# ESSAYS ON HETEROGENEITY, CONSUMPTION, AND MACROECONOMIC POLICIES

A Dissertation

by

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Submitted to the Graduate and Professional School of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

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May 2023

Major Subject: Economics

ABSTRACT

This dissertation consists of two chapters on heterogeneity, consumption, and its implications in macroeconomic policies.

First, we examine how the effects of government spending shocks depend on the balance-sheet position of households. Employing U.S. household survey data, we find that in response to a positive government spending shock, households with mortgage debt have a large, positive consumption response, while renters have a smaller rise in consumption. Homeowners without mortgage debt, in contrast, have an insignificant expenditure response. We consider a dynamic stochastic general equilibrium (DSGE) model with three types of households: savers who own their housing, borrowers with mortgage debt, and rule-of-thumb consumers who rent housing, and show that it can successfully account for these findings. The model suggests that liquidity constraints and wealth effects, tied to the persistence of public spending, play a crucial role in the propagation of government spending shocks. Our findings provide both empirical and theoretical support for the notion that household mortgage debt position plays an important role in the transmission mechanism of fiscal policy.

Second, we examine how consumers respond to anticipated income changes over time, and how their consumption responses vary depending on the magnitude of income changes. Using newly constructed individual-level data based on the Bank of Korea's household debt database, 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.

# DEDICATION

To my family, friends, and mentors.

# ACKNOWLEDGMENTS

I am highly indebted to the following people who have supported me throughout the process of completing this dissertation.

First and foremost, I would like to express my sincere gratitude to my advisor, Sarah Zubairy, for her guidance and encouragement throughout the process. In joint work, the second chapter of this thesis, we explore the differential impact of government spending shocks based on household heterogeneity. Her expertise in the field and unwavering support have been invaluable in shaping my growth as a researcher and have been a great source of inspiration. I am truly grateful to have Dr. Zubairy as my advisor, whom I deeply admire.

I am also grateful to the dissertation committee members: Dennis Jansen, Yoon Jo, and Hwagyun Kim, for their valuable research advice and feedback on my work. In particular, I thank Dr. Jansen and Dr. Jo for all the time devoted to providing helpful comments and a supportive research environment during my years at Texas A&M University.

Special thanks to my coauthors, Tatevik Sekhposyan and Sang-yoon Song, for their enthusiastic and constructive insights on our joint projects. My discussions with Dr. Sekhposyan have been instrumental in refining my ideas and developing new projects. It has been a wonderful journey to collaborate with her in shaping and exploring these new ideas. I also thank Sang-yoon for his support and dedication during my job market process.

I would like to acknowledge the invaluable assistance of the staff and resources of the economics department who have contributed to the success of this dissertation.

Finally, I owe everything to my family. My father, Joonyoung Song, has been a pillar of support, demonstrating an unwavering interest in my journey at every turn. My mother, Sukja Choi, has provided me with the emotional fortitude to persevere through all the challenges I've faced. I am also thankful to my sister, Yeji, for bringing such joy during challenging times. It would be remiss of me not to express my heartfelt gratitude towards my husband, Seongjin Kim, for his constant support and encouragement throughout my academic journey.

# CONTRIBUTORS AND FUNDING SOURCES


## Contributors

This work was supported by a dissertation committee consisting of Professor Sarah Zubairy, Dennis Jansen, and Yoon Jo of the department of Economics, and Hwagyun Kim of the Department of Finance.

Section 2 is a joint work with Professor Sarah Zubairy and Professor Sami Alpanda from the College of Business at the University of Central Florida.

Section 3 is a joint work with Dr. Sang-Yoon Song from the Bank of Korea. The data was provided by Sang-Yoon, from the following source: the household debt database from the Bank of Korea. The views expressed herein are those of the authors and do not necessarily reflect the official views of the Bank of Korea.

## Funding Sources

Graduate study was supported by assistantships from Texas A&M University, College of Liberal Arts Graduate Summer Research Grant, College of Liberal Arts Summer Dissertation Fellowship, Gail Frey Monson Memorial Scholarship, S. Charles Maurice Graduate Fellowship in Economics, Department Research Fellowship, and Private Enterprise Research Center Summer Scholarship.

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# 1. INTRODUCTION

Household heterogeneity plays a significant role in the propagation of macroeconomic policies. The impact of such policies is not uniform across all households, and factors such as income level, education, age, and debt levels can significantly affect how households react to these policies. Consequently, a comprehensive understanding of household heterogeneity is essential to evaluate the aggregate implications of macroeconomic policies accurately. Without considering the heterogeneity of households, the evaluation of economic policy propagation may be incomplete or even inaccurate, leading to less effective policy decisions. In contrast, a thorough comprehension of how different households respond to macroeconomic policies can help policymakers identify and implement policies that promote a more efficient economy.

The second chapter focuses on the impact of government spending shocks on households, specifically how their balance-sheet position affects these effects. By employing data from U.S. household surveys, we find that households with mortgage debt have a considerable and positive reaction in consumption. In contrast, renters show a less substantial increase in consumption in response to positive government spending shocks. Homeowners without mortgage debt, however, have no significant expenditure response. We construct a dynamic stochastic general equilibrium (DSGE) model with housing and featuring three types of households: savers who own their housing, borrowers with mortgage debt, and rule-of-thumb consumers who rent housing. Our model successfully explains the empirical results by demonstrating that liquidity constraints and wealth effects, associated with the continuity of public spending, have a crucial role in the mechanism of fiscal policy transmission.

In the third chapter, we examine how consumption patterns change over time in response to anticipated changes in discretionary income and if these changes vary with the magnitude of the income changes. Using an experimental approach and newly constructed individual-level data from the Bank of Korea household debt database, we find that the aggregate marginal propensity to consume (MPC) reaches its highest point (18%) upon the arrival of an income increase and then

experiences a rapid decline in the following quarter. Employing a natural experiment approach with newly constructed individual-level data (based on the Bank of Korea household debt database), we find that the aggregate MPC peaks (at 18 percent) upon the arrival of income increase and then sharply decreases in the following quarter. Notably, the MPC is heterogeneous and monotonically decreasing with the magnitude of income changes. In addition, the MPC is not strongly correlated with liquidity constraints. We also find that the size of anticipated income changes in comparison to one's quarterly income is the most predominant factor affecting spending sensitivity. Our research suggests that individuals may become selectively rational depending on the size of income changes, and the welfare loss from not completely smoothing consumption is relatively low for smaller income changes. Our policy simulation implies that the variation in MPCs from various levels of income shocks can enhance the efficacy of government policies aimed at stimulating the economy.

## 2. HOUSEHOLD DEBT AND THE EFFECTS OF FISCAL POLICY

### 2.1 Introduction

In the aftermath of the Great Recession, there has been growing interest in the role of household debt in the transmission of macroeconomic shocks, as policymakers have increasingly relied on fiscal policy to stabilize and stimulate the economy. This paper examines how the transmission of government spending shocks depends on the balance-sheet position or debt level of households in the economy.

Since mortgage debt constitutes the vast majority of household debt, we employ data on mortgagors, outright owners and renters to proxy for the financial position of households. This is in the spirit of Cloyne and Surico (2017) and Cloyne et al. (2020), who have shown that housing tenure status can be a useful proxy for debt and asset position, and exploiting information in the U.S. Consumer Expenditure Survey by tenure status allows us to circumvent the issue that few datasets have detailed information about household income, expenditures and liabilities over a long period of time. There might be concerns about selection bias and endogenous choice into tenure status, and we show in our particular case, that the share of households in each group does not respond significantly to aggregate public spending shocks.

Our first contribution is to provide new evidence on the heterogeneous effects of government spending effects, based on housing tenure status. Notably, we find that in response to a positive government spending shock, mortgagor households experience a large rise in their consumption. Renters also experience a rise in their consumption, but it is smaller than mortgagors. Outright homeowners without mortgage debt, in contrast, have an insignificant consumption expenditure response to a public spending shock. This heterogeneity cannot be explained by differences in the income responses, which have similar responses across the three types of households. We further show how consumption patterns differ across durable and non-durable consumption. Our results show that it is not the housing tenure status, per se, that matters but the level of household indebtedness or liquid wealth that differentiates the household response to a government spending shock. These results also provide further support for the importance of wealthy hand-to-mouth households in the propagation of aggregate shocks, which has been documented in earlier literature and described in the literature review. We show that these households also play a critical role in the transmission of government spending shocks.

Our second contribution is to provide a theoretical framework to rationalize these empirical findings and dig deeper into the transmission mechanism. We construct a dynamic stochastic general equilibrium (DSGE) model with housing, borrowing and lending across heterogeneous households, and financial frictions in the form of collateral constraints similar to Iacoviello (2005). In departure from most literature, the model features three types of households: savers who own their housing, borrowers with mortgage debt, and rule-of-thumb consumers who rent housing. Thus, we introduce a rental housing market alongside owner-occupied housing. Since our focus is on mortgage debt, we model fixed-rate mortgage loans which are amortized over the long term, similar to Kydland et al. (2016) and Alpanda and Zubairy (2017). We calibrate the parameters of the model in order to match micro-evidence and various data moments like housing shares of various types of households in the U.S. economy. While this model shares common features and mechanisms in earlier work, here we focus on the question of propagation of government spending shocks, and the role of different households with distinct housing tenure status.

We show that this model can successfully match aggregate responses and also account for the different responses across households to a public spending shock. Government spending shocks propagate through the economy primarily through wealth and liquidity effects. We show that labor income responds positively and similarly across all types of households. However, the negative wealth effect based on the expectation of higher taxes affects households differently. Saver households are hit hardest by this negative wealth effect given their portfolio of taxable assets. The renters living hand-to-mouth are least affected, with the borrower households affected intermediately. We show that the persistence of the spending shock generates different degrees of wealth effects and plays an important role in the propagation of the shock. For the borrower households, government spending shocks help relax their borrowing constraint and thus their ability to borrow and consume. Therefore, particularly for those households with a mortgage, liquidity constraints play a crucial role in the propagation of government spending shocks.

We also extend the model to account for durable and non-durable consumption, and overall match the responses seen in our empirical analysis. Notably, durable consumption responses are distinct from housing responses, particularly for the renters. We also consider robustness of the heterogeneous consumption responses to variations in the parameters of the model, introduction of additional lines of credit such as home-equity lines of credit or refinancing, and the stance of monetary policy. Our findings provide both empirical and theoretical support for the notion that household mortgage debt position plays an important role in the transmission mechanism of fiscal policy.

Our paper contributes to the growing literature that has shown that we need a departure from a representative agent model to understand the aggregate consumption dynamics in response to a government spending shock. Galí et al. (2007) show in a New-Keynesian model with two types of agents that the presence of liquidity constrained households matters for the aggregate consumption response. These non-Ricardian agents who can not borrow and save raise their consumption in response to a positive shock to public spending and if their share is large enough, lead to a rise in aggregate consumption. Similarly, others have considered the heterogeneous effects of government spending based on various features including income (Ma (2019) and references within) and age/ demographics (Basso and Rachedi (2021)).

The pre-existing literature also establishes that balance sheets matter and wealthy hand-to-mouth households play an important role in the propagation of aggregate shocks including fiscal innovations. Notably, Kaplan and Violante (2014b) show that wealthy hand-to-mouth or liquidity constrained households are important to explain the response to transfers in the form of tax rebate checks. Cloyne and Surico (2017) consider the role of tax shocks, and show empirically that mortgagor households have the largest response to tax shocks, focusing on survey data from the UK. Brinca et al. (2016) develop a life-cycle model with heterogeneous agents and incomplete markets, and find that the fiscal multiplier is highly sensitive to the fraction of the population facing binding credit constraints and to the average wealth level in the economy. In a similar spirit, we consider the role of household debt in the propagation of a different aspect of fiscal policy in the form of government spending shocks.

While our focus is on the different types of households, our paper is also related to studies that focus on the time and space variation in household indebtedness. For instance, Demyanyk et al. (2016) exploit U.S. regional data to document that relative fiscal multipliers are higher in areas with higher consumer indebtedness. Bernardini and Peersman (2018) employ historical data for the U.S. and show that the aggregate government spending multiplier is higher during periods of private debt overhang.

In a related study, Andres et al. (2021) use information on balance sheets of households in PSID to document the share of different types of households in the data based on their balance sheet position, but unlike us, they do not consider the consumption patterns of these households. They explore a related but different question from us, which is the role played by the observed changes in the distribution of households in the transmission mechanism of government spending shocks by calibrating a DSGE model with the empirical weights estimated in the PSID across subsequent waves. They find that the effects of fiscal shocks are sensitive to the fraction of households in the left tail of the wealth distribution.

## 2.2 Empirical Approach

### 2.2.1 Identification and Estimation methodology

In order to examine the effects of government spending shocks, we first need to specify our identification scheme. Notably, a challenge is to identify innovations to government spending that are exogenous and unanticipated. We follow the approach introduced in Ramey (2011), and employ the Survey of Professional Forecasters (SPF) forecast errors for federal spending to identify government spending shocks. In particular, we consider the difference between actual government spending growth and the one-quarter ahead forecast of its growth rate by professionals. The key identifying assumption of this approach is that the shocks are orthogonal to professional forecasts of future government purchases and the forecasters are incorporating all available information about the state of the economy and other aspects in their forecasts. Thus, the forecast errors capture any surprise or news about government spending.

Unlike existing identification strategies including SVARs (Structural Vector Autoregressions) with short-run timing restrictions on the government spending variable a la Blanchard and Perotti (2002), these shocks are not subject to anticipation effects, since professional forecasts plausibly incorporate all available information about the state of the economy. The other alternative based on military news from narrative accounts, Ramey (2011) have low predictive power in the post-Korean war sample, which is the sample under consideration here. In contrast, SPF forecast errors have been shown quantitatively to not to suffer from these anticipation effects and have large first-stage F-statistics for predicting total government and military spending in samples excluding these large military events (see Ramey (2011)).

In order to study the empirical effects of government spending shocks on both aggregate and disaggregate variables across various types of households, we employ the following VAR,

$$\mathbf{y}_t = \alpha_0 + \alpha_{1t} + A(L)\mathbf{y}_{t-1} + \mathbf{u}_t \tag{2.1}$$

where $\mathbf{y}_t$ is $n \times 1$ vector with variables of interest, $\mathbf{A}(L)$ is a polynomial in the lag operator, and $\mathbf{u}_t$ is an error term. In the baseline estimation with aggregate macroeconomic variables, we consider the following ordering: with SPF forecast errors first followed by log of real government spending, log real per capita GDP and consumption, household debt (both flow and stock), house price index, and the Federal Funds rate.[1] We use shocks to the first equation with SPF forecast errors (identified with a Cholesky decomposition) as the government spending shock of interest.[2]

[1]Data sources are available in the appendix. Here government spending constitutes total government spending on government consumption and investment at the federal and state level, which is the commonly used measure in the literature.

[2]Note, that this is different from a Blanchard and Perotti (2002) type identification, as we consider the innovation to the forecast error as the spending shock, and not the innovation to the government spending variable. We choose a lag length of four based on the Akaike information criterion (AIC). We apply a linear time trend and the impulse responses are calculated based on the three-period moving average. The moving average is based on three periods:

Table 2.1: Consumption, income, and share by housing tenure group

| Housing tenure group | Non-durable cons. | Durable cons. | Gross inc. | Net inc. | Share (%) |
|---|---|---|---|---|---|
| Mortgagors | 2,860 | 480 | 3,412 | 3,052 | 46% |
| Outright owners | 2,799 | 394 | 2,617 | 2,454 | 20% |
| Renters | 2,324 | 301 | 2,394 | 2,149 | 34% |

Notes: This table reports the mean value of real per capita values of non-durable and durable expenditure and gross and net income for one quarter (deflated by consumer price index) for the CEX, 1981:Q1-2007:Q1.

In addition to considering the responses of macroeconomic aggregate variables, we investigate the existence of heterogeneity across households with different financial positions in response to a positive government spending shock. Since mortgage debt constitutes the vast majority of household debt, we employ household survey data on consumption and income across housing tenure status to proxy for the households' balance sheet position following Cloyne et al. (2020).[3] Equation (2.2) indicates the order of a VAR analysis for three housing tenure groups: mortgagors, outright homeowners, and renters.[4]

Specifically, we consider SPF forecast errors first followed by log of real government spending, log real per capita GDP, and housing tenure group-specific consumption (i.e. aggregate consumption, $rCON_t^i$, non-durable and durable consumption, $rNDC_t^i$ and $rDC_t^i$, respectively) or income (i.e. gross and net income, $rGI_t^i$ and $rNI_t^i$, respectively) as the last variable.

$$\mathbf{y}_t \equiv \begin{pmatrix} SPF\ FE_t \\ \log\ rGOV_t \\ \log\ rGDP_t \\ \log\ X_t^i \end{pmatrix} \tag{2.2}$$

$(t-1, t, t+1)$ to smooth the responses over time. In our robustness analysis, we remove the moving average approach to smooth the IRFs and show that the results are unaffected.

[3]We employ the consumption and income series constructed by Cloyne et al. (2020) in our empirical analysis. The next section provides further details on these data.

[4]The lag operator is equal to two with housing tenure group-specific variables. Standard errors are bootstrapped with 68 percent confidence bands generated by Monte Carlo simulations.

where $i \in \{\text{mortgagors, outright homeowners, renters}\}$ and $X_t^i \in \{rCON_t^i, rNDC_t^i, rDC_t^i, rGI_t^i, rNI_t^i\}$.

#### 2.2.2 Data

In this subsection, we describe the data used in the empirical estimation. The key aggregate variables used in the baseline empirical analysis such as real per capita GDP, government spending, and consumption are from national income and product accounts (NIPA). Households' mortgage debt comes from the Board of Governors of the Federal Reserve System. The house price index in the baseline specification comes from the Census Bureau. We use alternative data on the house price index, including the Case-Shiller U.S. national home price index from S&P Dow Jones Indices LLC, all transactions house price index from the U.S. Federal Housing Finance Agency, and the median sales price of houses sold from the U.S. Department of housing and urban development. The SPF forecast errors are constructed using the SPF forecasts for federal spending which are available from the Federal Reserve Bank of Philadelphia. Since the SPF forecasts for federal spending are available starting 1981, it limits the start of our sample. We end our sample in 2007 in order to ensure we exclude the zero lower bound (ZLB) period. We also consider data from the U.S. Consumer Expenditure Survey (CEX) to investigate the heterogeneous responses across households. Survey of Consumer Finances (SCF) data is used to provide additional information about asset and wealth position across households in the baseline sample period.[5]

The CEX data contains the demographic characteristics (household size, birth year of household head, and educational attainment), housing-related variables (tenure status, outstanding mortgage debt, rental payments), consumption expenditure (weekly expenditure on non-durable and durable goods excluding housing), and income coverage (labor and non-labor income) for many decades.[6] Labor income includes wages and salaries and non-labor income includes income from investments and social payments, net of taxes.

[5] In our baseline empirical analysis with a VAR approach, the sample period covers from 1981:Q4 to 2007:Q1. We use SCF data from 1995 to 2007 at a 3-year frequency. The SCF data includes net liquid and illiquid asset positions across housing tenure groups following Kaplan et al. (2014) definition.

[6] Household size is used to determine the real per capita term and the birth year of household head gives information about life-cycle positions across households, considered in a robustness check.

Table 2.2: Share of each housing tenure group and wealthy HtM

PANEL A: Share of each housing tenure group

| | 1995 | 1998 | 2001 | 2004 | 2007 |
|---|---|---|---|---|---|
| *Number of observation* | | | | | |
| Mortgagors | 9,359 | 9,112 | 9,535 | 10,026 | 10,278 |
| Outright homeowners | 5,600 | 5,146 | 5,583 | 5,589 | 5,197 |
| Renters | 5,355 | 5,795 | 5,797 | 5,770 | 5,130 |
| Total | 20,314 | 20,053 | 20,915 | 21,385 | 20,605 |
| *Share of each group* | | | | | |
| Mortgagors | 0.46 | 0.45 | 0.46 | 0.47 | 0.50 |
| Outright homeowners | 0.28 | 0.26 | 0.27 | 0.26 | 0.25 |
| Renters | 0.26 | 0.29 | 0.28 | 0.27 | 0.25 |

PANEL B: Wealthy Hand-to-Mouth households

| | 1995 | 1998 | 2001 | 2004 | 2007 |
|---|---|---|---|---|---|
| *Wealthy HtM (Total)* | | | | | |
| Mortgagors | 0.16 | 0.12 | 0.11 | 0.13 | 0.15 |
| Outright homeowners | 0.04 | 0.03 | 0.03 | 0.03 | 0.03 |
| Renters | 0.06 | 0.06 | 0.06 | 0.05 | 0.05 |
| Total | 0.26 | 0.21 | 0.20 | 0.21 | 0.23 |

Notes: This table reports the share of each housing tenure group and the share of wealthy Hand-to-Mouth for the SCF 1995-2007.

Since mortgage debt accounts for the vast majority of household debt, we classify households by three housing tenure groups - mortgagors, outright owners, and renters - to proxy for the financial positions of households following Cloyne et al. (2020).[7] Table 2.1 describes the mean value of real per capita consumption (in non-durable and durable goods), income (gross and net income), and the share of each housing tenure group out of total population (%) across three housing tenure groups in the sample period for the 1981:Q4 to 2007:Q1. Mortgagors constitute the majority of households, with a share of about 47% of all households on average, followed by renters and then

[7]For each housing tenure group, the data includes group-specific consumption (i.e. non-durable and durable expenditures) and income (i.e. gross and net income) based on the CEX. The final series of data is aggregated and converted into a quarterly frequency, deflated by the Consumer Price Index (CPI).

outright owners.

