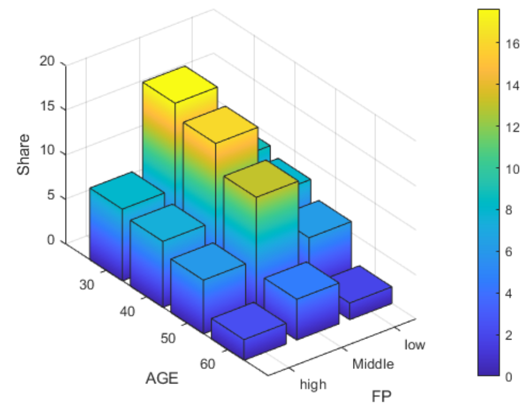
F.1 Consumption Response by the Absolute Payment Size

Figure F.1: MPC Herterogeneity by Payment Size (Level)

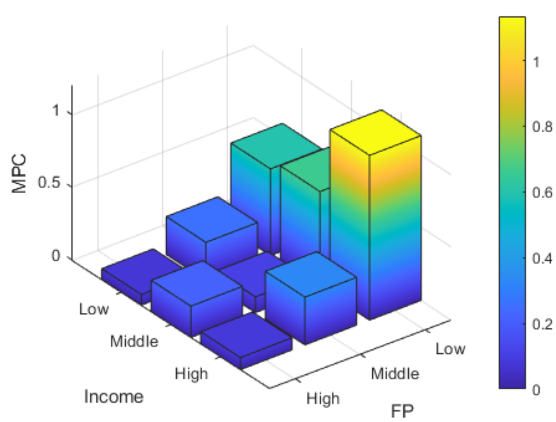
(a) MPC distribution, age, size



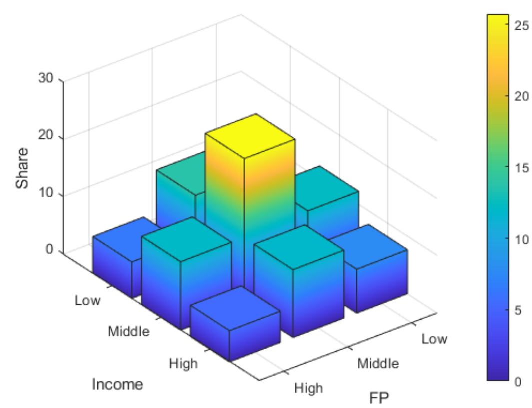
(b) Population share, age, size



(c) MPC distribution, income, size



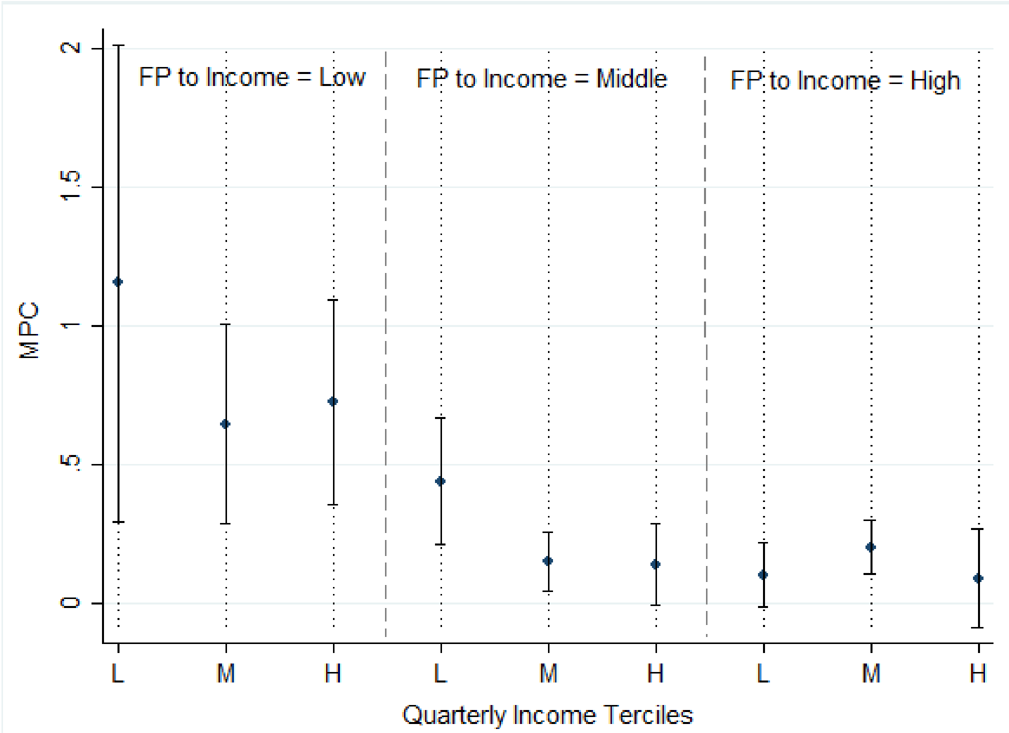
(d) Population share, income, size



Notes: Figure F.1 shows the conditional MPC heterogeneity (and population share) among age, income, and absolute payment size.

F.2 Marginal Propensity to Consume by Relative Size conditional on Income

Figure F.2: Conditional MPC Heterogeneity by Relative Size