SCF data includes basic demographic features similar to the CEX, liquid wealth such as checking and savings account, and illiquid wealth including home equity. Following Kaplan et al. (2014), we use the SCF data to define the wealthy hand-to-mouth (HtM) households who hold little or no liquid wealth despite owning sizable illiquid assets. Table 2.2 shows the share of each housing tenure group and wealthy hand-to-mouth based on SCF data.[8] Both the CEX and SCF data help us establish that mortgagors own sizable wealth based on housing (which is an illiquid asset) with a sizable debt mostly in the form of mortgages. Outright homeowners own both liquid and illiquid assets while renters tend to have low wealth. Housing tenure status can thus provide a useful proxy to represent the balance sheet positions of households. The share of each group varies over time but by a relatively insignificant amount.

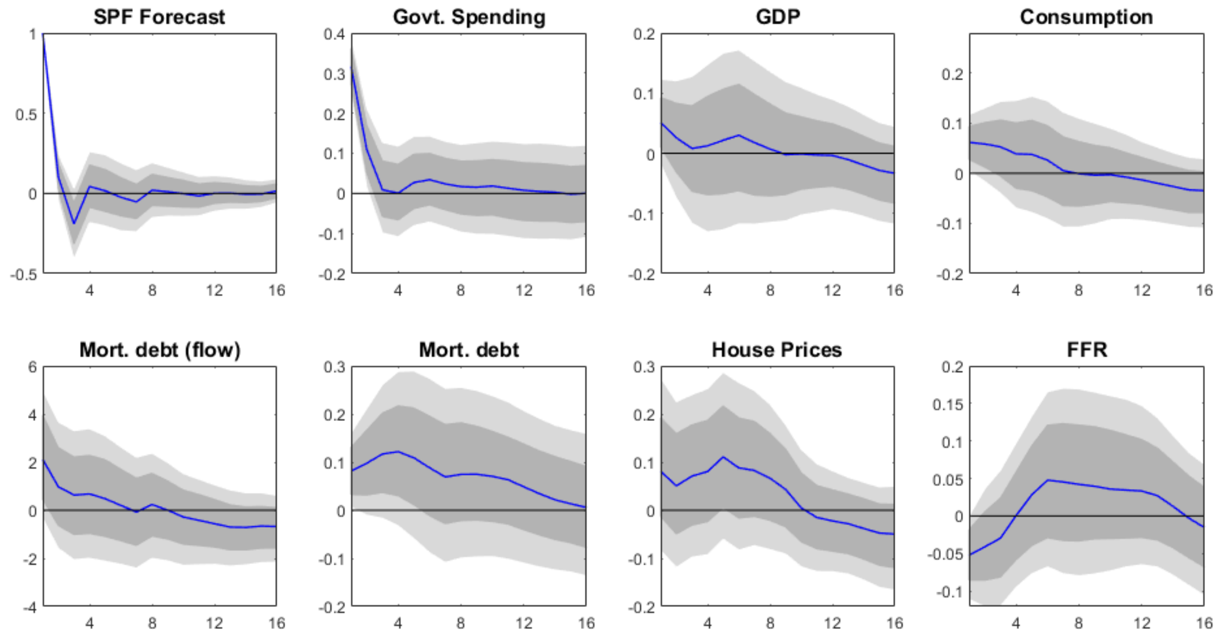
## 2.3 Aggregate and Disaggregate Effects of Government Spending Shocks

### 2.3.1 Aggregate Estimation Results

Figure 2.1 shows the impulse responses of key macroeconomic variables to a positive government spending shock. Government spending increases significantly in response to a shock to SPF forecast errors. Output and consumption rise for a few quarters and then fall. Consumption response peaks between four and five quarters. The rise in GDP, hours, consumption, and real wages is consistent with previous literature (Blanchard and Perotti, 2002; Galí et al., 2007; Ramey, 2011). We also find that both the stock and the flow of mortgage debt increase on impact while the persistence of flow response is relatively small. Lastly, real house prices increase in response to a positive government spending shock.

[8]Both the CEX and SCF show that mortgagors account for the majority share on average, followed by renters and outright owners. In section A.2, Table A.2 shows the share of asset and debt to income ratio of each housing tenure group.

Figure 2.1: Baseline impulse response functions of aggregate variables in response to a positive SPF shock



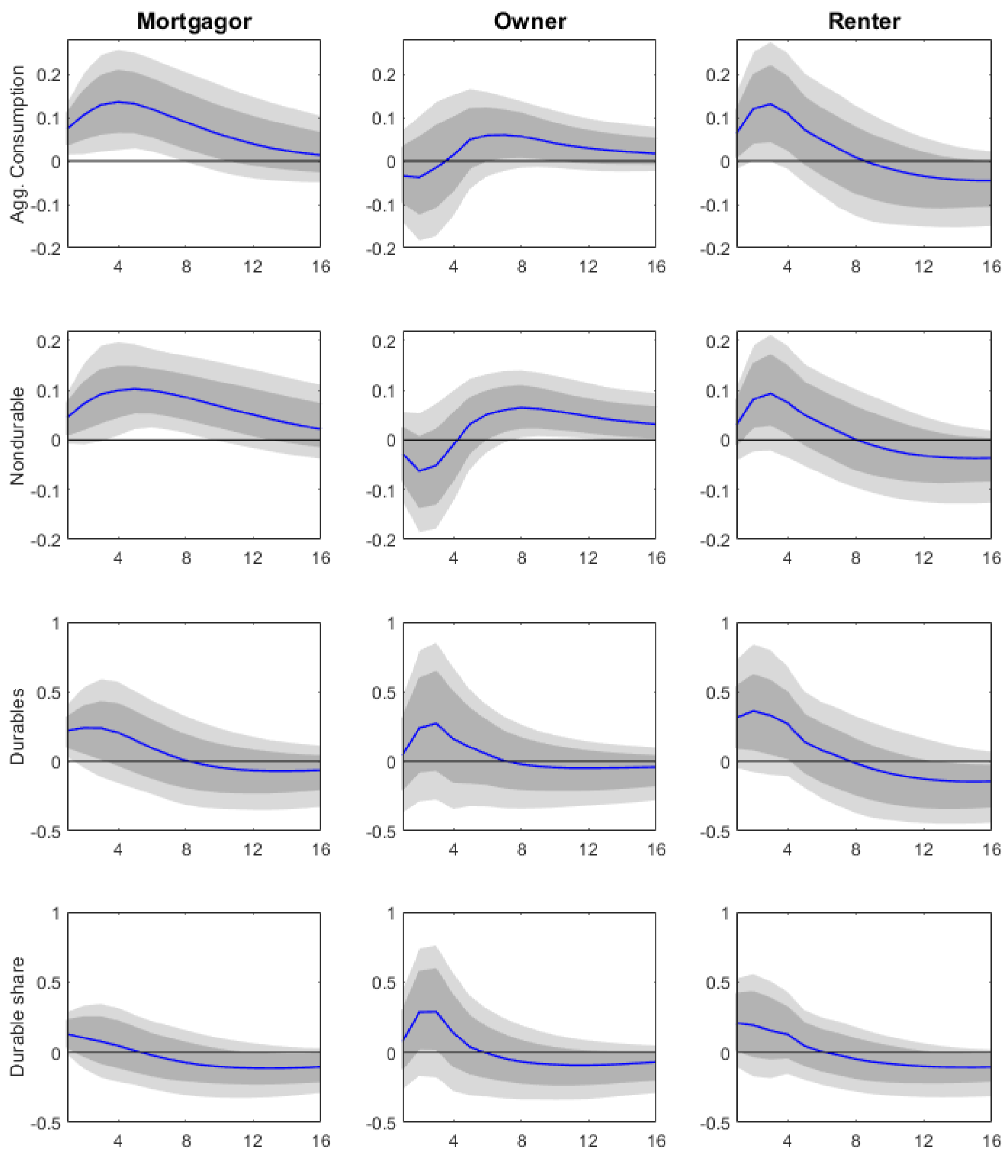

Notes: This figure shows the impulse responses functions of government spending, GDP, consumption, Mortgage debt (stock and flow), house price index, and FFR in response to a positive SPF shock with 68% and 90% confidence interval bands based on bootstrapped standard errors (shaded area).

### 2.3.2 Disaggregate Estimation Results by Housing Tenure Group

We now consider the response of housing tenure group-specific consumption and income. Consumption data accounts for non-durable and services consumption and durable expenditure, and income data includes net and gross income across households. In Figure 2.2, we show the dynamic effects of aggregate government spending shocks on consumption including aggregate, durable, non-durable consumption, and the share of durable goods across the three housing tenure groups. The first column of Figure 2.2 illustrates the responses for mortgagors and the second and third columns show the responses of outright homeowners and renters, respectively.

For aggregate consumption responses, we find sizeable differences across households: i) aggregate consumption of mortgagors rises significantly, ii) renters households also raise their consumption expenditures but to a smaller extent than mortgagors, and iii) outright homeowners have

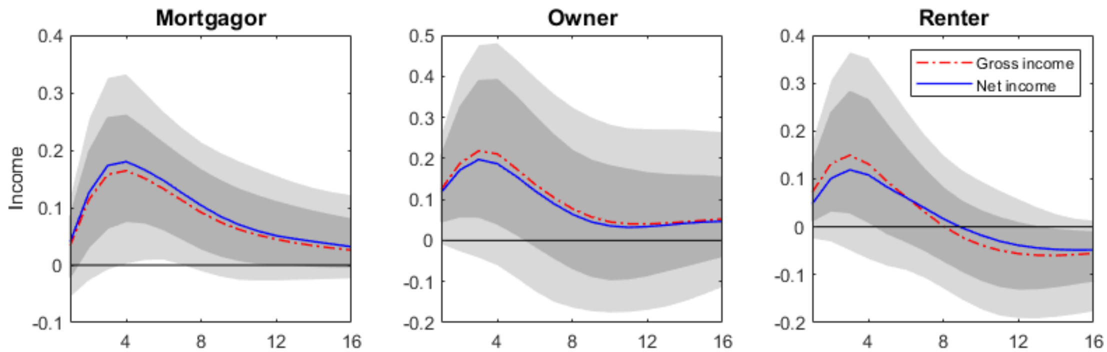
Figure 2.2: Consumption responses by housing tenure groups




Notes: This figure shows the impulse responses functions of aggregate consumption, durable, nondurable & services consumption, and durable share by housing tenure groups in response to a positive SPF shock with 68% and 90% confidence interval bands based on bootstrapped standard errors (shaded area).

an insignificant consumption response. When we decompose consumption into non-durable and durable expenditure, we find that mortgagors and renters increase both categories while outright homeowners have statistically insignificant responses for both. The response of the share of durable

Figure 2.3: Income responses by housing tenure groups




Notes: This figure shows the impulse responses functions of gross income (red dashed-dot) and net income (blue solid) by housing tenure groups in response to a positive SPF shock with 68% and 90% confidence interval bands based on bootstrapped standard errors (shaded area).

captures the relative changes in the share of durable expenditure in total consumption. The outright owners have a larger tendency to increase their durable share than the other two types of households. For mortgagors and renters, the peak aggregate and non-durable consumption responses occur after four to six quarters while durable consumption rises on impact and then falls gradually over time.[9]

Next, we consider the income response across the various types of households. When the income of a certain group is more sensitive to changes in economic conditions, it potentially drives the heterogeneity in the consumption response (Gornemann et al., 2012). Figure 2.3 shows the dynamic effects on gross and net income across the different housing tenure groups.[10] Both gross and net income of all types of households significantly rise in response to a positive government spending shock, which is consistent with the general equilibrium of aggregate demand shocks. However, there are no significant differences in the gross and net income responses across the different types of households. This suggests that with almost no heterogeneity in income responses

[9]In Figure A.4, we formally test whether these consumption responses across the various households are statistically significantly different. For aggregate consumption and non-durable consumption, the differences are statistically significantly different across mortgagers and owners, and renters and owners at short horizons, and at longer horizons for differences between mortgagers and renters. The IRF differential suggests that the response of durable consumption is not statistically significantly different across the different households.

[10]Net income is the sum of labor and non-labor household income after tax payment.

across households, the heterogeneous responses in consumption cannot be explained by income changes across households. In addition, the net income responses are similar across households, as are gross income responses, which suggest that differing tax burdens also do not seem to play a big role across the different households.

*Role of wealthy hand-to-mouth households.*— Our VAR analysis with group-specific data provides clear evidence of heterogeneity in consumption responses across the housing tenure groups. To test what is behind this consumption heterogeneity, we consider the role of wealthy hand-to-mouth households following Kaplan et al. (2014). First of all, the key distinction across the three housing tenure groups is related to the households' balance sheet status. By definition, mortgagors own a sizable illiquid asset such as housing with sizable debt. Outright homeowners own sizable wealth in both liquid and illiquid assets. Renters do not own sizable wealth nor have mortgage debt. In Table A.2, we show that these characteristics are also consistent in micro-data based on the SCF for 1995-2007.[11]

Our results showing mortgagor households exhibiting the largest consumption response to government spending shocks are also similar to the evidence provided in earlier work, that we build off of. Cloyne and Surico (2017) and Cloyne et al. (2020) show that households with mortgages adjust their expenditures the most in response to tax and monetary shocks, respectively. They also highlight the important role of liquidity of wealth.

Second, we show the distribution of wealthy hand-to-mouth in the total population and within group variation. As in Kaplan et al. (2014), we define the wealthy hand-to-mouth if households hold a positive net illiquid wealth and the net liquid wealth is less than half of their labor income.[12] In Table 2.2, we show the share of each housing tenure group and the share of wealthy HtM households. On average, mortgagor households account for almost half of the total population,

[11]Following Kaplan et al. (2014), we define net liquid assets as liquid assets minus liquid debt. This includes checking, saving, money market, and call accounts minus total credit card balances. The net illiquid asset contains the residential and non-residential real estate net of mortgages and related loans, retirement accounts, retirement accounts including future pensions, and saving bonds.

[12]Net illiquid wealth includes not only home equity but also savings in bonds, future pensions, and life insurance; therefore, we also have some renters households who are wealthy HtM.

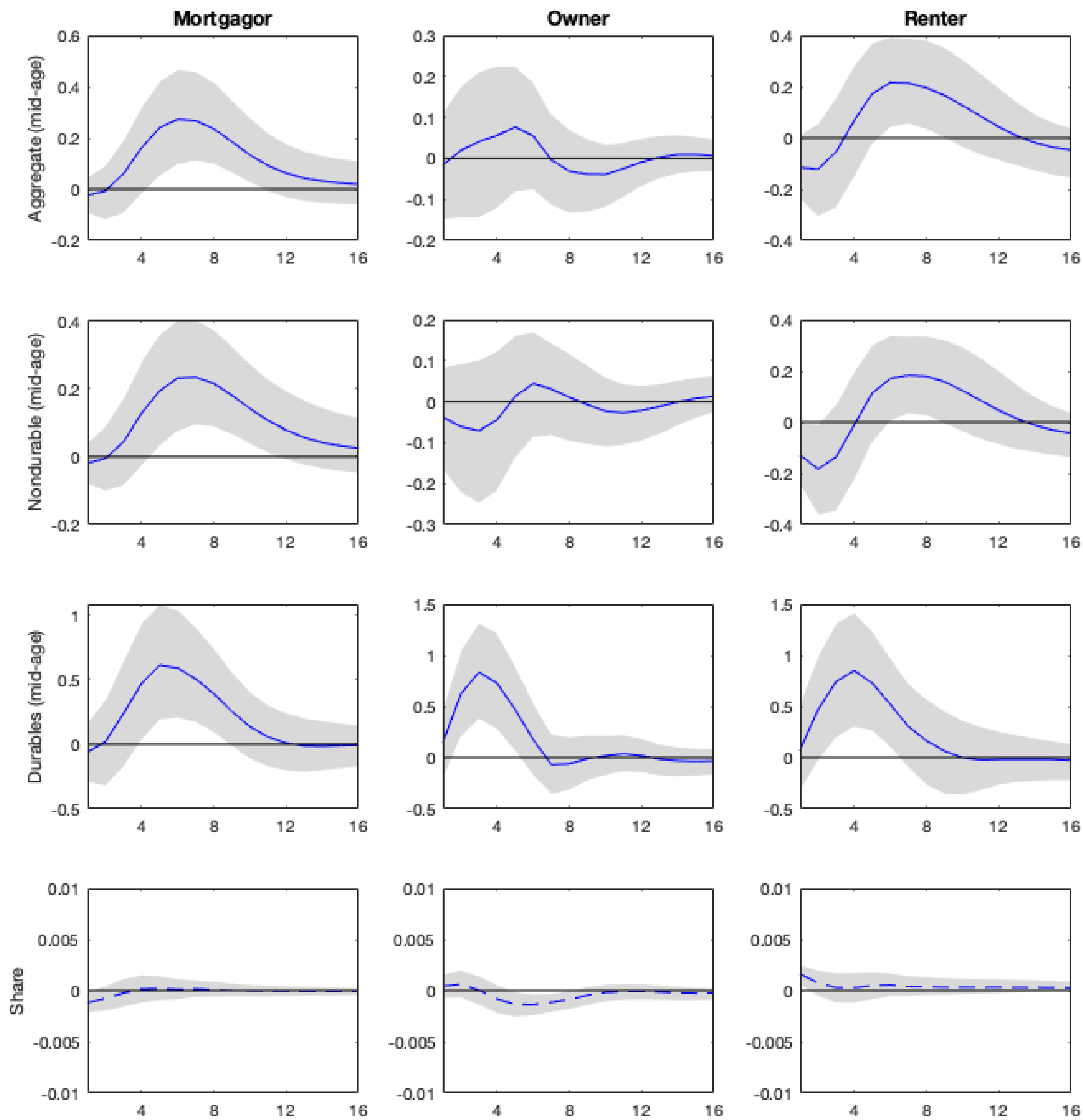
which is similar to that in CEX data. The total share of wealthy HtM households is around 25% where mortgagors have the largest share among the three groups. Mortgagors tend to have liquidity concerns and consume most of their disposable income despite owning a sizable illiquid asset. Renter households have little to no wealth, and therefore, are consistent with the notion of poor HtM. Kaplan et al. (2014) provide similar statistics for wealthy hand-to-mouth households and highlight implications of these types of households for the propagation of fiscal policy. Our paper illustrates their importance in the transmission of government spending shocks.

In summary, we find a significant increase in aggregate consumption responses following a positive government spending shock. This finding is mostly driven by mortgagors and there is clear evidence of heterogeneity of responses across households with different financial positions. Notably, this heterogeneity is not explained by changes in income. Based on household survey data, mortgagors exhibit behavior consistent with wealthy hand-to-mouth households while renters are more likely poor hand-to-mouth households. Our empirical findings suggest that the household balance sheet position plays an important role in the transmission mechanism of fiscal policy.

### 2.3.3 Robustness Checks

There are two potential concerns with our empirical analysis. First, there could be a selection issue in grouping. Each housing tenure group has its own demographic characteristics and each household is not randomly assigned to a specific group. Over the life-cycle positions, mortgagors are mostly in their mid-age (around 35 to 45), outright owners are in their late 60s, and renters tend to be young (mostly in their 20s). To address whether there are any life-cycle effects on household heterogeneity, we use sub-groups by controlling the effects of age to avoid any possibility of selection issues following Cloyne et al. (2020). We consider the middle-aged sub-group in each housing tenure group, using the demographic characteristics of the household head. We show in Figure 2.4, top three panels, that household heterogeneity does not come from demographic characteristics, and the life-cycle position does not change our main results. Notably, mid-aged mortgagor consumption is much more responsive than renters and outright owners in the same age group.

Figure 2.4: Robustness checks (Positive government spending shock)




Notes: This figure plots the dynamic effects of a positive SPF shock on consumption responses for middle-aged subgroups and tenure share responses for each housing tenure group: mortgagors, homeowners, and renters. The shaded area indicates 68 % confidence interval bands.

Second, there is a possibility of compositional changes in response to a positive government spending shock. First, note that the share of each housing tenure group is fairly stable over the sample period using the SCF data (see Table 2.2). Second, we also estimate the responses of housing tenure shares following a fiscal shock to test the existence of compositional changes. The share of each housing tenure group has an insignificant response to a positive government spending shock, shown in Figure 2.4, bottom panel, which suggests that there is only limited endogenous compositional change.

### 2.4 Theoretical Model Featuring Three Types of Households

In this section, we consider a closed-economy dynamic stochastic general equilibrium (DSGE) model to account for the empirical findings described in the previous section and determine the effects of government spending shocks on key macroeconomic variables. We extend the DSGE model with durable goods, housing, and household debt and features such as adjustment costs in capital and housing investment, costs of capital utilization, and price and wage rigidities. There are three types of households in the economy: patient households (savers), impatient households (borrowers), and renters, as in Alpanda and Zubairy (2016). Patient households own capital and housing, lend long-term debt to borrowers, and rent some housing to renters. Impatient households own housing, rent some housing to renters, and are subject to LTV constraints on their borrowing, similar to Kiyotaki and Moore (1997) and Iacoviello (2005). Renter households are hand-to-mouth. Our model also features a production side with non-housing goods producers, rental service producers, and residential and non-residential investment producers. We differentiate between the flow and stock of household debt with consideration of long-term fixed-rate mortgages as in Kydland et al. (2016), and Alpanda and Zubairy (2017). The model also includes housing related taxes as in Alpanda and Zubairy (2016). In our sensitivity analysis, we examine the role of habit formation and housing adjustment costs and introduce housing market related features such as refinancing and home equity.

#### 2.4.1 Households

##### *2.4.1.1 Patient Households*

The economy is populated by a continuum of measure one of infinitely-lived patient households indexed by $i$, whose intertemporal preferences over consumption, $x_{j,t}$, housing, $h_{P,t}$, and labor supply, $n_{P,t}$ are described by the following expected utility function:[13]

$$E_0 \sum_{t=0}^{\infty} \beta_P^t \upsilon_t \left[ \log x_{j,t}(i) + \xi_h \log h_{P,t}(i) - \xi_n \frac{n_{P,t}(i)^{1+\vartheta}}{1+\vartheta} \right], \tag{2.3}$$

where $E_t$ is the expectations operator conditional on information available at time $t$, $0 < \beta_P < 1$ is the time-discount parameter, $\xi_h$ and $\xi_n$ determine the relative importance of housing and labor in the utility function, and $\vartheta$ denotes the inverse of the Frisch-elasticity of labor supply. The habit-adjusted consumption basket with durable goods for households $j = \{P, I, R\}$, $x_{j,t}$, is given by

$$x_{j,t}(i) = c_{j,t}(i)^{\theta} s_{j,t}(i)^{1-\theta} - \mu_c c_{j,t-1}(i)^{\theta} s_{j,t-1}(i)^{1-\theta}, \tag{2.4}$$

where $\theta$ is a share parameter, $\mu_c$ is a parameter for habit persistence, $c_{j,t}$ denotes the non-durable consumption, and $s_{P,t}$ is the stock of durable consumption.[14] When $\theta = 1$ and $\mu_c = 0$, the above expression reduces to the case with no durable goods and no habit formation in the consumption basket. The preference shock, $\upsilon_t$, follows an AR(1) process:

$$\log \upsilon_t = \rho_\upsilon \log \upsilon_{t-1} + \varepsilon_{\upsilon,t}. \tag{2.5}$$

Patient households face heterogeneous labor services which are aggregated into a homogeneous labor service by perfectly-competitive labor intermediaries that use a standard Dixit-Stiglitz aggregator. These labor intermediaries rent labor services to goods producers, with the labor demand curve facing each patient household given by,

$$n_{P,t}(i) = \left( \frac{W_{P,t}(i)}{W_{P,t}} \right)^{-\eta_w} n_{P,t}, \tag{2.6}$$

where $W_{P,t}$ is the aggregate nominal wage rate and $n_{P,t}$ is labor services for patient households. $\eta_w$ is the elasticity of substitution between the differentiated labor services.

[13] As in Iacoviello (2005), the size of household is normalized to a unit measure for households.

[14] Durable stock follows the law of motion as $s_t = (1-\delta_s)s_{t-1} + \tilde{c}_t$ where $\tilde{c}_t$ denotes the purchases of new consumer durables.

The patient households' period budget constraint is given by

$$x_{P,t}(i) + q_{h,t}\left[\tilde{i}_{hP,t}(i) + \tilde{i}_{hRP,t}(i)\right] + q_{k,t}\tilde{i}_{k,t}(i) + \frac{B_t(i)}{P_t} + \frac{L_t(i)}{P_t} \leq \frac{W_{P,t}(i)}{P_t} n_{P,t}(i) + r_{hP,t} h_{RP,t}(i)$$
$$+ r_{k,t}k_{t-1}(i) + (1 + R_{t-1})\frac{B_{t-1}(i)}{P_t} + \left[R^M_{t-1}(i) + \kappa\right]\frac{D_{t-1}(i)}{P_t} + \frac{\Pi_t}{P_t} + tr_{P,t} - tax_{P,t} - adj.\ costs, \tag{2.7}$$

where $\tilde{i}_{hP,t}$, $\tilde{i}_{hRP,t}$, and $\tilde{i}_{k,t}$ denote the patient households' new investment in owner-occupied housing, rental housing owned by patient households, and capital, respectively, while $q_{h,t}$ and $q_{k,t}$ are the relative prices of stock of housing and capital. $r_{hP,t}$ and $r_{k,t}$ are the rental income that patient households earn from owning and renting out housing and capital.

The laws of motion of owner-occupied and rental housing owned by patient households, $h_{P,t}$ and $h_{RP,t}$, and capital stock holdings, $k_t$, for patient households are given by,

$$h_{P,t}(i) = (1 - \delta_h)\, h_{P,t-1}(i) + \tilde{i}_{hP,t}(i), \tag{2.8}$$

$$h_{RP,t}(i) = (1 - \delta_h)\, h_{RP,t-1}(i) + \tilde{i}_{hRP,t}(i), \tag{2.9}$$

$$k_t(i) = (1 - \delta_k)\, k_{t-1}(i) + \tilde{i}_{k,t}(i), \tag{2.10}$$

where $\delta_h$ and $\delta_k$ are the depreciation rates for housing and capital.

Patient households receive government transfers, $tr_{P,t}$, and lump-sum profits from goods producer, $\Pi_t$. Households also pay taxes on their consumption, income, capital and interest income, and their owned property. Note that the property tax on housing, $\tau_p$, is deductible when paying income taxes. The total tax burden of patient households is given by,

$$tax_{P,t} = \tau_c x_{P,t}(i) + \tau_{yP}\left[\frac{W_{P,t}(i)}{P_t} n_{P,t}(i) + r_{hP,t}h_{RP,t}(i) - \delta_h h_{RP,t-1}(i) - \tau_p q_{h,t}\left[h_{P,t}(i) + h_{RP,t}(i)\right]\right]$$
$$+ \tau_k (r_{k,t} - \delta_k)\, k_{t-1}(i) + \tau_b\left(R_{t-1}\frac{B_{t-1}(i)}{P_t} + R^M_{t-1}(i)\frac{D_{t-1}(i)}{P_t}\right) + \tau_p q_{h,t}\left[h_{P,t}(i) + h_{RP,t}(i)\right],$$

where $\tau_c$ is the consumption tax rate, $\tau_{yP}$ denotes the income tax rate on patient households, and

$\tau_k$ and $\tau_b$ are the tax rates on capital and interest income, respectively.

Patient households purchase one-period nominal government bonds, $B_t$, and lend to impatient households, $L_t$, and receive a predetermined nominal interest rate of $R_t$ on the bonds and collect mortgage payments as the sum of interest and principal payments. The law of motion for the stock of household debt, $D_t$, is as follows,

$$\frac{D_t(i)}{P_t} = (1-\kappa)\frac{D_{t-1}(i)}{P_t} + \frac{L_t(i)}{P_t}, \tag{2.11}$$

where $\kappa$ is the constant amortization rate which determines the principal payment amount paid out of the stock of mortgage debt.

Each period, new lending, $L_t$, is subject to a fixed mortgage interest rate; hence, the effective interest rate on the mortgage stock, $R_t^M$, is determined as follows,

$$R_t^M(i)\frac{D_t(i)}{P_t} = (1-\kappa)\frac{D_{t-1}(i)}{P_t}R_{t-1}^M(i) + \frac{L_t(i)}{P_t}R_t^F, \tag{2.12}$$

which can be rewritten as,

$$R_t^M(i) = \left(1 - \frac{L_t(i)}{D_t(i)}\right)R_{t-1}^M(i) + \frac{L_t(i)}{D_t(i)}R_t^F, \tag{2.13}$$

where $R_t^F$ denotes a fixed mortgage interest rate on new mortgage loans.

Note that when $\kappa = 1$, our model features the full amortization rate (i.e. one-period debt) and Eq.(2.11) implies that the stock and the flow of mortgage debt are equal to each other (i.e. $D_t = L_t$). Then, the effective interest rate of mortgages (coupled with $R_t^M(i) = R_t^F$ and the Euler condition for government debt) is equal to the interest rate on government debt (i.e. $R_t^M = R_t^F = R_t$ for all t).

Wage rigidities is introduced via Rotemberg (1982) type of quadratic cost of wage adjustments, given by,

$$\frac{\kappa_w}{2}\left(\pi^{-1}\frac{W_{P,t}(i)}{W_{P,t-1}(i)} - 1\right)^2 \frac{W_{P,t}}{P_t}n_{P,t}, \tag{2.14}$$

where $\kappa_w$ denotes a scale parameter and $\pi$ is the steady state inflation rate. Our model also features quadratic adjustment costs in housing and capital stocks with $\kappa_h$ and $\kappa_k$ as their corresponding level parameter values.[15] Housing adjustment costs ensure that housing stocks are not sold rapidly across patient and impatient households, and the amount of substitution between housing and non-housing sectors is limited.

The patient households' objective is to maximize utility subject to their budget constraints with the No-Ponzi conditions. The first-order condition of owner-occupied housing sets the marginal cost of obtaining one more unit of housing equal to the marginal utility gains from housing services and expected present discounted value of capital gains net of taxes, which is as follows (ignoring housing stock adjustment costs):

$$q_{h,t} = \frac{\upsilon_t \xi_h}{\lambda_{P,t} h_{P,t}} + E_t \left[ \left( \beta_P \frac{\lambda_{P,t+1}}{\lambda_{P,t}} \right) \left[1 - \delta_h - \tau_{p,t+1}(1 - \tau_{yP})\right] q_{h,t+1} \right], \tag{2.15}$$

where $\lambda_{P,t}$ is the Lagrange multiplier on the budget constraint. Similarly, the first-order conditions for rental housing and capital imply that their marginal costs are equal to the expected marginal gain in net tax rental income and capital gains. The rest of the optimality conditions are included in the appendix.[16]

#### *2.4.1.2 Impatient Households*

The economy is also populated by a continuum of unit measure of infinitely-lived impatient households. The utility function of impatient households is identical to patient households, except for their time-discount factor. Similar to Iacoviello (2005), the discount factor of impatient households is smaller than patient households which facilitates borrowing and lending across agents (i.e. $\beta_I < \beta_P$). Labor services are also heterogeneous across impatient households, and are aggregated into a homogeneous labor service using a standard Dixit-Stiglitz aggregator by perfectly-competitive labor intermediaries. The labor demand function of each impatient household is then

[15] Capital adjustment costs are defined as $(\kappa_k/2)[(k_t(i)/k_{t-1}(i)) - 1]^2 q_{k,t} k_t$, Owner-occupied and rental housing adjustment costs are specified as $(\kappa_h/2)[(h_{P,t}(i)/h_{P,t-1}(i)) - 1]^2 q_{h,t} h_{P,t}$ and $(\kappa_h/2)[(h_{R,t}(i)/h_{R,t-1}(i)) - 1]^2 q_{h,t} h_{R,t}$, respectively.

[16] See section A.5 for more details.

given by,

$$n_{I,t}(i) = \left(\frac{W_{I,t}(i)}{W_{I,t}}\right)^{-\eta_w} n_{I,t}, \tag{2.16}$$

where $W_{I,t}$ is the aggregate nominal wage rate and $n_{I,t}$ denotes the labor services of impatient households.[17]

The impatient households' budget constraint is as follows:

$$\begin{aligned}(1+\tau_c)x_{I,t}(i) + q_{h,t}\left[\tilde{i}_{hI,t}(i) + \tilde{i}_{hRI,t}(i)\right] + \left[R^M_{t-1}(i) + \kappa\right]\frac{D_{t-1}(i)}{P_t} \leq \frac{W_{I,t}(i)}{P_t} n_{I,t}(i) \\ + (1+\tau_{yI})r_{hI,t}h_{RI,t}(i) + \frac{L_t(i)}{P_t} + tr_{I,t} - \tau_p q_{h,t}[h_{I,t}(i) + h_{RI,t}(i)] \\ - \tau_{yI}\left[\frac{W_{I,t}(i)}{P_t} n_{I,t}(i) - \tau_p q_{h,t}[h_{I,t}(i) + h_{RI,t}(i)] - R^M_{t-1}(i)\frac{D_{t-1}(i)}{P_t}\right] - adj.\ costs,\end{aligned} \tag{2.17}$$

where $x_{I,t}$ denotes consumption. $\tilde{i}_{hI,t}$ and $\tilde{i}_{hRI,t}$ denote residential housing investment and rental housing owned by impatient households, respectively.

Impatient households also receive lump-sum transfers from the government, $tr_{I,t}$, and pay taxes on their consumption and income. Similar to patient households, the property tax on housing, $\tau_p$, is deductible when paying income taxes, $\tau_{yI}$. There also exists quadratic adjustment costs on their wages (to capture wage stickiness) and housing stocks. In our model, only patient households are assumed to own rental housing and capital. These assumptions, particularly the latter one, capture the fact that the impatient households have liquidity constraints and thus are the wealthy hand-to-mouth households.

The law of motion for the stock of debt held by the impatient households, $D_t$, and the evolution of the effective mortgage rate, $R^M_t$, follow Eq.(2.11) and (2.12), as shown previously. The law of motion of housing and rental housing for the impatient households are similar to patient households: $h_{I,t}(i) = (1-\delta_h)\, h_{I,t-1}(i) + i_{hI,t}(i)$ and $h_{RI,t}(i) = (1-\delta_h)\, h_{RI,t-1}(i) + i_{hRI,t}(i)$.

[17] $\eta_w$ is the elasticity of substitution between the differentiated labor services as shown in the patient households' problem. Also, $\theta_w = \eta_w/(\eta_w - 1)$, where $\theta_w$ is the real wage markup over the marginal rate of substitution at the steady state.

Impatient households face a borrowing constraint which is given by,

$$\frac{L_t(i)}{P_t} = \phi q_{h,t}\left[\tilde{i}_{hI,t}(i) + \tilde{i}_{hRI,t}(i)\right], \tag{2.18}$$

where $\phi$ is the LTV ratio on new housing investment. As our model features a borrowing constraint with the flow instead of the stock of housing, the purchase of housing in the current period increases the level of housing in next period, and therefore, households face a lower need of investing. This dampens the marginal gain in the next period of the borrowing constraint in that corresponding period.[18]

The impatient households' first-order condition with respect to housing (ignoring adjustment costs) is given as,

$$(1-\phi\mu_t)q_{h,t} = \frac{\upsilon_t \xi_h}{\lambda_{I,t} h_{I,t}} + E_t\left[\left(\beta_I \frac{\lambda_{I,t+1}}{\lambda_{I,t}}\right)\{(1-\delta_h)(1-\phi\mu_{t+1}) - \tau_p(1-\tau_{yI})\} q_{h,t+1}\right], \tag{2.19}$$

where $\mu_t$ is the Lagrange multiplier for impatient households' borrowing constraint. Eqn.(2.19) implies that the marginal cost of obtaining a unit of housing is equal to the marginal utility gain from housing and expected present discounted value of net-of-tax capital gains.

The optimality condition with respect to new borrowing is given by,

$$1 - \mu_t = \Omega_{dI,t} + \Omega_{rI,t} R_t^F, \tag{2.20}$$

where $\Omega_{dI,t}$ and $\Omega_{rI,t}$ denote the Lagrange multiplier on the laws of motion for mortgage debt and the effective mortgage interest rate, respectively. The rest of the optimality conditions are discussed in section A.5.

[18] In our sensitivity analysis, we also examine the role of refinancing and home equity withdrawal by adding features related to these. Typically, mortgage equity withdrawals constitute less than two percent on existing equity per quarter in data.

*2.4.1.3 Renter Households*

There is a continuum of unit measure of infinitely-lived renter households indexed by $i$ with utility function identical to impatient households. Note that renter households have an identical discount factor to impatient households (i.e. $\beta_R = \beta_I < \beta_P$), and solve a problem that is not intertemporal, as they live hand-to-mouth, consuming their disposable income in each period. The budget constraint of the renter households is given by,

$$(1+\tau_c)x_{R,t}(i) + \frac{P_{hP,t}}{P_t}h_{RP,t}(i) + \frac{P_{hI,t}}{P_t}h_{RI,t}(i) \leq (1-\tau_{yR})\frac{W_{R,t}(i)}{P_t}n_{R,t}(i) + tr_{R,t} - adj.costs, \tag{2.21}$$

where $x_{R,t}$, $\tau_c$, and $\tau_{yR}$ denote consumption and proportional taxes on consumption and income for renter households, respectively. Renter households earn wage income and get transfers from the government, $tr_{R,t}$, and rent housing, $h_{R,t}$, from patient and impatient households where $h_{R,t} = h_{RP,t}(i)^{\mu_h} h_{RI,t}(i)^{1-\mu_h}$ with $\mu_h$ representing the share for rental housing owned by patient households.[19] Note that there are adjustment costs for wage stickiness similar to patient and impatient households.

The first-order condition with respect to rental housing owned by patient households is given by,

$$p_{hP,t} = \frac{\upsilon_t \xi_h \mu_h}{\lambda_{R,t} h_{RP,t}}. \tag{2.22}$$

where $\lambda_{R,t}$ is the Lagrange multiplier on the renters' budget constraint. Similarly, the first-order condition with respect to rental housing owned by impatient households is given by,

$$p_{hI,t} = \frac{\upsilon_t \xi_h (1-\mu_h)}{\lambda_{R,t} h_{RI,t}}. \tag{2.23}$$

Eqn.(2.22) and Eqn.(2.23) imply that the marginal cost of acquiring a unit of rental housing is equal to the marginal utility gain. The rest of the first-order conditions for renter households are

[19] We also normalize for the amount of government transfers across three types of households with allowance of the size related to their labor share in the production.

discussed in the appendix.

### 2.4.2 Production

#### *2.4.2.1 Non-housing Goods Producers*

There is a continuum of monopolistically competitive non-housing goods producers indexed by $j$, whose production technology is given by,

$$y_{n,t}(j) = z_t \left[u_t(j) k_{t-1}(j)\right]^{\alpha} \left[n_{P,t}(j)^{\psi_P} n_{I,t}(j)^{\psi_I} n_{R,t}(j)^{\psi_R}\right]^{1-\alpha} - f_n, \tag{2.24}$$

where $y_n$ is non-housing output, $\alpha$ is the capital share in production function, and $\psi_i$ (for $i = P, I, R$ where $\psi_P + \psi_I + \psi_R = 1$) denotes the labor share of each household: patient, impatient, and renters households. $u_t$ and $z_t$ denote the capital utilization rate and exogenous aggregate productivity shock which follows an AR(1) process. $f_n$ is a fixed cost of production.

The final goods producers follow a standard Dixit-Stiglitz model to aggregate heterogeneous goods into a homogeneous good and the demand curve for the final goods producer is given by:

$$y_{n,t}(j) = \left(\frac{P_t(j)}{P_t}\right)^{-\eta_n} y_{n,t}, \tag{2.25}$$

where $y_{n,t}$ and $\eta_n$ are aggregate non-housing output and the elasticity of substitution between goods, respectively. Firm $j$'s objective is to maximize its profit, subject to a utilization cost and a price adjustment cost. For more details on the non-housing goods' producers problem, see section A.5.

#### *2.4.2.2 Investment Goods and Rental Services Producers*

There is a unit measure of perfectly-competitive investment goods producers following Bernanke et al. (1999). Non-residential investment goods producers purchase new capital investment goods from final-goods producers at a relative price of 1 and turn their $i_{k,t}$ units of goods into $\tilde{i}_{k,t} = z_{k,t} i_{k,t}$ units of effective investment goods. These goods are sold to end-users later at the relative price of $q_{k,t}$. Our model's production function also captures adjustment costs in the change in investment that are similar to those in Christiano et al. (2005) and Smets and Wouters (2007).

Non-residential investment goods producers maximize their expected discounted value of future profits, given by,

$$\max E_0 \sum_{t=0}^{\infty} \beta_P^t \frac{\lambda_{P,t}}{\lambda_{P,0}} \left[ q_{k,t}\tilde{i}_{k,t} - q_{k,t}\frac{\kappa_{ik}}{2}\left(\frac{i_{k,t}}{i_{k,t-1}} - 1\right)^2 \tilde{i}_{k,t} - i_{k,t} \right], \tag{2.26}$$

where $\kappa_{ik}$ is the adjustment cost parameter in capital investment. $\tilde{i}_{k,t}$ is effective investment goods where $\tilde{i}_{k,t} = z_{k,t}i_{k,t}$ and $z_{k,t}$ denotes the investment-specific technological change in new capital which follows an AR (1) process.

Residential investment goods producers solve an analogous problem to the capital investment goods producers and maximize their profit subject to the law of motion of housing. The total housing investment (i.e., $i_{h,t} = i_{hP,t} + i_{hI,t} + i_{hR,t}$) is purchased from final-goods producers at a relative price of 1 and turned into $\tilde{i}_{h,t}$ units of effective housing investment goods that can be purchased by end users at the relative price $q_{h,t}$.

Rental services producers maximize their expected discounted value of future profits, given by,

$$\max E_0 \sum_{t=0}^{\infty} \beta_P^t \frac{\lambda_{P,t}}{\lambda_{P,0}} \left[ \frac{P_{hP,t}(i)}{P_t} h_{RP,t}(i) + \frac{P_{hI,t}(i)}{P_t} h_{RI,t}(i) - r_{hP,t}h_{RP,t}(i) - r_{hI,t}h_{RI,t}(i) \right.$$
$$\left. - \frac{\kappa_{ph}}{2}\left(\frac{P_{hP,t}(i)}{P_{hP,t-1}(i)\pi} - 1\right)^2 \frac{P_{hP,t}}{P_t} h_{RP,t} - \frac{\kappa_{ph}}{2}\left(\frac{P_{hI,t}(i)}{P_{hI,t-1}(i)\pi} - 1\right)^2 \frac{P_{hI,t}}{P_t} h_{RI,t} \right], \tag{2.27}$$

where $\kappa_{ph}$ is the price adjustment cost parameter in rental services.

The demand curve faced by rental services owned by households $j$ where $j = \{P, I\}$ is given by,

$$h_{Rj,t}(i) = \left(\frac{P_{hj,t}(i)}{P_{hj,t}}\right)^{-\eta_h} h_{Rj,t}, \tag{2.28}$$

where $\eta_h$ is the elasticity of substitution between rental services.