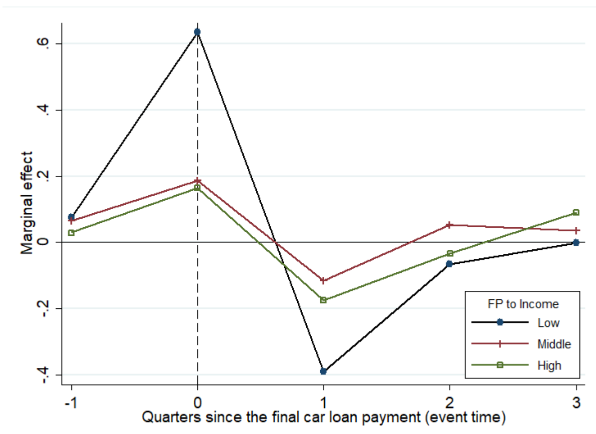
Notes: Figure F.2 displays the spending responses by income terciles conditional on the final payment size relative to quarterly income (*FP to Income*). Bars and lines show the estimated coefficients and 95 percent confidence intervals, respectively. Standard errors are clustered at the individual level.

G Robustness Analysis

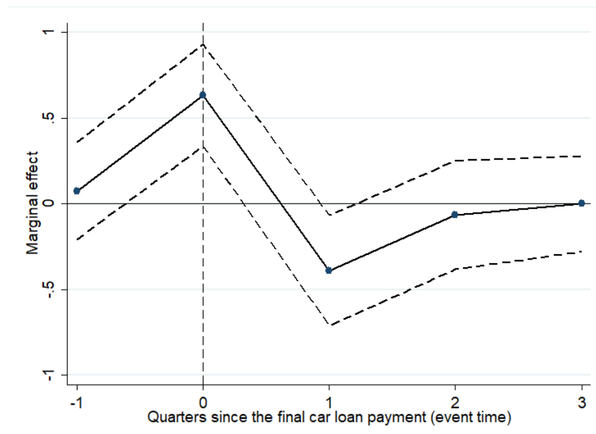
G.1 Heterogeneity in Consumption Dynamics

Figure G.1: Consumption dynamics (**marginal**) by payment size relative to income

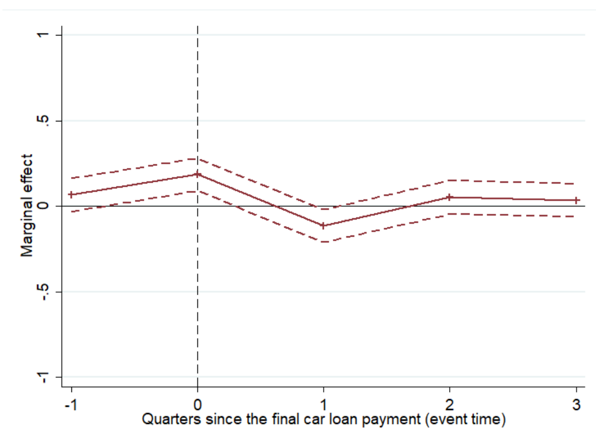
(a) Consumption responses by *FP to Income*