The optimality condition with respect to housing rental rate is given by,

$$\left(\frac{\pi_{hj,t}}{\pi}-1\right)\frac{\pi_{hj,t}}{\pi}=E_t\left[\beta_P\frac{\lambda_{P,t+1}}{\lambda_{P,t}}\left(\frac{\pi_{hj,t+1}}{\pi}-1\right)\frac{\pi_{hj,t+1}}{\pi}\frac{\pi_{hj,t+1}}{\pi_{t+1}}\frac{h_{Rj,t+1}}{h_{Rj,t}}\right]-\frac{\eta_h-1}{\kappa_{ph}}\left(1-\theta_h\frac{r_{hj,t}}{p_{hj,t}}\right), \tag{2.29}$$

where $\theta_h$ is the real housing services markup over the marginal rate of substitution at the steady state.

The relative price of rental housing services for $j=\{P,I\}$ and rental inflation is given by

$$\frac{\pi_{hj,t}}{\pi_t}=\frac{p_{hj,t}}{p_{hj,t-1}}. \tag{2.30}$$

### 2.4.3 Government and Monetary Policy

The government issues bonds, collects taxes, and pays transfers to households (patient, impatient, and renters households). Note that the aggregate tax revenue is generated from consumption, income, property, capital and interest rate income taxes from various types of households, as detailed earlier in their respective budget constraints.

The aggregate level of transfer payments to households is given by,

$$tr_t=\Xi y_n-\varrho_b b_{t-1}, \tag{2.31}$$

where $\Xi$ denotes a level parameter and $\varrho_b$ determine the response of transfers to government debt.[20] government debt cannot follow a Ponzi scheme. We ensure this condition by Aggregate transfers, $tr_t$, are distributed to each type of households based on their respective labor shares (i.e. $tr_{i,t}=\psi_i tr_t$ for $i=\{P,I,R\}$).

The government faces a budget constraint as follows,

$$tax_t+b_t=\left(\frac{1+R_{t-1}}{\pi_t}\right)b_{t-1}+g_t+tr_t, \tag{2.32}$$

[20]Following Leeper et al. (2010), government debt cannot follow a Ponzi scheme. We ensure this condition by the adjusted level of either taxes, government spending, or transfers.

where $g_t$ is government expenditure which follows an exogenous AR(1) process:

$$\log g_t = (1 - \rho_g) \log g + \rho_g \log g_{t-1} + \varepsilon_{g,t}, \tag{2.33}$$

where $\varepsilon_{g,t}$ represents an i.i.d government spending shock with variance $\sigma_g^2$.

The central bank sets monetary policy following a Taylor rule, given by,

$$R_t = R + a_\pi \log \left( \frac{\pi_{c,t}}{\pi} \right) + a_y \log \left( \frac{y_t}{y} \right), \tag{2.34}$$

where $R$ denotes the steady-state level of nominal interest rate in gross terms. $a_\pi$ and $a_y$ are the coefficients of inflation and output gap, respectively.

### 2.4.4 Market Clearing Conditions

The goods market clears

$$x_t + i_t + g_t = y_{n,t} - \text{adj.costs}, \tag{2.35}$$

where $x_t = x_{P,t} + x_{I,t} + x_{R,t}$ denote total consumption. Total investment is $i_t = i_{k,t} + i_{h,t}$ where $i_{k,t}$ is non-residential investment and $i_{h,t} = i_{hP,t} + i_{hI,t} + i_{hR,t}$ is residential investment.

A competitive equilibrium is defined as the set of prices, allocations, and policies where households maximize the discounted present value of utility, firms maximize their profits, and all markets clear.

### 2.4.5 Calibration

We calibrate the model parameters so that the model's steady state matches some of the key statistics in the U.S. macroeconomic and financial data and our model is set in a quarterly frequency.[21] Table 2.3 summarizes our calibration values and Table 2.4 represents the steady-state ratios of the model and its counterparts in the data.

[21] Data target ratios come from the National Income and Product Accounts (NIPA), Flow of Funds Accounts (FOF), the 2001 Residential Financial Survey (RFS), and the 2011 American Housing Survey (AHS). The calibration methodology of using steady-state relationships in the model is similar to Cooley et al. (1995). Parameters related to durable stock are based closely on the findings in Mertens and Ravn (2011), and other parameters are mostly drawn from Alpanda and Zubairy (2016, 2017).

Table 2.3: Model parameters

| Description | Symbol | value |
|---|---|---|
| Discount factor | $\beta_P$, $\beta_I$, $\beta_R$ | 0.9916, 0.9852, 0.9852 |
| Inverse labor supply elasticity | $\vartheta$ | 1 |
| Level for housing and labor in utility | $\xi_h, \xi_n$ | 0.13, 0.6 |
| Habit formation in consumption behaviors | $\mu_c$ | 0.85 |
| Share for non-durable consumption | $\theta$ | 0.7 |
| Share for rental housing owned by patient households | $\mu_h$ | 0.9 |
| LTV ratio on new regular mortgages | $\phi$ | 0.85 |
| Amortization rate on household loans | $\kappa$ | 0.018 |
| Capital share in production | $\alpha$ | 0.3 |
| Depreciation rates | $\delta_h$, $\delta_k$, $\delta_s$ | 0.01, 0.013, 0.025 |
| Investment adj. cost | $\kappa_{ih}$, $\kappa_{ik}$, $\kappa_{dc}$ | 1.00, 2.00, 100 |
| Stock adj. cost | $\kappa_h$, $\kappa_k$, $\kappa_s$ | 2.00, 2.00, 100 |
| Labor shares in production | $\Psi_P$,$\Psi_I$, $\Psi_R$ | 0.26, 0.47, 0.27 |
| Tax rates | | |
| Consumption tax rate | $\tau_c$ | 0.05 |
| Capital income tax rate | $\tau_\kappa$ | 0.40 |
| Interest income tax rate | $\tau_b$ | 0.15 |
| Property tax rate | $\tau_p$ | 0.0035 |
| Income tax rate | $\tau_{yP}$, $\tau_{yI}$, $\tau_{yR}$ | 0.30, 0.30, 0.20 |
| Transfers | $\Xi$ | 0.024 |
| Response of transfers to gov. debt | $\varrho_b$ | 5.00 |
| AR(1) Government spending shock | $\rho_g$ | 0.85 |
| Taylor rule for inflation response | $a_\pi$ | 1.50 |
| Taylor rule for output gap | $a_y$ | 0.01 |

The time-discount factor of patient households, $\beta_P$, is set to 0.9916, implying a steady-state annualized real interest of nearly 4 percent. The time-discount factors of impatient and renter households, $\beta_I$ and $\beta_R$, are fixed at 0.9852 to match a Lagrange multiplier on household debt equivalent to a 200 basis point spread on the risk-free rate.[22] The labor disutility parameter, $\xi_n$, and the housing preference parameter, $\xi_h$, are set to 0.13 and 0.6 to match aggregate housing to GDP share, and are close to the estimate in Justiniano et al. (2015). The inverse of the Frisch labor supply elasticity is set to 1. This value is picked as a compromise between the estimated values in

[22] As in Alpanda and Zubairy (2016), this value reflects the spread between 30-year mortgages and 10-year Treasury bonds of around 170 bps on average over 1971-2014.

Table 2.4: Model steady-state ratios

| Description | Symbol | Model | Data target |
|---|---|---|---|
| Total consumption/GDP | $c/y$ | 0.61 | 0.61 |
| Share of patient household | $c_P/c$ | 0.55 | |
| Share of impatient household | $c_I/c$ | 0.27 | |
| Share of renter household | $c_R/c$ | 0.17 | |
| Total investment/GDP | $i/y$ | 0.19 | 0.19 |
| Non-residential investment/GDP | $i_k/y$ | 0.14 | 0.14 |
| Residential investment/GDP | $i_h/y$ | 0.05 | 0.05 |
| Government expenditure/GDP | $g/y$ | 0.20 | 0.20 |
| Tax revenue/GDP | $tax/y$ | 0.33 | |
| Transfers/GDP | $tr/y$ | 0.02 | |
| Wage share in non-housing income | $1-\alpha$ | 0.70 | |
| Share of patient households | $\psi_P$ | 0.26 | 0.26 |
| Share of impatient households | $\psi_I$ | 0.47 | 0.47 |
| Share of renter households | $\psi_R$ | 0.27 | 0.27 |
| Capital stock/GDP (qtr) | $k/y$ | 11.06 | |
| Durable stock/GDP (qtr) | $s/y$ | 7.28 | |
| Share of patient households | $s_P/s$ | 0.60 | |
| Share of impatient households | $s_I/s$ | 0.25 | |
| Share of renter households | $s_R/s$ | 0.15 | |
| Housing stock/GDP (qtr) | $h/y$ | 4.97 | |
| Share of patient households | $h_P/h$ | 0.61 | |
| Share of impatient households | $h_I/h$ | 0.28 | |
| Share of renter households | $h_R/h$ | 0.09 | |

the Real Business Cycle and New Keynesian literature (Smets and Wouters, 2007).

The steady-state non-residential investments to GDP ratio is about 14% while the capital-to-GDP ratio is 1.85 on annualized basis in the data. Based on these values, we calibrate the quarterly depreciation rate for capital stocks, $\delta_k$, to 1%. Capital investment adjustment cost parameters, $\kappa_{ik}$, is calibrated to be 2, which is rounded to be close to estimates as in Eberly et al. (2012) and Justiniano et al. (2015).[23] The capital share in production, $\alpha$, is set to 0.3 using the capital-output ratio and the model-implied after-tax rental rate of capital.

The steady-state LTV ratio, $\phi$, is calibrated to be 0.85 in order to match the first mortgage loan

[23] Housing investment adjustment cost, $\kappa_{ih}$, is treated similar to capital adjustment cost and is set to 1.00.

ratio (median value) to the purchase of one unit of mortgaged properties estimated by Duca et al. (2011). In data, the residential investments to GDP ratio is about 5% while the housing-to-GDP ratio is about 1.24. In order to match these, we calibrate the depreciation of houses, $\delta_h$, to 0.01.[24] The amortization rate on households loans, $\kappa$, is set to 0.018 to imply the duration of mortgage loans around 18 years in the model.[25]

We calibrate the wage share of impatient households, $\Psi_I$, to 0.47 and their share of housing, $h_I/h$, to 0.28. The wage share of rental households $\Psi_R$ is set to 0.27 with the rental housing share, $h_R/h$, of 0.09 which is similar to those values from the RFS and AHS surveys. The wage share of patient households, $\Psi_P$, is thus set to 0.26 and the share of patient households' housing, $h_P/h$, to 0.61.[26]

The steady-state government expenditure to GDP ratio, $g/y$, is set to 20% based on the NIPA data average over the sample period under consideration. The steady-state transfers to GDP ratio is calibrated at 0.01 and the level parameter for transfers, $\Xi$, is set to 0.02. The responsiveness of transfers to government debt is assumed to be 5, in order to ensure that the government intertemporal budget holds and to preserve determinacy within the model. Income tax rates for the patient and impatient households, $\tau_{yP}$ and $\tau_{yI}$, are set to 0.3 while the renters households income tax rate, $\tau_{yR}$, is set to 0.2 to imply tax progressivity. The consumption tax rate and property tax rate, $\tau_c$ and $\tau_p$, are set to 0.05 and 0.0035, respectively. We also calibrate the capital and interest rate income tax, $\tau_k$ and $\tau_b$, as 0.40 and 0.15 following Alpanda and Zubairy (2016). The government shock persistence, $\rho_g$, is set to 0.85. In our sensitivity analysis, we alter this persistence parameter to explore the role of the negative wealth effect of the shock. The Taylor rule coefficients of inflation response and output gap, $a_\pi$ and $a_y$, are set to 1.50 and 0.01, respectively.

[24]This value is also consistent with estimates in Hull (2017) and Wilhelmsson (2008).

[25]This mortgage loan duration is close to AHS average duration of outstanding loan data.

[26]We aim to target the average share of each housing tenure group based on the SCF data (1995 to 2007). Altering this value to match the CEX share (1981 to 2007) also gives consistent simulation results.

## 2.5 Model Results

In this section, we analyze the effects of government spending shocks based on the benchmark parameters. First, we present the dynamic effects on aggregate variables. We then compare consumption and income responses among different types of households and illustrate some of the possible transmission mechanisms of heterogeneity.

### 2.5.1 Benchmark Results

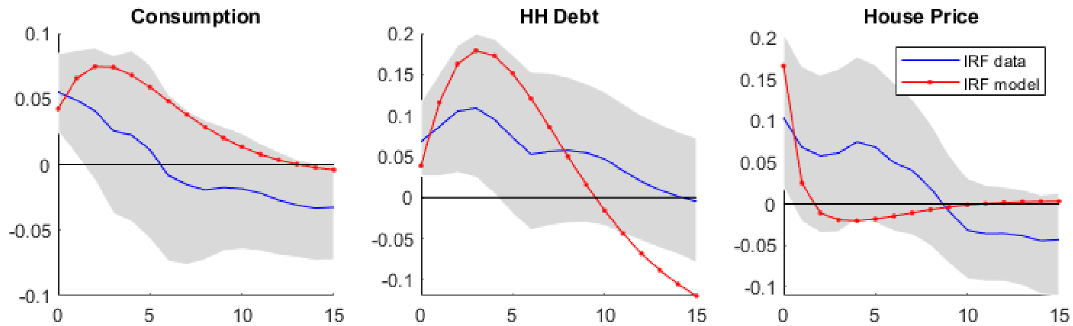
Figure 2.5 illustrates the effects of a positive government spending shock based on the baseline calibration parameter values described in Section 2.4.5 for some of the key aggregate variables, along with their empirical counterparts. In response to a positive government spending shock, aggregate consumption increases significantly, and has a hump-shaped response. Also, there is a corresponding hump-shaped increase in the stock of household debt that is within the confidence bands of the empirical response. Note that we are also able to generate a rise in house prices to a positive government spending shock on impact quantitatively, though not the persistence of the corresponding empirical response, although the response is within the estimated confidence bands. Khan and Reza (2017) have shown that most standard models face a challenge in generating a positive response of house prices to a government spending shock, and even their proposed fix does not generate a hump-shaped response.[27] Additional model responses are shown in Figure A.9 in the appendix. Notably, in the model private investment is crowded out, which is consistent with findings from Galí et al. (2007) and Mountford and Uhlig (2009).[28] Labor and real wages both rise. Inflation and interest rate all also rise on impact.

Figure 2.6 displays the dynamic responses among three types of households - patient, impatient, and renters - to a positive shock to government spending. Our model generates heterogeneous consumption responses across agents: impatient households (borrowers) have a large and persis-

[27] In a recent contribution, Larsen et al. (2022) are able to match the persistent response of house prices to government spending shocks by considering a model featuring endogenous entry in the intermediate goods sector and a taste for variety, which generates increasing returns in aggregate production.

[28] A positive government spending shock crowds out non-residential investment on impact and residential investment with a delay in our model results.

Figure 2.5: Impulse responses in the benchmark model

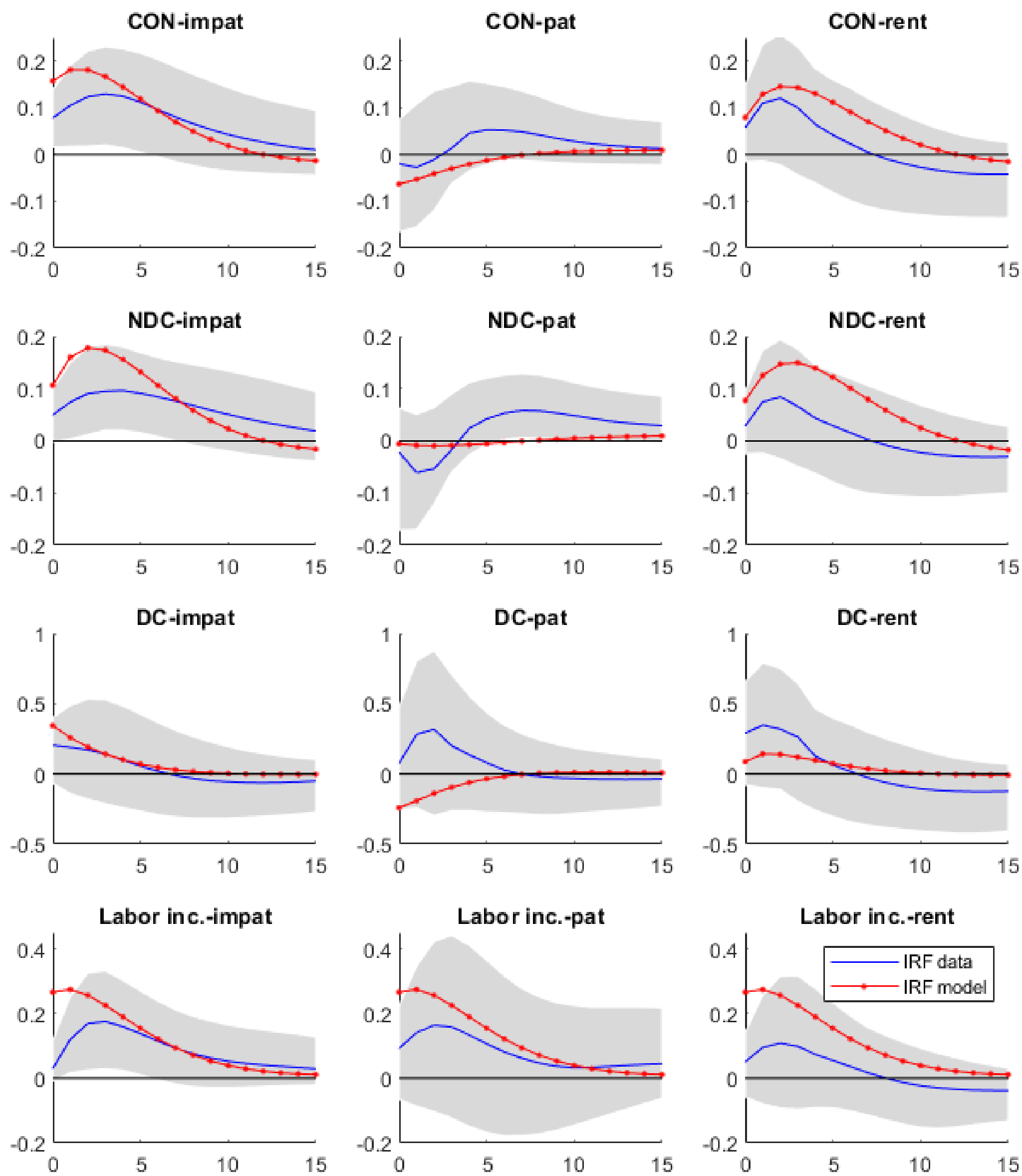



Notes: This figure shows the impulse responses functions of key aggregate variables in response to a positive government spending shock.

tent increase, patient households' (savers) consumption declines on impact at a relatively small magnitude, renters households have a similar response to impatient households but the increase is slightly smaller. The responses of housing stock and investment rise for impatient households while the stock of housing owned by the patient household falls. Labor, wage, and labor income increase for all households. Overall, we do not find any heterogeneity in the labor market responses. Notably, the rise in labor income is of the same magnitude across all types of households.

Higher government spending generally induces negative wealth effects for all agents and the supply of labor increases, which results in the rise of output. With higher labor income for all types of households, the heterogeneous consumption responses may be explained as following. Impatient households respond the most and this may be explained by the effects on their borrowing power and liquidity constraints. Patient households tend to cut their consumption while supplying more labor, which is more like a representative household's behavior. Renters are more like hand-to-mouth consumers as they do not hold any assets, and therefore, spend their disposable labor income on consumption expenditures. The general equilibrium effects of a positive government spending shock with the rise in aggregate demand is consistent, though there exists heterogeneity across households.

Figure 2.6: Impulse responses in the benchmark model across households




Notes: This figure shows the impulse response functions of key variables across different households (patient, impatient, and renters) in response to a positive government spending shock.

### 2.5.2 Transmission Mechanisms

Given the model results, we explore the potential transmission mechanisms of a government spending shock on heterogeneous consumption responses. In the standard RBC model, households face higher taxes following a positive government spending shock, and therefore experience negative wealth effects (Aiyagari et al., 1992; Baxter and King, 1993). This negative wealth effect induces the representative household to decrease consumption and increase labor supply, implying output rises as a result.[29] The investment response depends on the persistence of government spending shocks. The presence of nominal rigidities implies a shift in the labor demand in response to increased demand due to public spending. As a result, we see an overall rise in wages.[30]

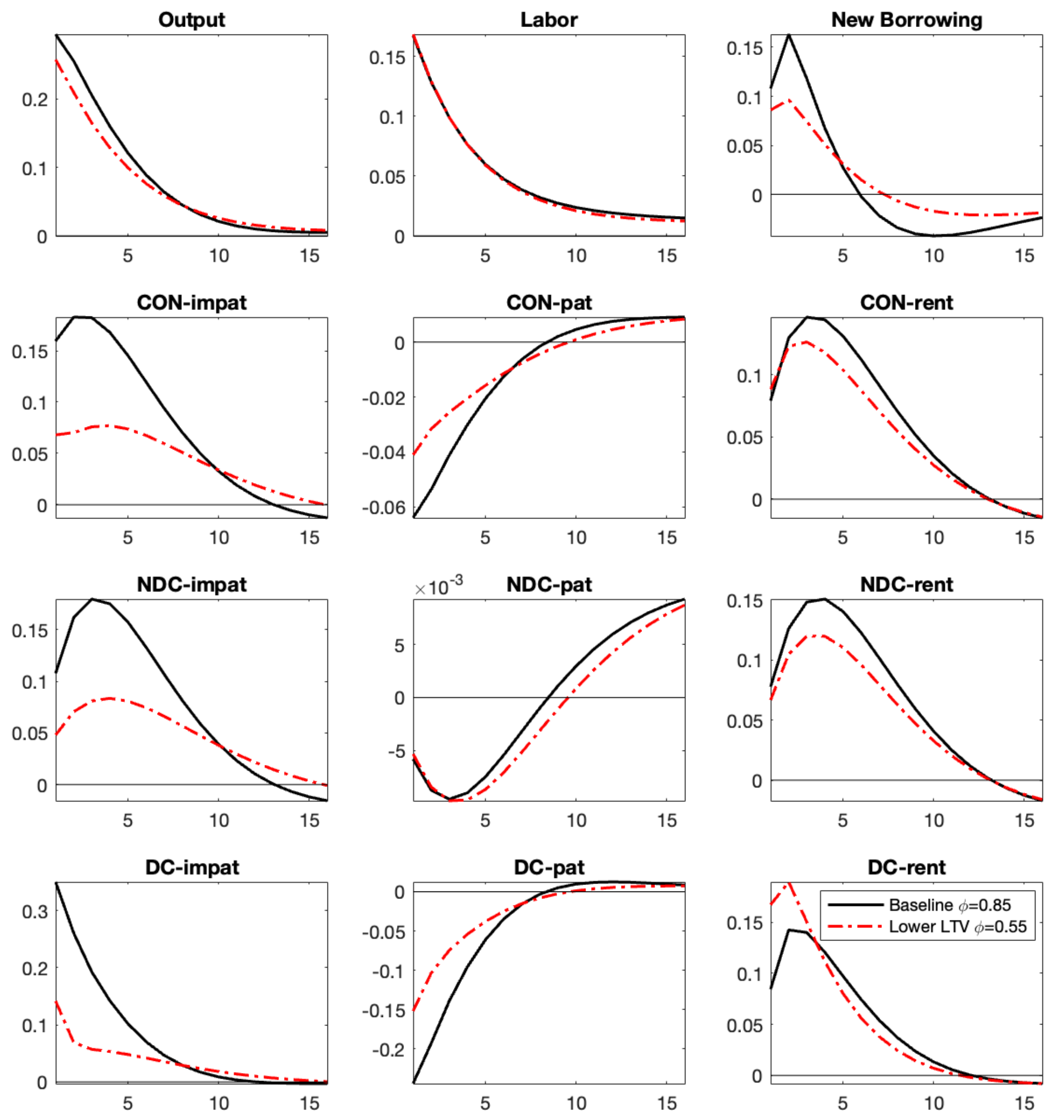
Our paper contributes to the new-Keynesian literature studying the effects of fiscal shocks by extending the model with households in different financial positions. In this case, the households' consumption responses following a government spending shock are determined by the income effect, credit effect, and wealth effect. As shown above, since wages and labor for all three households rise, the labor income goes up for all of them, and that too to a similar degree and puts upward pressure on their consumption. Thus the differences across the various households are likely driven by the other two channels. In particular, the two potential transmission channels we consider are as follows: (i) liquidity constraints, and (ii) the persistence of shock propagating the negative wealth effect.

In the benchmark model, the impatient household faces a borrowing constraint given by $d_t = \phi q_{h,t} h_{I,t} \left(i\right)$. Since house prices rise in response to a government spending shock, this implies that the credit constraint for the impatient household is loosened by the spending shock. The steady-state LTV ratio, $\phi$, plays an important role in dictating the degree of borrowing ability of these households, in response to house price changes. As shown in Figure 2.7, the lower level of LTV ratio (i.e. a larger down-payment requirement) clearly affects the consumption responses of impatient households negatively, while the consumption responses of patient and renters households are almost identical. At $\phi = 0.50$, output, labor, and labor income are almost identical while the new borrowing slightly falls and the lower borrowing power induces impatient households to relatively reduce their consumption. Despite the negative wealth effect following a positive govern-

[29]In a standard RBC model, a higher labor supply lowers the real wage and consumption is crowded-out

[30]The presence of rule-of-thumb consumers generates the positive response of consumption and wages when government spending increases (Galí et al., 2007).

Figure 2.7: Impulse responses to a positive government spending shock for varying values of $\phi$

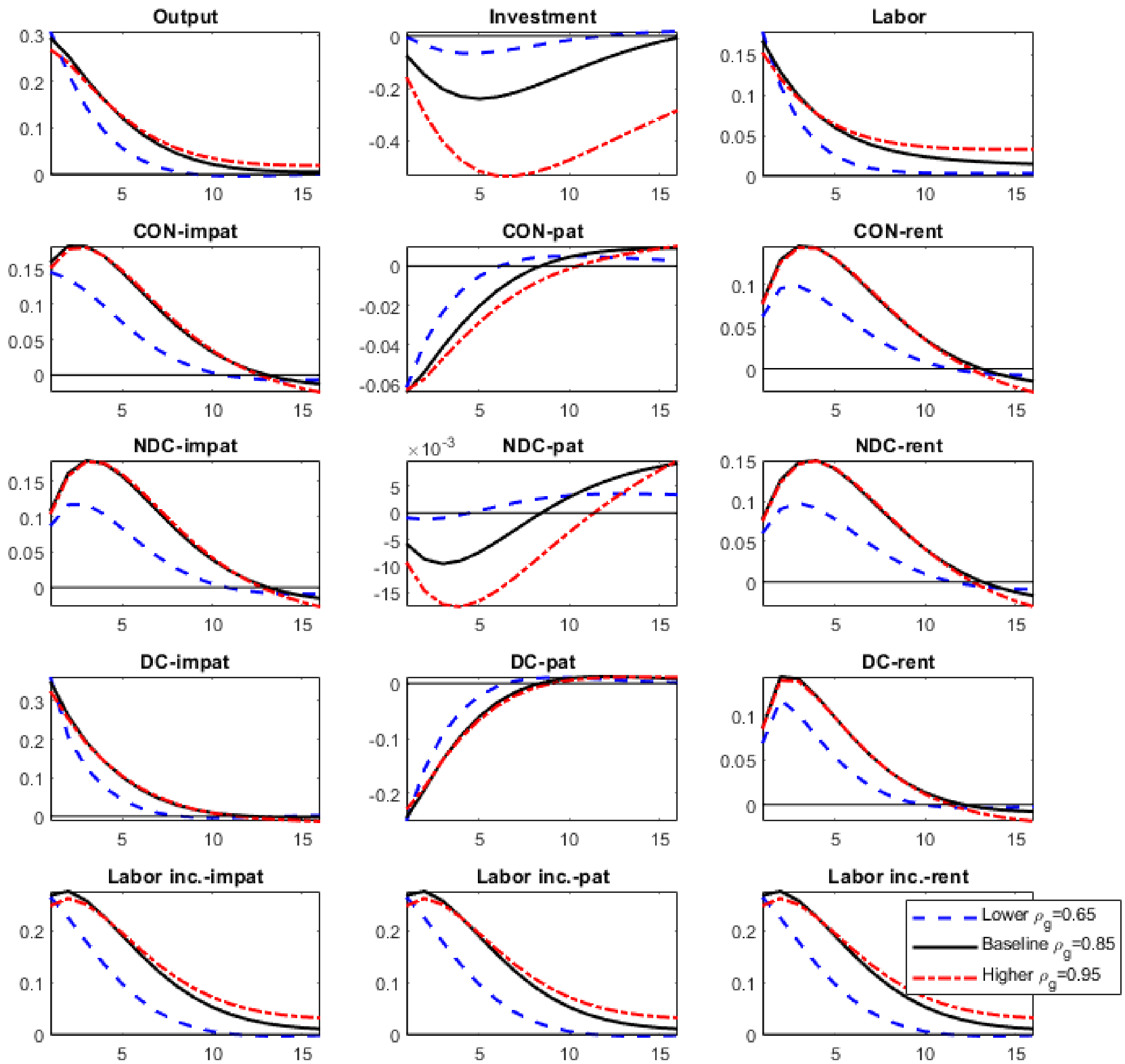



Notes: This figure shows the impulse response functions of key variables across different households (patient, impatient, and renters) in response to a positive government spending shock. The solid line indicates the baseline model results. The red dotted line represents the lower LTV ratio which lowers the borrowing ability of impatient households.

ment spending shock, the liquidity and credit effects still boost impatient households' consumption expenditures overall.

One of the main features that affects consumption and labor responses is through the negative

Figure 2.8: Impulse responses to a positive government spending shock for varying values of $\rho_g$




Notes: This figure shows the impulse response functions of key variables across different households (patient, impatient, and renters) in response to a positive government spending shock. The solid line indicates the baseline model results. The blue dash-dotted line represents the lower $\rho_g$ and the red dotted line represents the higher $\rho_g$ indicating the high persistence of the shock.

wealth effect channel following a positive government spending shock. High spending generates the expectation of higher taxes today or in the future. For the renter households, since they consume their disposable income each period, only current taxes matter and if taxes do not rise immediately, they do not face these negative wealth effects on their consumption. These types of consumers are highlighted in Galí et al. (2007). On the other hand, the patient households are the Ricardian households in the model and bear the largest brunt of this negative wealth effect.[31] In Figure 2.8, we show the impulse responses with different degrees of shock persistence, which determines the size of the negative wealth effect. The baseline shock persistent, $\rho_g$, is set to 0.85. When we consider a less persistent shock, and $\rho_g$ equal to 0.65, the increase in output, labor, and consumption on impact are almost identical to the baseline result while the effects of the shock is less persistent. Consumption response heterogeneity across households is reduced as patient households no longer endure the significant negative wealth effect, and therefore, cut their consumption by less. Impatient and renters households have larger responses but this only lasts up to four quarters after the shock. Similarly, when we consider a more persistent shock, and $\rho_g$ to be 0.9, then the decline in the consumption response of the patient household is even larger on impact.

In summary, we find that the liquidity constraints and the persistence of the shock play an important role in the propagation of government spending shocks, with the former of particular importance to the mortgagors and the latter of particular importance to the patient households (savers). Notably, our findings provide theoretical support for the notion that household mortgage debt positions play an important role in the transmission mechanism of fiscal policy. In the next section, we consider an extended version of the model with durable goods and further test the robustness of our results to alternative parameterizations.

### 2.6 Extensions and Robustness Analysis

In this section, we further distinguish between the effects on durable and non-durable consumption across the different types of households. We then discuss some robustness analysis for our model results.

[31] This is particularly the case since they are taxed on both owner-occupied and rental housing via property taxes and house prices rise in response to a spending shock. They are also subject to taxes on interest income which will rise as borrower household increase borrowing in response to increased spending.

### 2.6.1 Robustness to Alternative Parameterization

In Figure 2.9, we conduct several robustness analyses by altering the baseline parameterization. In our sensitivity analyses, we consider the case with (i) habit formation in consumption, (ii) refinancing and equity withdrawal on existing loans, and (iii) low adjustment costs in the housing stock.

*The role of habit formation.—* In the baseline model calibration, we focus on the case without habit formation in consumption. In this subsection, we add habit formation to model specification to explore the effects on expenditure heterogeneity.[32] As shown in the first row of Figure 2.9, adding a moderate habit formation does not alter heterogeneous consumption responses across different types of households qualitatively. With habit formation, the consumption response is hump-shaped while the impact response is slightly lower than the baseline case.

*Role of refinancing and equity withdrawal.—* In the benchmark model, the new lending is determined by the steady-state LTV ratio associated with new investment in housing. In our sensitivity analysis, we consider the role of refinancing and home equity withdrawal to consider additional effects on mortgage debt. From our model, note that the effective interest rate on mortgage stock is given by,

$$R_t^M(i)d_t(i) = (1-\Phi)(1-\kappa)\frac{d_{t-1}(i)}{\pi_t}R_{t-1}^M(i) + \left[l_t(i) + \Phi(1-\kappa)\frac{d_{t-1}(i)}{\pi_t}\right]R_t^F, \tag{2.36}$$

where $\Phi$ is the refinancing rate.

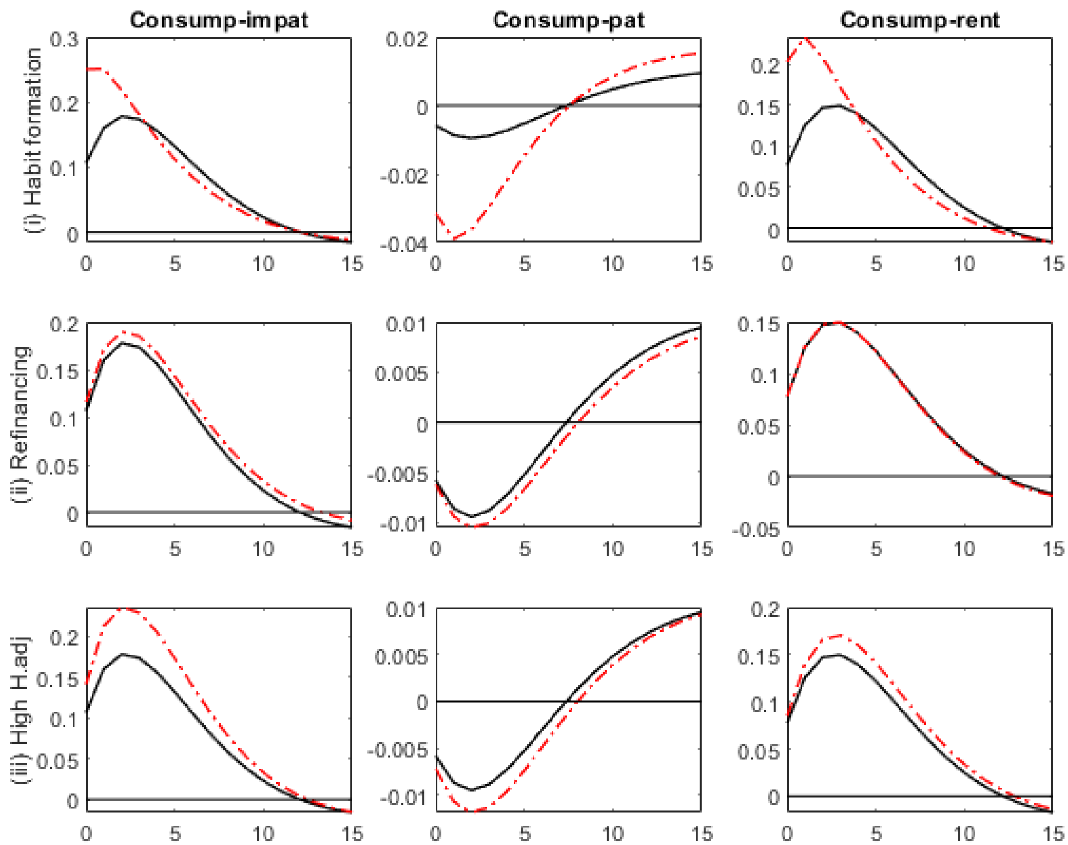
With the home equity withdrawal rate, $\Upsilon$, the new lending is then given by

$$l_t = \phi q_{h,t}\tilde{i}_{hI,t}(i) + \Upsilon\left[q_{h,t}(1-\delta_h)h_{I,t-1}(i) - (1-\kappa)\frac{d_{t-1}(i)}{\pi_t}\right]. \tag{2.37}$$

Following Greenspan and Kennedy (2005) and Alpanda and Zubairy (2017), we set the refi-

[32] In the figure, we show the moderate level of habit formation with $\mu_c = 0$ and imposing a moderate value of habit formation, $\mu_c = 0.3$ still provides similar results.

Figure 2.9: The effects of fiscal policy under alternative parameterizations




Notes: This figure shows the dynamics of consumption responses with alternative parameterizations in response to a positive government spending shock. The solid line indicates the baseline model results and the red dash-dotted line represents corresponding alternative features.

nancing rate to 0.0475 and the home equity withdrawal rate to 0.0172.[33] Figure 2.9 second row displays the sensitivity of consumption variations with alternative parameterization. Allowing refinancing and home equity withdrawal enhances the borrowing ability of impatient households, which slightly increases their consumption response but the changes are rather small in magnitude. This suggests that for the propagation of fiscal shocks, the additional channel coming from

[33]The ratio of repayments from refinancing is averaged around 4.4% (implying 7.8 years of an interest rate duration) quarterly during 1991-2005 based on the data provided by Greenspan and Kennedy (2005). Following Alpanda and Zubairy (2016), we consider the average interest rate duration of 7.1 years with the refinancing rate, $\Phi$, to 0.0475. We also set the home equity withdrawal rate to 0.0172 to match the 1.72% of existing equity of borrowers during 1991-2005.

refinancing does not alter the results considerably.

*Adjustment costs in housing stock.*— The third row of Figure 2.9 shows the consumption responses when the degree of housing stock adjustment costs, $\kappa_h$, change. When we increase adjustment costs in housing stock, $\kappa_h$ to be 10.00, the house price rises by more and housing stock accumulates more slowly. Impatient households face a rise in their collateral values which further strengthens their borrowing ability. As a result, the consumption of impatient households rises by more.

### 2.6.2 Alternative Monetary Stance: Considering ZLB

In this subsection, we discuss how the effects of government spending shocks are different when monetary policy is constrained by zero lower bound (ZLB). In particular, we consider the following monetary policy rule:

$$R_t = \max\left[R + a_\pi \log\left(\frac{\pi_{c,t}}{\pi}\right) + a_y \log\left(\frac{y_t}{y}\right), 0\right]$$

A vast literature has shown that the aggregate effects of government spending are amplified when short-term rates are constrained by the ZLB (Eggertsson (2011); Christiano et al. (2011)).[34]

In response to a positive government spending shock, output and consumption increase significantly and these effects are amplified under ZLB. Even a moderate duration of ZLB generates heterogeneous consumption responses while the differences in the effects compared to the baseline case are largest for patient households. Patient households' consumption response is similar to that of a representative agent setup, and is crowded out in normal times while it increases during the ZLB period.

Under ZLB, the rise in government spending is inflationary due to a rise in demand, which decreases the real interest rate as nominal rates are bound at zero. A lower real interest rate generates the intertemporal substitution effects, which stimulates current consumption. This effect becomes

[34] We generate this scenario by employing the Occbin code of Guerrieri and Iacoviello (2015), by introducing a preference shock driven recession that takes the interest rate to the ZLB.

Table 2.5: Output and consumption multipliers

| | Normal times | ZLB (1 quarter) | ZLB (4 quarters) | %Δ (Base, ZLB 1Q) |
|---|---|---|---|---|
| PANEL A: Output multipliers | | | | |
| One-year Integral | 1.31 | 1.45 | 1.58 | 0.11 |
| Two-year Integral | 1.28 | 1.42 | 1.58 | 0.11 |
| PANEL B: Consumption multipliers | | | | |
| One-year Integral | 0.41 | 0.49 | 0.56 | 0.20 |
| Two-year Integral | 0.40 | 0.48 | 0.57 | 0.20 |
| PANEL C: Consumption multipliers for **Impatient** Households | | | | |
| One-year Integral | 0.27 | 0.30 | 0.33 | 0.11 |
| Two-year Integral | 0.26 | 0.30 | 0.34 | 0.15 |
| PANEL D: Consumption multiplier for **Patient** Households | | | | |
| One-year Integral | -0.02 | 0.01 | 0.03 | 1.50 |
| Two-year Integral | -0.02 | 0.00 | 0.02 | 1.00 |
| PANEL E: Consumption multipliers for **Renter** Households | | | | |
| One-year Integral | 0.16 | 0.18 | 0.20 | 0.13 |
| Two-year Integral | 0.16 | 0.18 | 0.21 | 0.13 |

evident under ZLB for all types of households while the magnitude of consumption response increases the most for impatient households.

In Table 2.5, we compute the cumulative output and consumption multipliers.[35] We find that the one-year cumulative output multiplier is 1.45 in the ZLB period which is higher than that of 1.31 in normal times.[36] At longer horizons, the output multiplier increases even more under ZLB.

[35] All horizons are shown in Figure A.11 in the section A.7.

[36] Miyamoto et al. (2018) find the on-impact output multiplier as 1.5 in the zero lower bound and Christiano et al.

Similarly, we compute the cumulative consumption multipliers at the aggregate and disaggregate levels. We find that the consumption multiplier is around 0.41 during normal times while it is higher during ZLB periods. Impatient and renter households have positive consumption multipliers in both normal times and in the ZLB scenario, while the magnitude is much higher for the latter case. However, patient households have qualitatively different consumption multipliers during and outside of the ZLB periods, with the largest percentage change overall as well, though the size of the magnitude is small. From this exercise, we conclude that the effects of government spending shock on the economy are amplified and output and consumption for all types of agents are crowded-in, under ZLB periods.

### 2.7 Conclusion

Employing U.S. household survey data, this paper examines how the effects of government spending shocks depend on the balance-sheet position of households. Since mortgage debt constitutes the vast majority of household debt, we use housing tenure status to proxy for the financial positions of the households. In response to a positive government spending shock, we find that mortgagor households experience a large, positive consumption response, while renters have a smaller rise in consumption. Outright homeowners without mortgage debt, in contrast, have an insignificant consumption expenditure response to a public spending shock. We consider a dynamic stochastic general equilibrium (DSGE) model with housing and financial frictions, and provide a theoretical framework to rationalize these empirical findings and transmission mechanism. Our model features three types of households: savers who own their housing, borrowers with mortgage debt, and rule-of-thumb consumers who rent housing. We show that this model can successfully match heterogeneous consumption responses. The model suggests that liquidity constraints and wealth effects tied to the persistence of public spending, play a crucial role in the propagation of government spending shocks. Our findings provide both empirical and theoretical support for the

(2011) also find that the multiplier is substantially larger than one. The amplification effect of ZLB on our baseline government spending multiplier is relatively smaller than some of these documented studies, as Abo-Zaid and Kamara (2020) point out that a model with credit constraints potentially dampens the consumption response relative to one in the absence of these constraints.

notion that household mortgage debt position plays an important role in the transmission mechanism of fiscal policy.