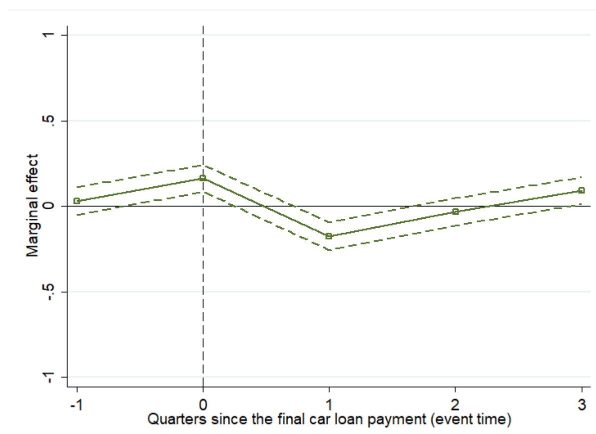
(b) *FP to Income* = Low



(c) *FP to Income* = Middle



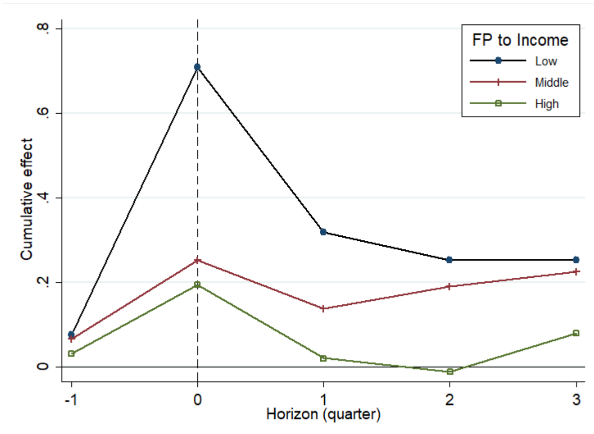
(d) *FP to Income* = High



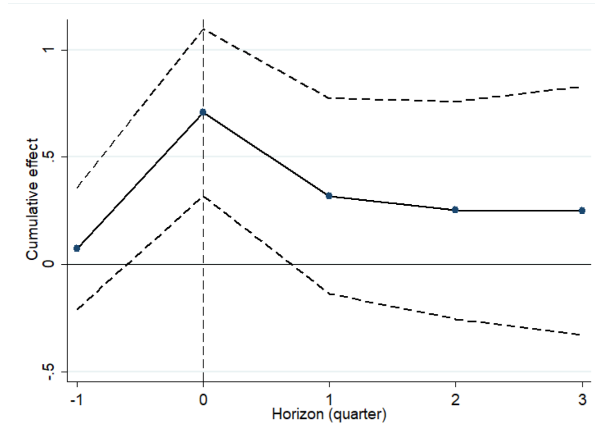
Notes: Figure G.1 displays the marginal effects on consumption by the payment size relative to income (*FP to Income*) terciles. Solid lines indicate the marginal response and the dashed lines indicate the 95 percent confidence intervals.

Figure G.2: Consumption dynamics (**cumulative**) by payment size relative to income

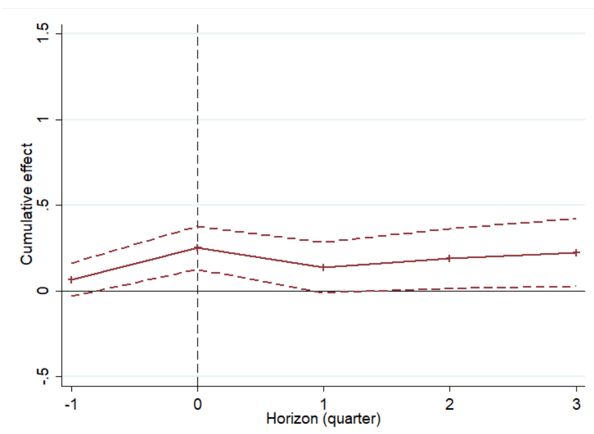
(a) Consumption responses by *FP to Income*