This paper shows the importance of housing tenure status in the propagation of government spending shocks. Given the substantial variation in homeownership across countries, these findings might have implications for the relative magnitudes of the effects of government spending shocks on aggregate variables across countries. This is left for future research.

# 3. CONSUMPTION RESPONSE TO ANTICIPATED INCOME CHANGES: EVIDENCE FROM THE MAGNITUDE EFFECT

## 3.1 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

[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.

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 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

[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, 2014a; Kueng, 2018; Coibion et al., 2020; Karger and Rajan, 2020).

[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.

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 experimental 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 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

[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.

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

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, 2014a; 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

[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.

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 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

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

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.

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 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.

[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.

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 3.2 describes the institutional background and data. Section 3.3 explains our econometric methodology. Section 3.4 shows the estimation results, and Section 3.5 presents several robustness analyses. Section 3.6 discusses the theoretical support, and Section 3.7 evaluates the policy implications of our findings. Section **??** concludes.

## 3.2 Data and Institutional Background

### 3.2.1 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 was extracted. The data set also contains detailed micro-level information, including annual income, consumption expenditure based on actual financial transactions, credit information, and demographic information such as age and region.[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 re-

[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.

Table 3.1: 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*: This table represents the fraction of total consumption represented by credit and debit card usage across all issuing banks and financial institutions in South Korea for the sample period from 2012 to 2016.

search.[20] Our data set contains a larger number of observations with little measurement error or 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, average credit/debit card usage represents approximately 75 percent of total consumption (see Table 3.1). 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 valuable 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

[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 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.

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.

### 3.2.2 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.

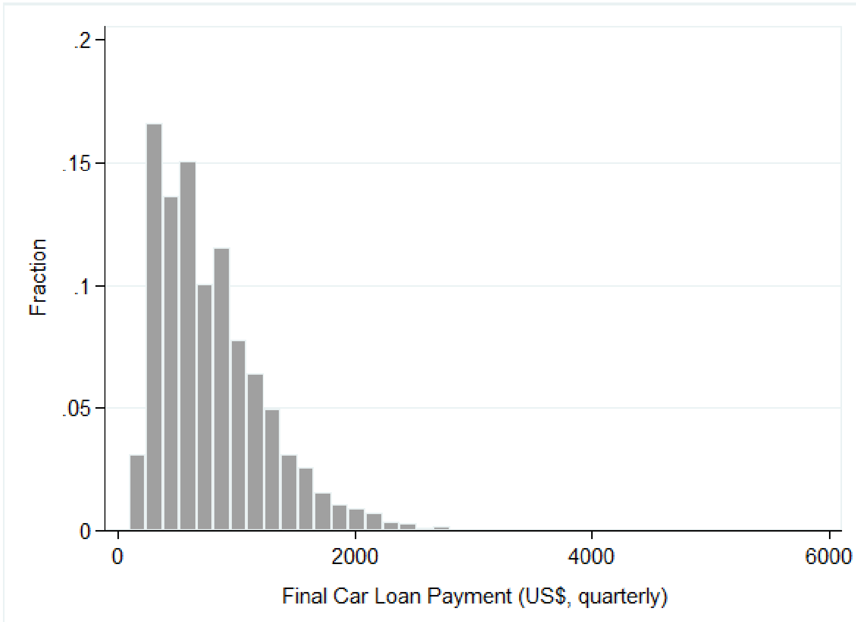
#### *3.2.2.1 Auto Loans in South Korea*

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

[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.

Figure 3.1: Distribution of final car loan payment, 2012–2016




*Notes*: This figure 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.

the loan payments.

Figure 3.1 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.

### *3.2.2.2 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

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

Table 3.2: 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).

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 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 3.2 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 trans-

[25] We plan to extend our final sample to include multi-time car buyers in future analysis.

actions 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 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.

*3.2.2.3 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, the upper panel of Figure 3.2 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 3.1, 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

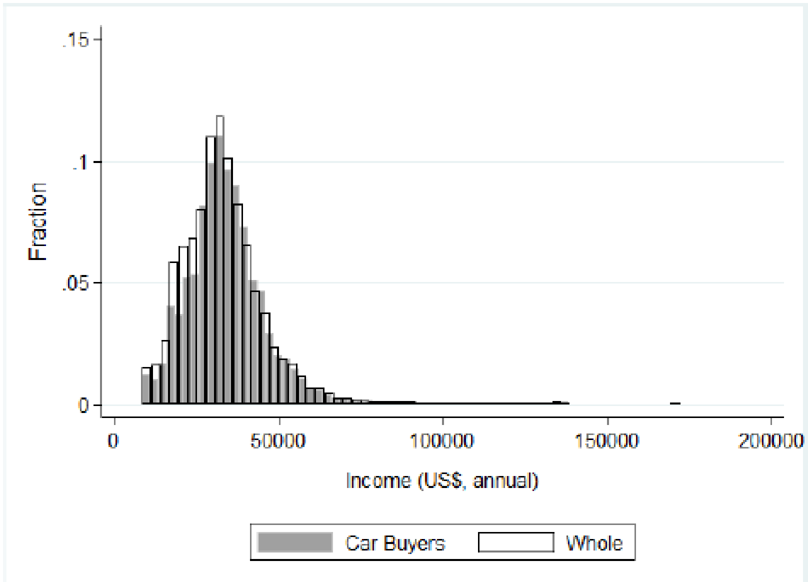
[26] This data does not contain detailed information on the consumption category.

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

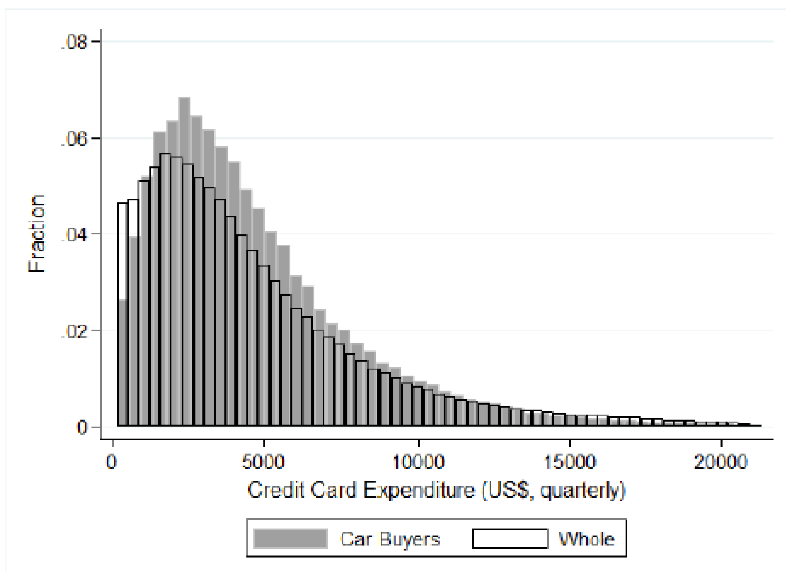
[28] The distribution of annual income for the car buyer group has a lower fraction of individuals with an annual income under $30,000. However, the total distribution of the car buyer group has similar minimum and maximum values as the whole sample. This means we have car buyers with a medium to high 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

Figure 3.2: Representativeness: Income and consumption

(a) Distribution of Annual Income




(b) Distribution of Credit Card Expenditure




*Notes*: This figure shows the distribution of annual income (upper panel) and quarterly credit card expenditure (bottom panel) 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).

observations — 12 times more than our final sample size.

Second, the distribution of consumption expenditure suggests a similar pattern as in the bottom panel of Figure 3.2. 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 the appendix. [29]

## 3.3 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).[30] 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.[31] 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

deviation of distribution relative to the whole sample.

[29] See section B.2

[30] 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).

[31] See Section 3.2.2.1 for more details.

constructed longitudinal panel data described in Section 3.2 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 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.

### 3.3.1 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.[32] 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:[33]

$$\Delta c_{it} = \alpha_t + \gamma_i + Region_i + \sum_{s=n}^{m} \beta_s \cdot FP_{i,t-s} + \lambda' x_{it} + \epsilon_{it} \tag{3.1}$$

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

[32] 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. In addition, the key identifying assumption of the analysis is based on the fact that the end date of each individual's car loan payment is independent of others.

[33] 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).

car loan was paid off for the event window from $t = n$ to $t = m$.[34] 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, $\beta$, measures the excess sensitivity of consumption expenditure from predictable income changes.[35] 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, $\beta_0$, measures the immediate response of changes in consumption after the final payment in US dollars. Monetary amounts are CPI-adjusted values using the mean exchange rate in 2020. The marginal coefficient, $\beta_s$ 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.[36]

We also control for time, region, and individual fixed effects that are captured by $\alpha_t, \gamma_i$, 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). $\epsilon_{it}$ 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. $Cov[FP_{i,t-s}, \epsilon_{it}] = 0$).

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

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

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

### 3.3.2 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 3.4, 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 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 (3.1), 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.[37]

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.

### 3.3.3 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).[38] 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

[37]Note that for the absolute size, the coefficient of parametric regression, $\beta_s$, 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.

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

much of each variable matters conditional upon another.[39]

*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:

$$\Delta c_{it} = \alpha_t + \gamma_i + Region_i + \sum_{D} \beta_D \cdot FP_{it} \times \mathbb{1}(y_{it} \in D) + \lambda' x_{it} + \epsilon_{it} \tag{3.2}$$

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 $\beta_D$ 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:

$$\Delta c_{it} = \alpha_t + \gamma_i + Region_i + \sum_{D_z} \beta_{D_z} \cdot FP_{it} \times \mathbb{1}(z_{it} \in D_z) + \sum \delta_{D_z} \times \mathbb{1}(z_{it} \in D_z) + \lambda' x_{it} + \epsilon_{it} \tag{3.3}$$

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 ($3 \times 3$) subgroups by construction.

To examine the conditional MPC heterogeneity across three factors, we first stratify individuals

[39] 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.

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.[40]

### 3.4 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 3.3, 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.

#### 3.4.1 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).[41] Table 3.3 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

[40] 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.

[41] 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.

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.[42]

Table 3.3 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 3.3, Panel (a) displays the estimation results of the coefficient, $\beta_s$, which measures the marginal effects over time. Panel (b) indicates the cumulative effects over time.[43] In this estimation, we include one quarter of lead and three quarters of lags.[44] As a result, the estimates of one leading term indicate that there is no anticipation effect

[42]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 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).

[43]In Appendix B.3, we also show how the income process evolves over time.

[44]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.

Table 3.3: Consumption response to anticipated income changes

| Dep. Var: $\Delta c_{it}$ | (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.

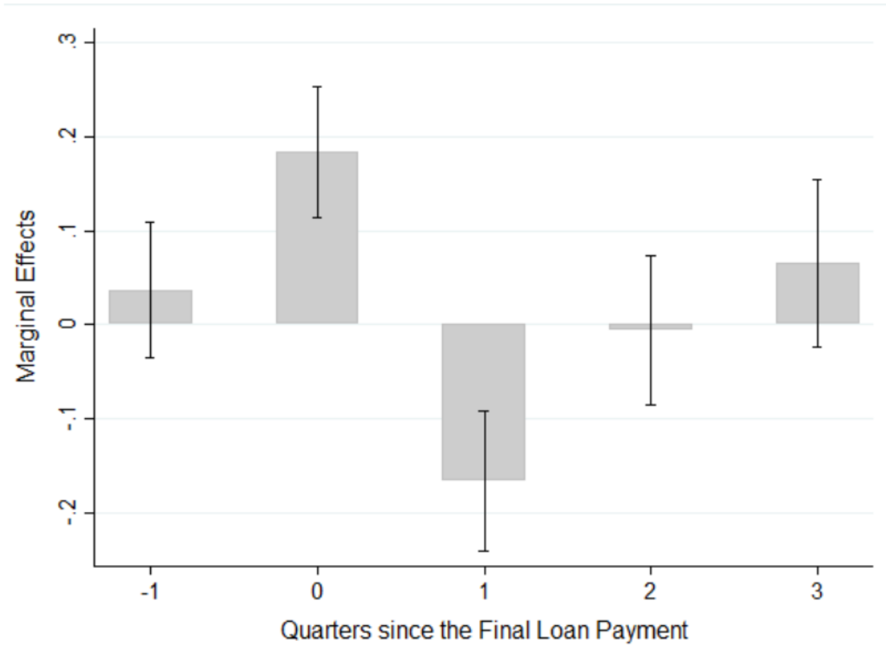
prior to the predictable income changes with 95 percent confidence intervals. We find that for highly predictable income changes where the payment is predetermined, individuals do not adjust their consumption significantly prior to the quarter with anticipated changes.

The point estimate of 0.18 at $t = 0$ in Panel (a) is statistically significant.[45] The marginal effect captured by the estimated coefficients, $\beta_s$, is highest in quarter zero. This means that an individual deviates from consumption smoothing most significantly in the quarter with anticipated 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.

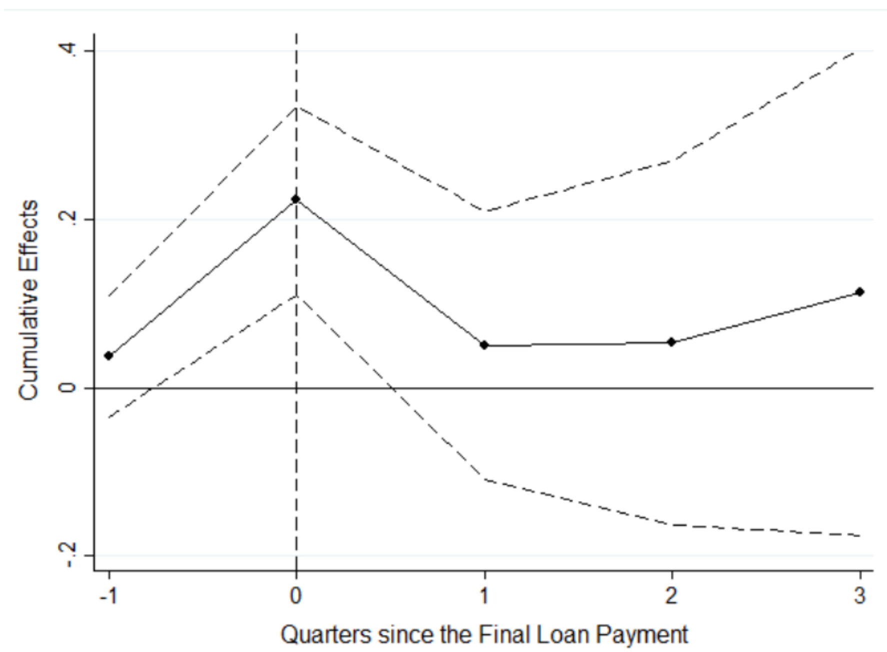
[45] In Figure 3.3 Panel (a), the point estimates of the regression coefficients are 0.04, 0.18, -0.17, -0.01, and 0.07 for the corresponding periods from $t - 1, t, ...,$ up to $t + 3$, respectively.

Figure 3.3: Consumption response by time

(a) Marginal Effects on Marginal Propensity to Consume




(b) Cumulative Effects on Marginal Propensity to Consume




*Notes*: Panel (a) illustrates leads and lags of the regression coefficients estimated by the standard parametric regression equation (Equation 3.1). 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.

### 3.4.2 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 3.3 in Section 3.4.1 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). Table B.2 in the appendix 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 3.4). Each row represents the coefficient estimates of being in each subgroup (low (reference group), middle, and high) for each type of size.[46] 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 3.4 report the estimation results for the subset of three types of magnitudes. Column (4) includes

[46] Each group's heterogeneity is explained in detail in Section 3.4.3.

Table 3.4: The effect on consumption by absolute and relative magnitudes

| Dep. Var: $\Delta c_{it}$ | (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.

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 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 3.4, Panel (a) presents the relationship between the payment size (in \$100 US dollars) and quarterly income (in \$1,000).[47] 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.

### 3.4.3 Marginal Propensity to Consume Heterogeneity

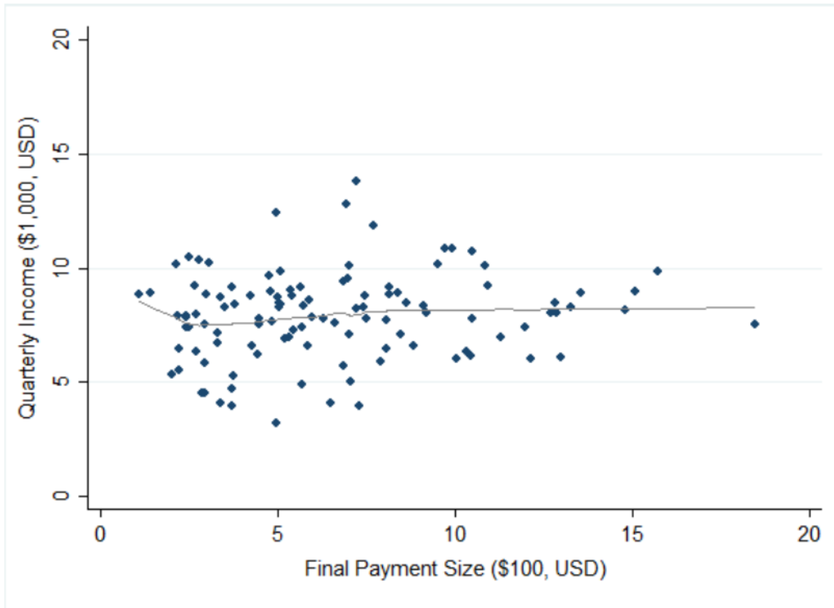
#### *3.4.3.1 MPC Heterogeneity by Distribution*

In this subsection, we show MPC heterogeneity by the distribution of different types of magnitudes. The consumption response is estimated based on Equation (3.2), 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 3.4, 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

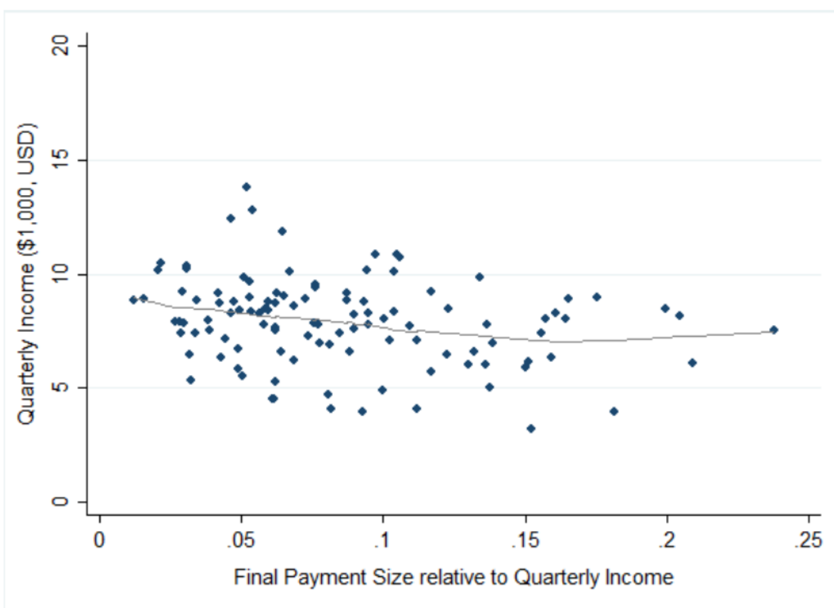
[47] To clearly depict the relationship between payment size and income, we stratify our sample to 1,100 observations. Appendix B.5, Figure B.5 shows the scatter plot for the full sample during the study period. Although the data becomes noisy, we still observe no strong correlation between the relative size of the car loan payments and quarterly income.

Figure 3.4: Distribution of final car loan payment, 2012–2016

(a) Quarterly Income and Final Payment Size




(b) Quarterly Income and Relative Final Payment Size




*Notes*: 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.

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.[48] Overall, we find that MPC monotonically decreases by absolute size, and that there is a large group heterogeneity across size distributions.

*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

[48] 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.

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.

#### *3.4.3.2 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).[49] 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.[50]

*Age and Income.*— In Figure 3.5, 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

[49]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.

[50]In Appendix B.6, we also report the conditional MPC heterogeneity across absolute payment size, age, and income.

dimension along these two variables.[51] 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.

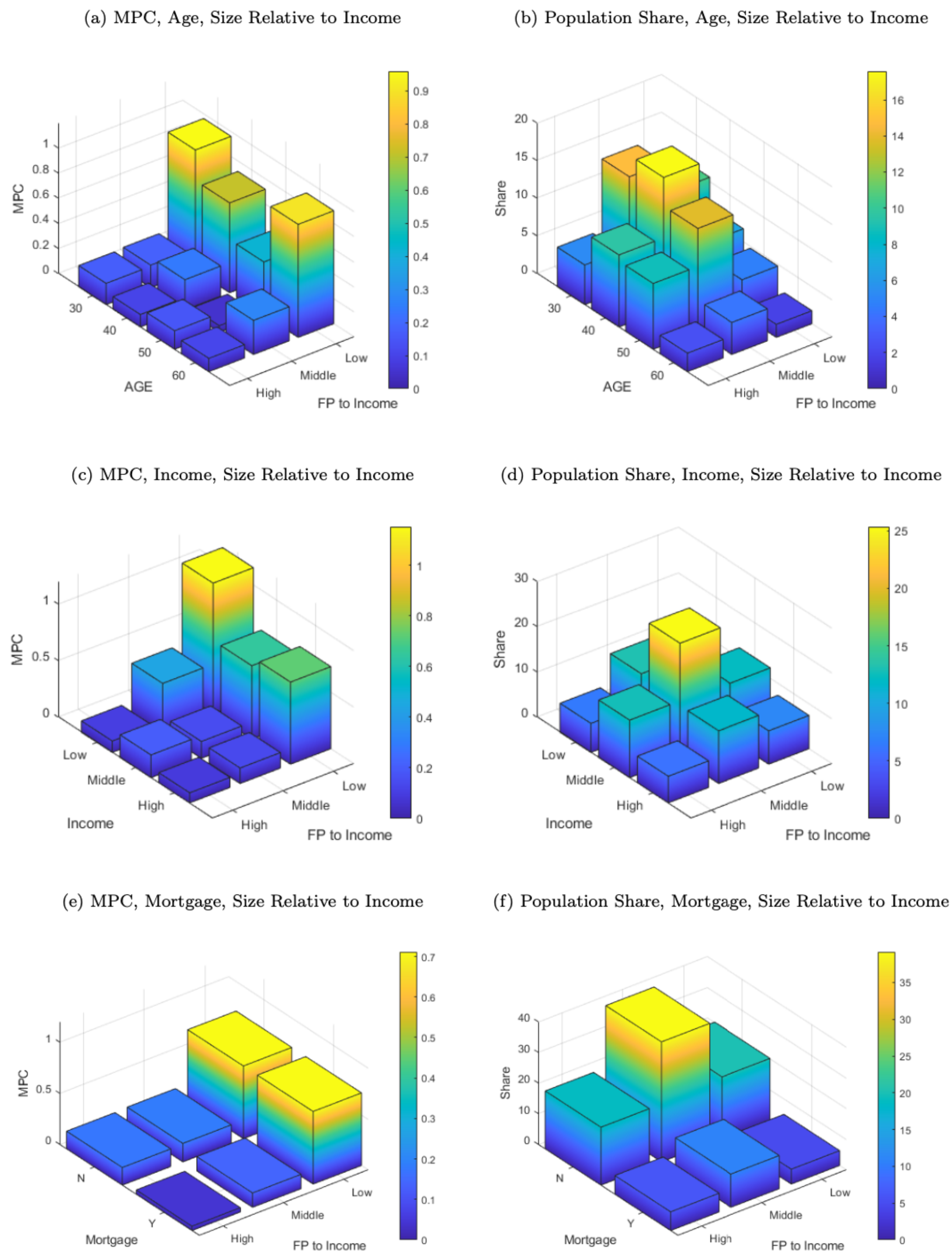
Panel (e) of Figure 3.5 displays the conditional MPC distribution of being affected by this extra credit constraint. We find that there is a sizable MPC response with low size regardless of mortgage debt status. This result suggests that there is a strong size effect regardless of the liquidity channel 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 3.6 displays the MPC sorted by the relative size tercile, conditional on the same level of income with 95 percent confidence interval bands.[52] Similar to Figure 3.5, the MPC is highest

[51] See Figure 3.4 for more details.

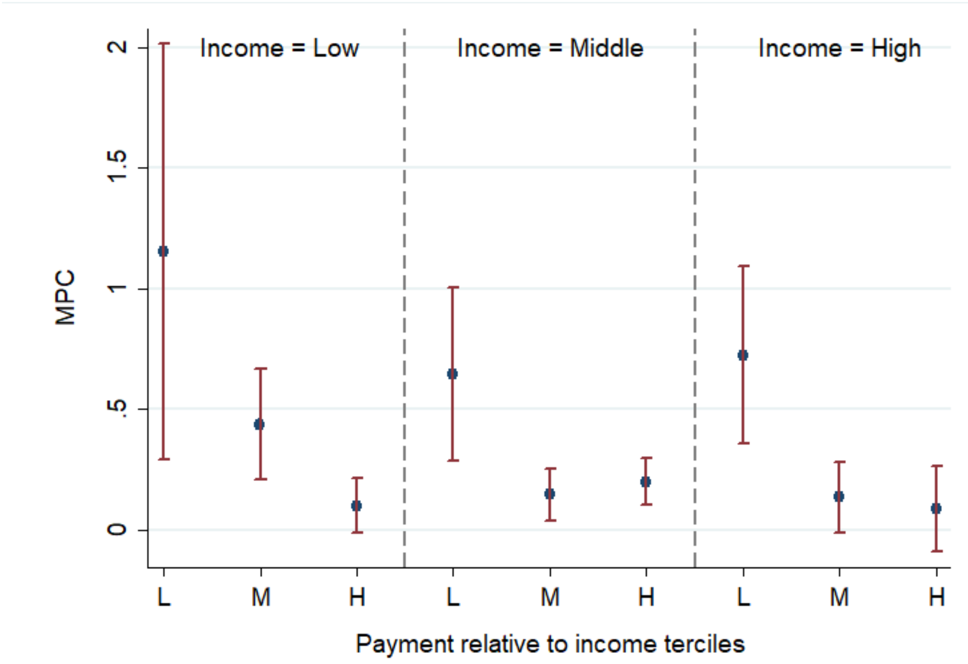
[52] This figure is a two-dimensional view of Figure 3.5, Panel (c). Figure 3.6 illustrates the statistical significance

Figure 3.5: Heterogeneous consumption responses




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

Figure 3.6: MPC by income given the relative size to income (FP to Income)




*Notes*: This figure 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.

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

Figure B.7 in the appendix 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.

level of differences across income groups.

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.

### 3.5 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).[53] 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:

$$\Delta c_{it} = \alpha_t + \gamma_i + Region_i + \sum_{q_y} \beta_{q_y} \cdot FP_{it} \times \mathbb{1}(y_{it} \in q_y) + \sum_{q_y} \gamma_{q_y} \times \mathbb{1}(y_{it} \in q_y) + \lambda' x_{it} + \epsilon_{it} \quad (3.4)$$

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

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

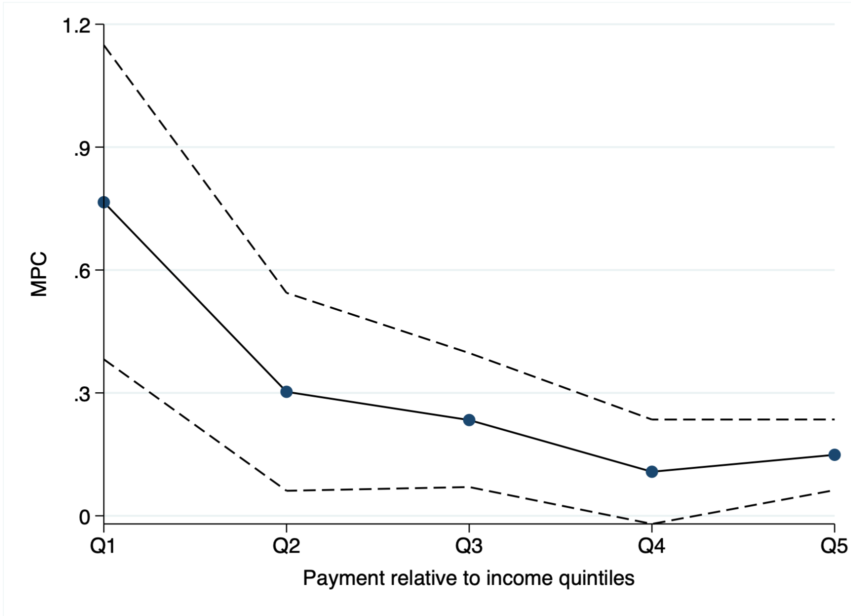
FP to Income ratio is in the $q$th quintile, and 0 otherwise. We decompose the average effects on excess sensitivity into five quintiles, where $Q1$ denotes the lowest 20 percent and $Q5$ the highest 20 percent group in the distribution. The coefficient, $\beta_{q_y}$, measures how consumption expenditure responds to a one-unit increase in observed $y$, which is $FP\ to\ Income$.

Figure 3.7 plots the coefficient, $\beta_{q_y}$, that measures the excess sensitivity for individual $i$'s observed size relative to income in the $q$th 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.[54] 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. 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 B.7 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 B.8 and B.9, 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-

[54] 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 3.7: Effects by payment size relative to income (FP to Income) quintiles




*Notes*: This figure 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.

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. Table B.3 in the appendix 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.

### 3.6 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).[55] 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).[56] 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 em-

[55] In Appendix B.8, we include the basic theoretical assumption under the PIH.

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

pirical 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 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:

$$\max_{\{c_t\}_{t=\tau}^{T}} E_t \sum_{t=\tau}^{T} \beta^t u\left(c_t\right) \tag{3.5}$$

subject to

$$m_t = m_{t-1} + r a_{t-1} + e^{y_t} - d_t - c_t \tag{3.6}$$

$$a_t = a_{t-1} + d_t \tag{3.7}$$

$$y_t = p_t + \tau_t + \epsilon_t^T \tag{3.8}$$

$$p_t = \rho p_{t-1} + \epsilon_t^P \tag{3.9}$$

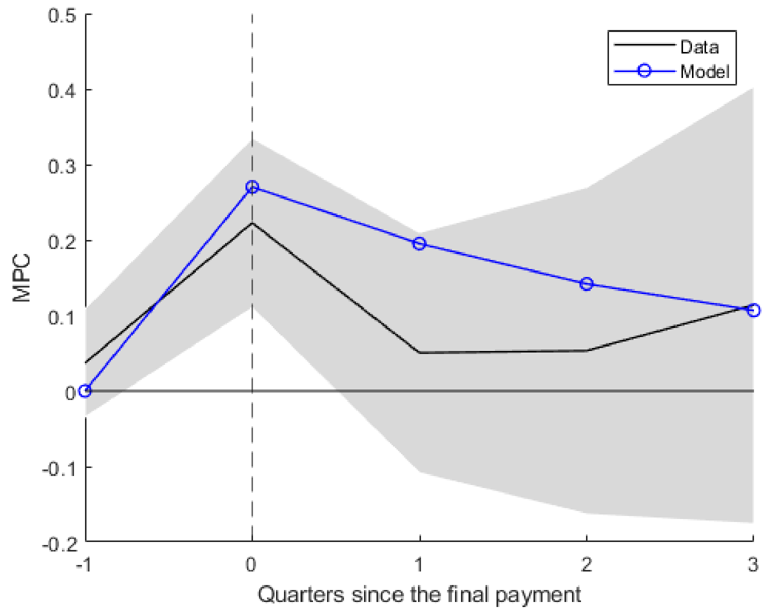
$$m_t \geq 0 \quad \forall t = \tau, ..., T \tag{3.10}$$

where $\beta$ 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. $\tau_t$ is deterministic income component at age $t$. $\rho$ is parameter value for persistence of income. $\epsilon_t^T$ is transitory income shock and $\epsilon_t^P$ 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 3.8, 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' 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

Figure 3.8: Consumption response in data versus model




*Notes:* This figure shows the cumulative MPC for data (black solid line) versus the model (blue circle) with 95% confidence interval bands.

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:

$$Welfare\,loss\,(c_i^{deviate}, c_i^{pih}) \approx \frac{\delta}{2} \cdot \sum_t \zeta_t \left( \frac{c_t^{deviate} - c_t^{pih}}{c_t^{pih}} \right)^2 \tag{3.11}$$

where $\delta$ captures the curvature of the utility function. $\zeta_t$ 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 $u(c) = c^{1-\delta}/(1-\delta)$.[57] We set the standard value of $\delta = 2$ considered in the literature. After considering the envelope theorem, equation 3.11 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.

### 3.7 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.[58] 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

[57] In Appendix B.9, we describe a detailed derivation for the welfare loss statistics.

[58] 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.

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. Consumers thus have advance information on the size and arrival time of payments.[59] 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.[60] 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

[59] 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.

[60] 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.

Table 3.5: Effect of government transfers on consumption response

| Policy<br>Transfer: 1 percent of GDP | Aggregate<br>MPC | Aggregate<br>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.

economy.[61] 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:

$$MPC_j = \sum_i \frac{\overbrace{\beta_i \tau_i(j)}^{MPC_i \times \Delta\, \text{income}_i(j)}}{\underbrace{T}_{\text{Total transfers}}} \tag{3.12}$$

where $\beta_i$ 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 $j$.[62] 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:

$$g(C)_j = \frac{\sum_i \beta_i \tau_i(j)}{\sum_i c_i} \tag{3.13}$$

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

[62]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.

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.[63] 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 3.5 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 under this policy is therefore higher than that of the first policy.[64] 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.

### 3.8 Conclusion

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

[63] The tercile distribution follows the main estimation strategy used in our empirical analysis.
[64] The income cut-off for the second policy is $40,800; the average income level is $35,364 for the total sample.

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 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.

# 4. SUMMARY AND CONCLUSIONS

In this dissertation, I investigate the role of household heterogeneity on macroeconomic variables and its implications on macroeconomic policy.

In the second chapter, we employ the data from U.S. household surveys to investigate how the effect of government spending shocks depends on households' financial positions. To measure this, the study uses housing tenure status, as mortgage debt constitutes a significant portion of household debt in the U.S. As a result, we find that households with mortgage debt experience a significant and positive consumption response to positive government spending shocks, while renters experience a smaller rise in consumption. On the other hand, outright homeowners without mortgage debt do not respond significantly to public spending shocks.

To explain these empirical findings and transmission mechanisms, this chapter employs a dynamic stochastic general equilibrium (DSGE) model with housing and financial frictions. The model includes three types of households, namely savers who own their housing, borrowers with mortgage debt, and rule-of-thumb consumers who rent housing. We find that the model can successfully account for the heterogeneous consumption responses observed in the data. The model also suggests that liquidity constraints and wealth effects, which are linked to the persistence of public spending, play a crucial role in the propagation of government spending shocks. These findings emphasize the importance of considering housing tenure status in evaluating government spending shocks and its propagation. As homeownership rates vary across countries, this study's results may have implications for the relative magnitudes of the effects of government spending shocks on aggregate variables across countries. However, further research is required to explore these implications.

Understanding how households respond to anticipated changes in income is critical for predicting consumption responses to government interventions, such as fiscal stimulus packages. The Permanent Income Hypothesis (PIH) suggests that consumption growth is unaffected by the shape and path of anticipated income changes, but evidence of excess sensitivity challenges this theory.

Despite this, little attention has been given to how the size of income changes affects consumption response. In the third chapter, we contribute to the literature by examining how consumption dynamics vary with the magnitude of predictable income changes, using newly constructed longitudinal panel data from the BOK household debt database.

Using the natural experiment of predetermined income changes following the final car loan payment, we find that the average Marginal Propensity to Consume (MPC) is approximately 18%. The response of consumption expenditure peaks upon the arrival of the income changes, then sharply declines in the following quarter. There is evidence of significant heterogeneity in spending response, with the MPC decreasing as the size of income change increases. This implies that the welfare cost of deviating from optimal consumption decisions is less significant for smaller income changes. The study also highlights the importance of the relative size of income changes in explaining spending sensitivity. However, the literature has often emphasized the role of binding liquidity constraints. To investigate this, we consider the impact of age, income, and extra debt constraints on MPC heterogeneity. The main estimation results suggest a strong size effect, even for individuals who are liquidity constrained.

Overall, these findings contribute to a better understanding of household consumption behavior and its influencing factors. The results of this study suggest that the magnitude of predictable income changes plays a significant role in determining the consumption response of households. Our policy experiment indicates that considering the size of anticipated income changes when designing stabilization policies could lead to a more effective way to stimulate the economy. Further research could investigate the potential impact of using income changes of different magnitudes over varying time horizons as a means of stimulating the economy.

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# APPENDIX A

# APPENDIX TO CHAPTER 2

## A.1 Data Sources

### A.1.1 Aggregate Data

Table A.1: Data description

| Data | Description | Source |
|---|---|---|
| NGDP | Nominal GDP | BEA |
| PGDP | GDP deflator | BEA |
| GOV | Nominal government purchases | BEA |
| NCONS | Nominal personal consumptoin expenditure | BEA |
| NCDUR | Personal consumption expenditures: Durable goods | BEA |
| NCDC | Personal consumption expenditures: Nondurable goods | BEA |
| NCSV | Personal consumption expenditures: Service goods | BEA |
| Population | Population, thousands (POPTHM) | FRED |
| Hours | Total hours worked | BLS |
| PBUS | Nonfarm business Sector: Implicit price deflator | BLS |
| Wages | Nonfarm business sector: Compensation per hour | BLS |
| Tbill3 | 3-month Treasury bill (TB3MS) | FRED |
| HHDEBT | Households and nonprofit organizations; | FRED |
| | debt securities and loans; liability (CMDEBT) | |
| HPI | House price index (Baseline: Census Bereau); | |
| | Price Indexes of New Single-Family Houses Sold Including Lot Value | Census Bereau |
| | All-Transactions House Price Index for the United States, Index | FRED |
| | Median sales price for new houses sold (MSPNHSUS) | FRED |
| | S&P Case-Shiller U.S. National Home Price Index (extended) | FRED |
| Recession | NBER recession periods | FRED |
| SPF shock | Survey of Professional Forecasters forecast error shock | Ramey (2011) |
| GB shock | Green Book forecast error shock | Ramey (2011) |

Note: This table reports the data source for key aggregate variables. Real values are all deflated by GDP deflator for the sample period, 1981:Q1-2007:Q1.

### A.1.2 Data by Housing Tenure Groups

We use the U.S. Consumer Expenditure Survey (CEX) data which is available from the U.S. Bureau of Labor Statistics for the sample period, 1981-2007. We use the household expenditure and income data constructed by different types of housing tenure groups following Cloyne et al. (2020). Consumption data covers non-durable goods and services (food, alcohol, tobacco, clothing and footwear, leisure goods, household services) and durable expenditures (motor vehicles, durable leisure goods, durable household goods). In terms of income data, labor income includes wages and salaries and non-labor income includes income from investments and social payments, net of taxes. Households are excluded from the sample if (i) the income data is missing or the net income is negative, (ii) the expenditure is in either top or the bottom 1% of distribution, (iii) the household head is aged either below 25 or above 74 years old.

The U.S. Survey of Consumer Finance (SCF) data which is available from the Federal Reserve is also used for the sample period, 1995-2007. This household survey data includes a triennial cross-sectional survey of U.S. households. We use the information on households' balance sheets, wealth and asset positions, pensions, demographic characteristics, and income to classify households who are wealthy hand-to-mouth following Kaplan et al. (2014).