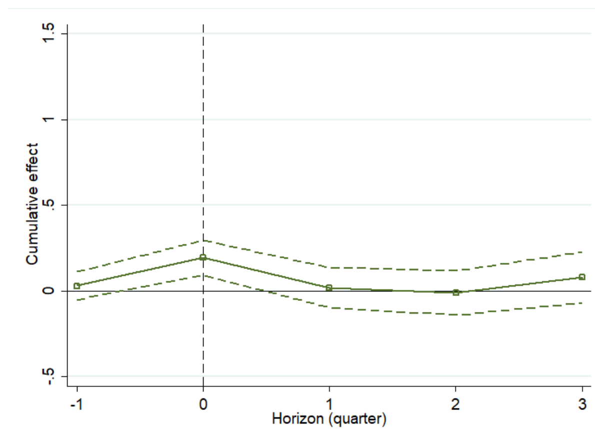
(b) *FP to Income* = Low



(c) *FP to Income* = Middle



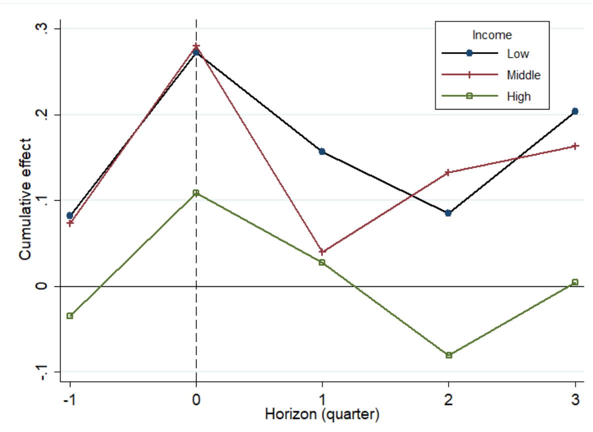
(d) *FP to Income* = High



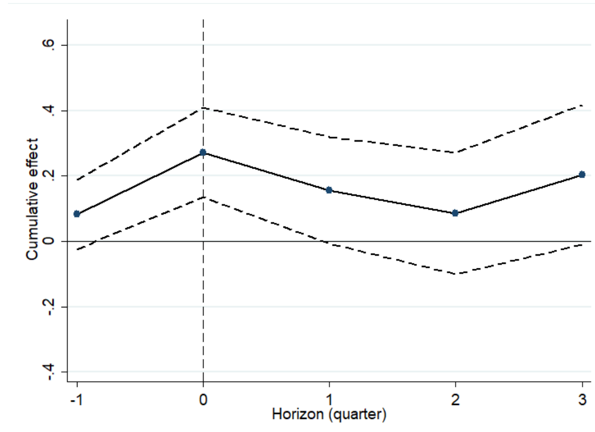
Notes: Figure G.2 displays the cumulative effects on consumption by the payment size relative to income (*FP to Income*) terciles. Solid lines indicate the marginal response and the dashed lines indicate the 95 percent confidence intervals.

Figure G.3: Consumption dynamics (**cumulative**) by income

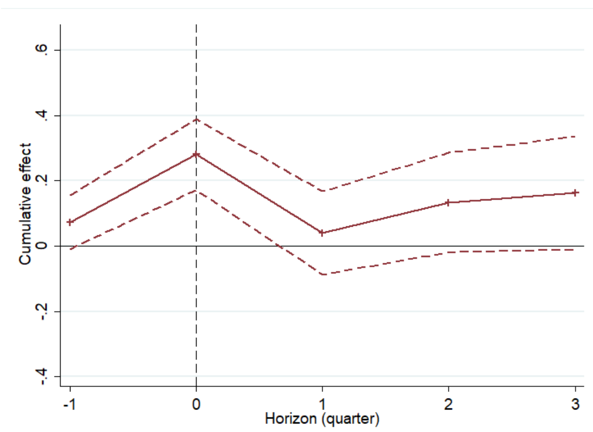
(a) Consumption responses by *Income*



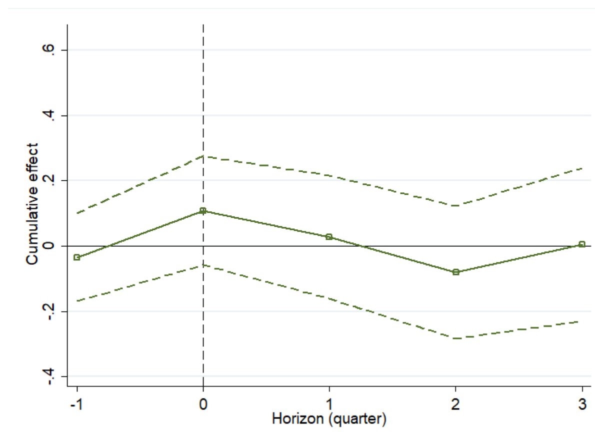
(b) *Income* = Low



(c) *Income* = Middle



(d) *Income* = High



Notes: Figure G.3 displays the marginal effects on consumption by quarterly income terciles. Solid lines indicate the marginal response and the dashed lines indicate the 95 percent confidence intervals.

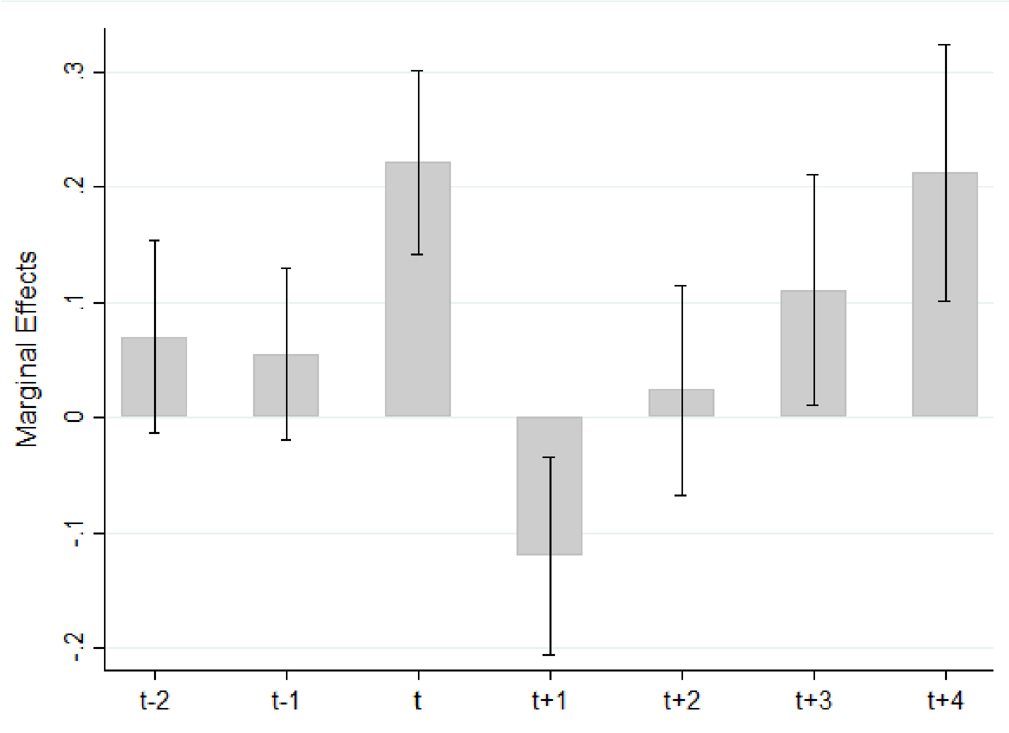
G.2 Estimation Results in Korean WON

Table G.1: Excess Sensitivity

	(1)	(2)	(3)	(4)	(5)	(6)
	$\triangle C_{i,t}$	$\triangle C_{i,t}$	$\triangle lnC_{i,t}$	$\triangle C_{i,t}$	$\triangle C_{i,t}$	$\triangle lnC_{i,t}$
FP	0.196***	0.179***		0.203***	0.177***	
	(0.028)	(0.028)		(0.029)	(0.028)	
FP to Income			0.350***			0.357***
			(0.044)			(0.045)
Constant	0.232	0.809	0.022*	0.104	2.461**	0.049**
	(0.429)	(0.530)	(0.011)	(0.489)	(1.198)	(0.025)
Control Variables	×	○	○	×	○	○
Time and Region FE	○	○	○	○	○	○
Individual FE	×	×	×	○	○	○
R^2	0.000	0.023	0.024	0.002	0.02	0.021
Observations	141,933	141,933	141,933	141,933	141,933	141,933

Notes. FP and FP to Income indicates the final car loan payment and the payment relative to quarterly income. 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 to quarterly income greater than 1.5 were excluded from the sample. Robust standard errors in parentheses are clustered at the individual level. *, ** and *** represent significance at the 10%, 5% and 1%, respectively.

Figure G.4: Marginal Effects on Marginal Propensity to Consume



Notes: Figure G.4 shows leads and lags of the regression coefficients based on original currency (Korean won) estimated by the standard parametric regression equation (Equation 1). t indicates the period of income increase. Bars and lines show the estimated coefficients and 95 percent confidence intervals, respectively. Standard errors are clustered at the individual level.

H Permanent Income Hypothesis (PIH)

According to the standard intertemporal consumption model (PIH), individual i solves the utility maximization problem as,

$$\max_{\{c_{i,t+s}\}_{s=0}^{\infty}} E_t \sum_{s=0}^{\infty} \beta^s u\left(c_{i,t+s}\right) \tag{H.1}$$

subject to

$$\sum_{s=0}^{\infty} \left(\frac{1}{1+r}\right)^s c_{i,t+s} = \bar{a}_{i,t} + \sum_{s=0}^{\infty} \left(\frac{1}{1+r}\right)^s y_{i,t+s} \tag{H.2}$$

where E_t is the expectations operator conditional on information available at time t. $c_{i,t}$ is consumption for individual i at time t, $\bar{a}_{i,t}$ is initial assets, and $y_{i,t}$ is income for individual i at time t. β is the time-discount parameter.

As our data do not preserve information related to asset, we assume that initial assets are fixed for agents. For this simple model, we consider the quadratic utility function, $u\left(c_{i,t+s}\right) = c_{i,t+s} - (\gamma/2)c_{i,t+s}^2$, and assume that the real return follows $r = 1/\beta - 1$. Then, the optimal consumption choice is a function of expected net present value of future income, and that any predictable income changes would not affect the consumption growth. At time t, we have $c_{i,t} = (r/1+r) * [\bar{a}_{i,t} + E_t\left(\sum_{s=0}^{\infty}(1/1+r)^s y_{i,t+s}\right)]$. The change in consumption is then given by,

$$\Delta c_{i,t} = \frac{r}{1+r}\left[E\left(\sum_{s=0}^{\infty}\left(\frac{1}{1+r}\right)^s y_{i,t+s}|\Omega_{i,t}\right) - E\left(\sum_{s=0}^{\infty}\left(\frac{1}{1+r}\right)^s y_{i,t+s}|\Omega_{i,t-1}\right)\right] \tag{H.3}$$

where $\Omega_{i,t}$ is the information set for individual i at time t.

If $E(\cdot|\Omega_{i,t}) = E(\cdot|\Omega_{i,t-1})$, agents have no additional news in their information set. When income changes are fully anticipated, that is, the information is given in advance to agents (i.e. $E(y_{i,t+s}|\Omega_{i,t}) = E(y_{i,t+s}|\Omega_{i,t-1})$), the change in consumption shown in equation (H.3) becomes zero (i.e. $\Delta c_{i,t} = 0$) and agents choose to smooth consumption. In other words, the optimal consumption choice for a rational and forward looking agent is to have no growth in consumption to anticipated income changes. Conversely, individuals only adjust their consumption when there is innovation to their income where $E(y_{i,t+s}|\Omega_{i,t}) - E(y_{i,t+s}|\Omega_{i,t-1}) > 0$. This is the basic mechanism behind the intertemporal consumption behavior of PIH. Under this theory, prudent agents have no consumption growth out of predetermined income changes.

I Welfare Loss Analysis

To derive the potential welfare loss of deviating from the consumption smoothing behavior, we first define the optimal consumption decision under the life-cycle permanent income hypothesis. Consider the optimal consumption plan, c^{pih}_{i,w_t}, where each individual maximizes the life-time utility $U(c) = \sum_t \gamma^t u(c_t)$ given wealth w and prices p as follows:

$$c^{pih}_{i,w_t} = arg\ max_{c_t}\{U(c_t) \text{ s.t. } p_{t+1}c_t \leq w\} \tag{I.1}$$

where $p_{t+1}c_t = \sum_t \frac{c^{pih}_{i,t}}{R^t}$ and $U(c) = \sum_t \beta^t u(c_{i,t})$. By the envelope theorem, we get

$$U(c^{pih}_w) - U(c^{deviate}_w) \approx -\frac{1}{2}\gamma^t \cdot \frac{\partial^2 u(c^{pih}_t)}{\partial c^2} \cdot (c^{pih}_t)^2 \cdot \left(\frac{c^{deviate}_t - c^{pih}_t}{c^{pih}_t}\right)^2 \tag{I.2}$$

We use the amount of wealth, $\tilde{w}$, for each individual to keep at the utility level under $c^{deviate}_w$ to get the value function as follows:

$$U(c^{pih}_w) - U(c_{\tilde{w}}{}^{pih}) \approx -\left(\frac{\tilde{w} - w}{w}\right)\sum_t \gamma^t \cdot \left(\frac{\partial u(c^{pih}_t)}{\partial c} \cdot c^{pih}_t\right) \tag{I.3}$$

For simplicity, we consider $\gamma = 1$. Then, combining above two equations gives the potential welfare loss function (i.e. equation 11).

$$Welfare\ loss\ (c^{deviate}_i, c^{pih}_i) \approx \frac{\delta}{2} \cdot \sum_t \zeta_t \left(\frac{c^{deviate}_t - c^{pih}_t}{c^{pih}_t}\right)^2 \tag{I.4}$$

where δ captures the curvature of the utility function. ζ_t is the utility weight function where $\zeta_t = \gamma^t \frac{\partial u(c^{pih}_t)}{\partial c} c^{pih}_t / \sum_i \gamma^n \frac{\partial u(c^{pih}_n)}{\partial c} c^{pih}_n = \frac{\gamma^t u(c^{pih}_t)}{U(c^{pih})}$ as we assume the utility function $u(c) = c^{1-\delta}/(1-\delta)$. The consumption plan at time t, c_t, is defined as

$$c_t = \begin{cases} c^{pih} & \text{without predictable income changes} \\ c^{pih} + MPC \cdot FP & \text{with predictable income changes} \end{cases} \tag{I.5}$$

where FP indicates the amount of predictable income changes following the final car loan payment at time t. Then, the deviation from the optimal consumption plan is defined as $c^{deviate}_t$ where

$$\frac{c^{deviate}_t - c^{pih}_t}{c^{pih}_t} = \begin{cases} 0 & \text{without predictable income changes} \\ \frac{(1-MPC)\cdot FP}{c^{pih}} & \text{with predictable income changes} \end{cases} \tag{I.6}$$

and therefore, the welfare loss from deviation becomes

$$Welfare\ loss\ (c_i^{deviate}, c_i^{pih}) \approx \frac{\delta}{2} \cdot \left(\frac{(1 - MPC) \cdot FP}{c^{pih}} \right)^2 \tag{I.7}$$

where c^{pih} is equal to permanent income and FP/c^{pih} represents the final payment size relative to one's quarterly income.