## A.2 Asset, Wealth, and Debt to Income Ratio

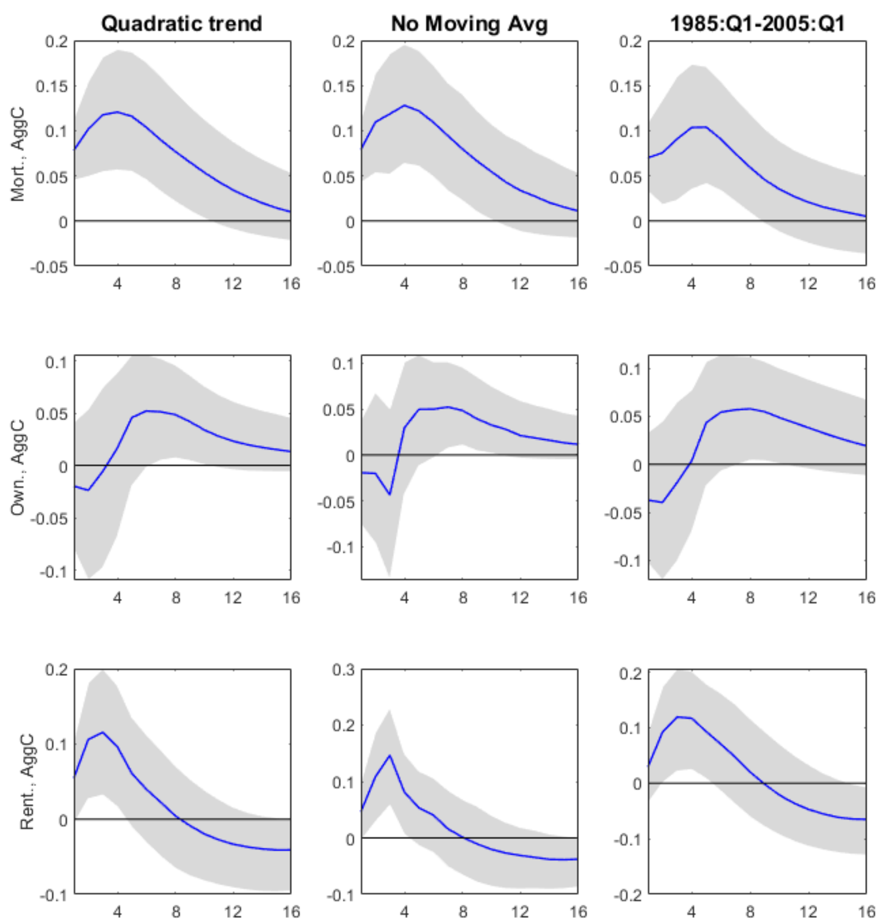
Table A.2: Asset, wealth, and debt to income ratio by housing tenure

| | PANEL A: 1995 SCF | | PANEL B: 1998 SCF | | PANEL C: 2001 SCF | | PANEL D: 2004 SCF | | PANEL E: 2007 SCF | |
|---|---|---|---|---|---|---|---|---|---|---|
| *Asset* | Mean | 95% Conf. interval | Mean | 95% Conf. interval | Mean | 95% Conf. interval | Mean | 95% Conf. interval | Mean | 95% Conf. interval |
| Mortgagors | 540,976 | [525,118, 556,834] | 664,010 | [644,196, 683,824] | 799,320 | [775,740, 822,899] | 850,222 | [826,873, 873,570] | 957,274 | [931,649, 982,900] |
| Outright homeowners | 599,946 | [575,176, 624,715] | 820,483 | [782,035, 858,931] | 1,028,879 | [983,941, 1,073,817] | 1,186,705 | [1,134,975, 1,238,434] | 1,367,399 | [1,304,774, 1,430,025] |
| Renters | 77,098 | [70,687, 83,508] | 75,459 | [69,744, 81,174] | 88,321 | [79,961, 96,681] | 85,913 | [77,562, 94,265] | 97,034 | [87,667, 106,402] |
| *Net liquid asset* | | | | | | | | | | |
| Mortgagors | 46,492 | [42,967, 50,018] | 90,778 | [84,409, 97,147] | 115,131 | [107,793, 122,468] | 90,039 | [84,657, 95,421] | 92,356 | [86,910, 97,803] |
| Outright homeowners | 105,282 | [97,034, 113,530] | 173,283 | [160,420, 186,146] | 203,731 | [187,892, 219,571] | 236,670 | [217,578, 255,762] | 250,772 | [232,421, 269,123] |
| Renters | 12,747 | [9,303, 16,192] | 11,994 | [10,610, 13,379] | 19,304 | [15,210, 23,399] | 14,421 | [10,749, 18,092] | 16,826 | [13,571, 20,082] |
| *Net illiquid asset* | | | | | | | | | | |
| Mortgagors | 178,597 | [173,314, 183,881] | 213,069 | [206,743, 219,396] | 258,878 | [251,567, 266,188] | 283,353 | [275,083, 291,623] | 324,389 | [315,765, 333,013] |
| Outright homeowners | 208,039 | [201,820, 214,258] | 261,544 | [252,092, 270,995] | 348,328 | [334,778, 361,879] | 408,219 | [392,586, 423,852] | 467,158 | [447,044, 487,272] |
| Renters | 18,921 | [17,124, 20,719] | 19,671 | [17,592, 21,750] | 20,040 | [18,003, 22,078] | 14,286 | [12,769, 15,804] | 18,605 | [16,509, 20,700] |
| *Home equity* | | | | | | | | | | |
| Mortgagors | 96,065 | [93,634, 98,495] | 107,436 | [104,563, 110,309] | 136,836 | [132,925, 140,746] | 168,845 | [163,892, 173,798] | 192,533 | [187,676, 197,391] |
| Outright homeowners | 148,703 | [144,692, 152,714] | 170,233 | [164,526, 175,939] | 212,581 | [205,845, 219,318] | 270,776 | [261,220, 280,331] | 303,421 | [289,629, 317,214] |
| Renters | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *Debt to income* | | | | | | | | | | |
| Mortgagors | 1.80 | [1.74, 1.87] | 2.76 | [1.97, 3.54] | 1.80 | [1.74, 1.86] | 2.39 | [2.29, 2.50] | 2.47 | [2.41, 2.53] |
| Outright homeowners | 0.51 | [0.30, 0.71] | 0.25 | [0.22, 0.28] | 0.28 | [0.24, 0.33] | 0.32 | [0.28, 0.35] | 0.51 | [0.42, 0.60] |
| Renters | 0.43 | [0.39, 0.47] | 0.56 | [0.47, 0.64] | 0.95 | [0.40, 1.51] | 0.43 | [0.40, 0.46] | 0.49 | [0.45, 0.53] |

Note: This table reports mean and 95% confidence interval value of an asset, net liquid asset, net illiquid asset (including home equity), and debt to income ratio by housing tenure group. Data are from SCF for 1995-2007 and each series is in the corresponding year's dollar.

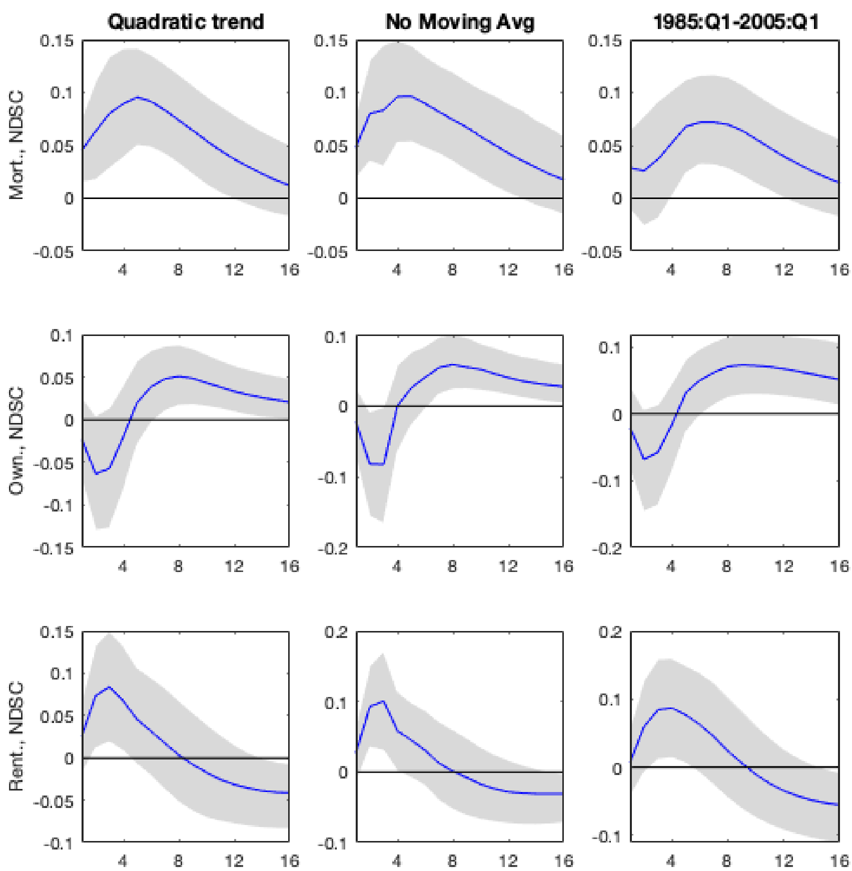
### A.3 Robustness Checks for Empirical Analysis

Figure A.1: Impulse responses of aggregate consumption in response to a positive govt spending shock



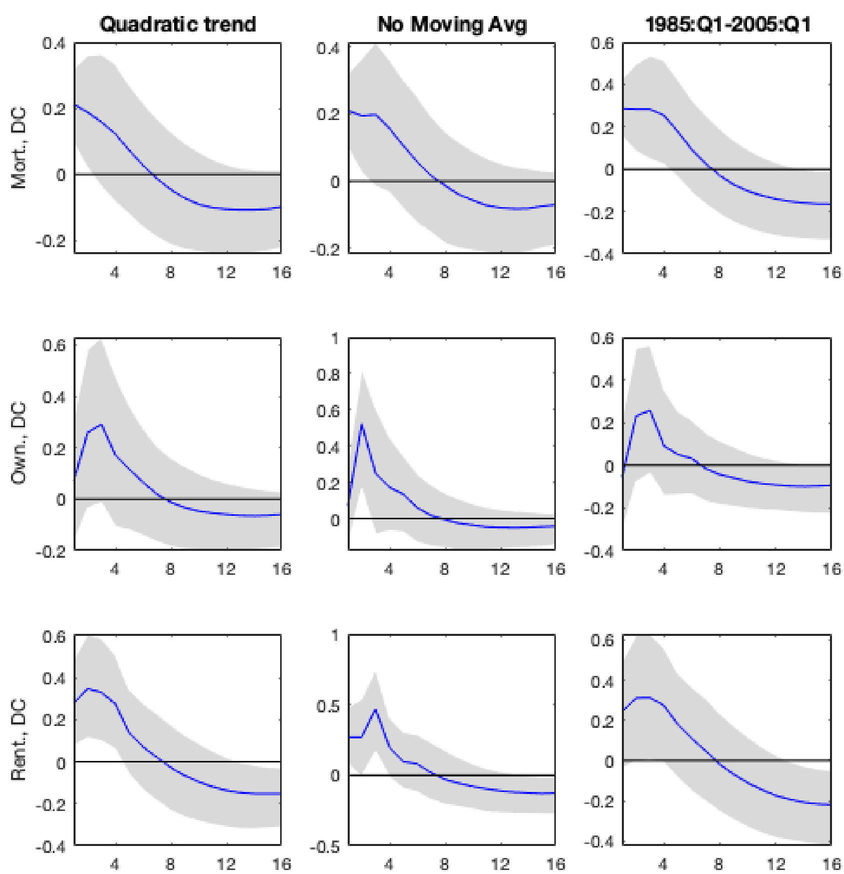

Notes: This figure plots the impulse response functions of aggregate consumption in response to a positive government spending shock with 68 % confidence interval bands based on bootstrapped standard errors (shaded area).

Figure A.2: Impulse responses of non-durable consumption in response to a positive govt spending shock



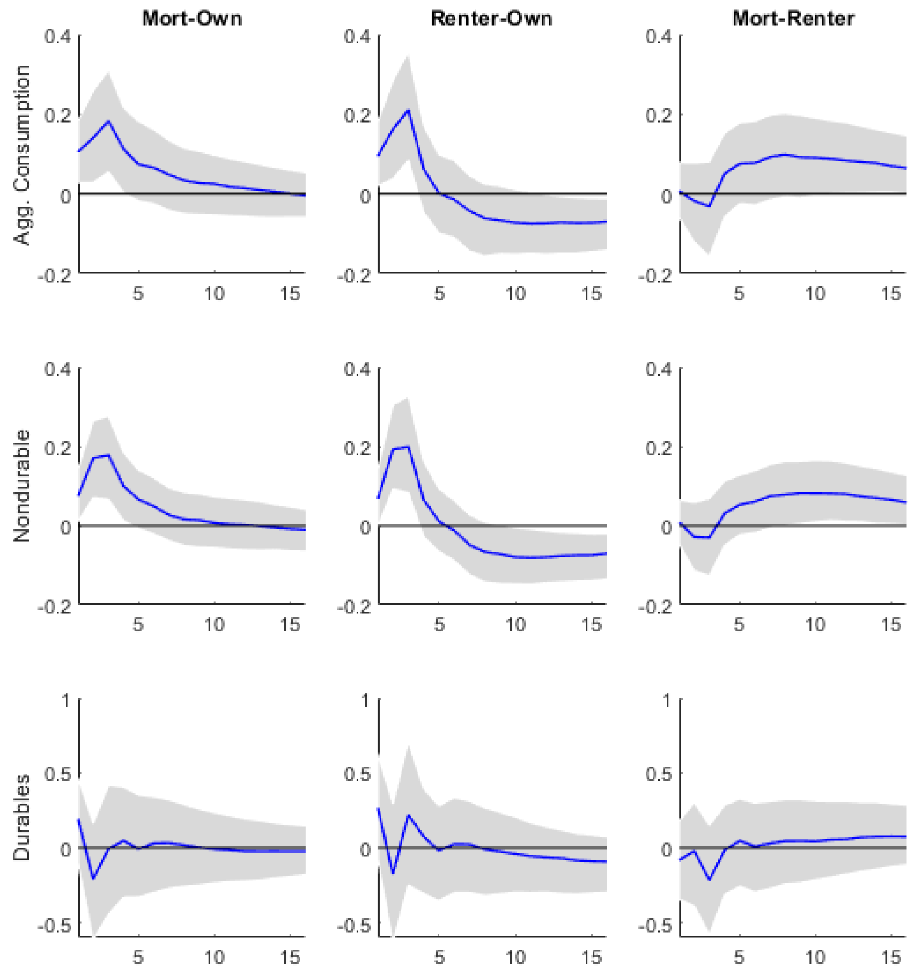

Notes: This figure shows the impulse responses functions of non-durable consumption responses to a positive SPF shock by each housing tenure group. The shaded area indicates 68 % confidence interval bands.

Figure A.3: Impulse responses of durable consumption in response to a positive govt spending shock



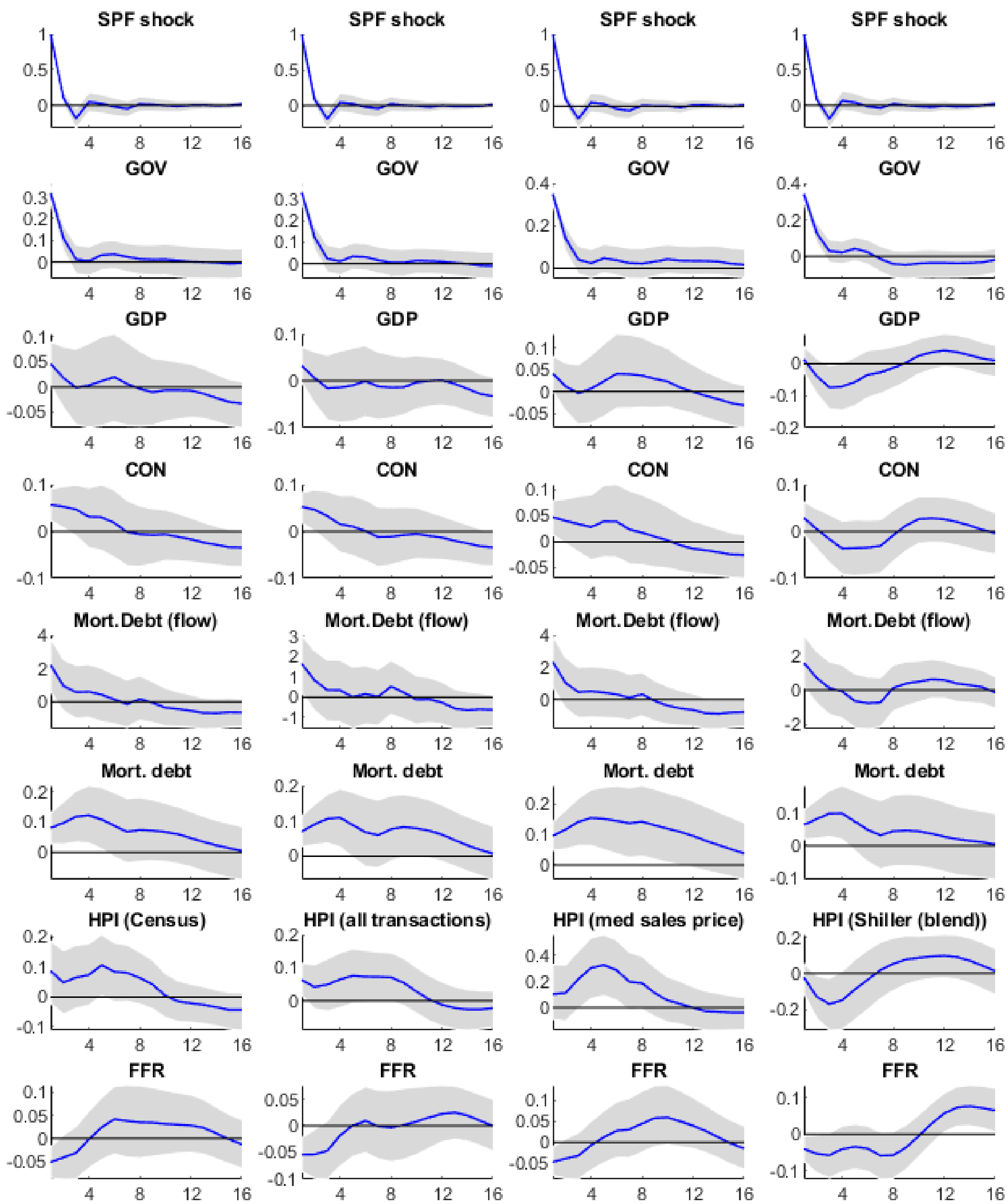

Notes: This figure shows the impulse responses functions of durable consumption responses to a positive SPF shock by each housing tenure group. The shaded area indicates 68% confidence interval bands.

Figure A.4: Impulse responses of difference in consumption across three types households in response to a positive govt spending shock




Notes: This figure shows the difference in impulse response across three types of agents to a positive SPF shock by each housing tenure group. The first column indicates the difference in consumption response (aggregate, non-durable, and durable) across mortgagors and outright homeowners. The second and third columns represent the difference in consumption across renters and outright homeowners and mortgagors and renters households, respectively. The shaded area indicates 68% confidence interval bands.

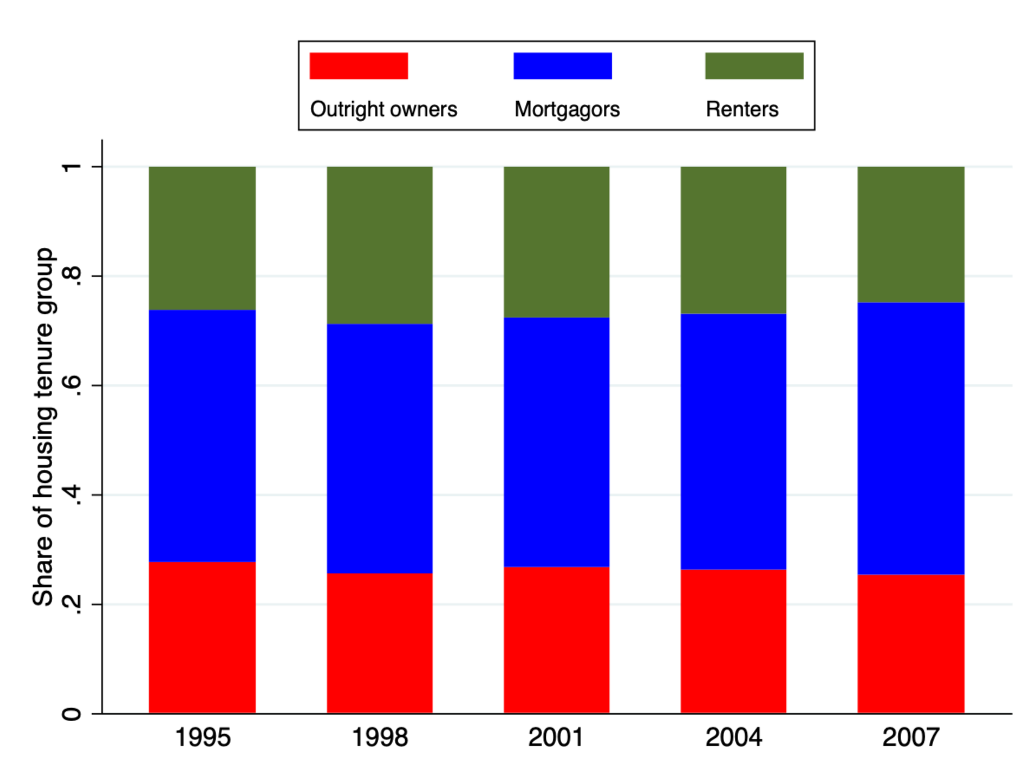
Figure A.5: Impulse responses across alternative house price index




Notes: This figure shows the impulse responses of key aggregate variables across different measures of the house price index in response to a positive SPF shock. The shaded area indicates 68% confidence interval bands.

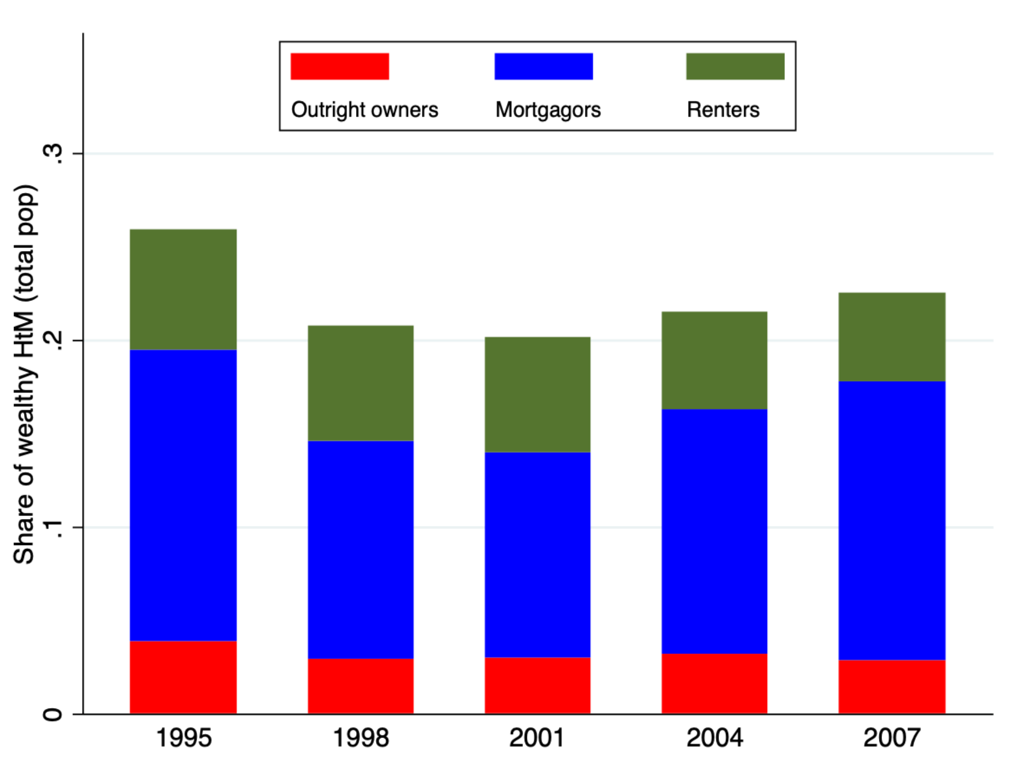
## A.4 Share of Housing Tenure Groups

Figure A.6: Share of housing tenure group (total population, SCF)



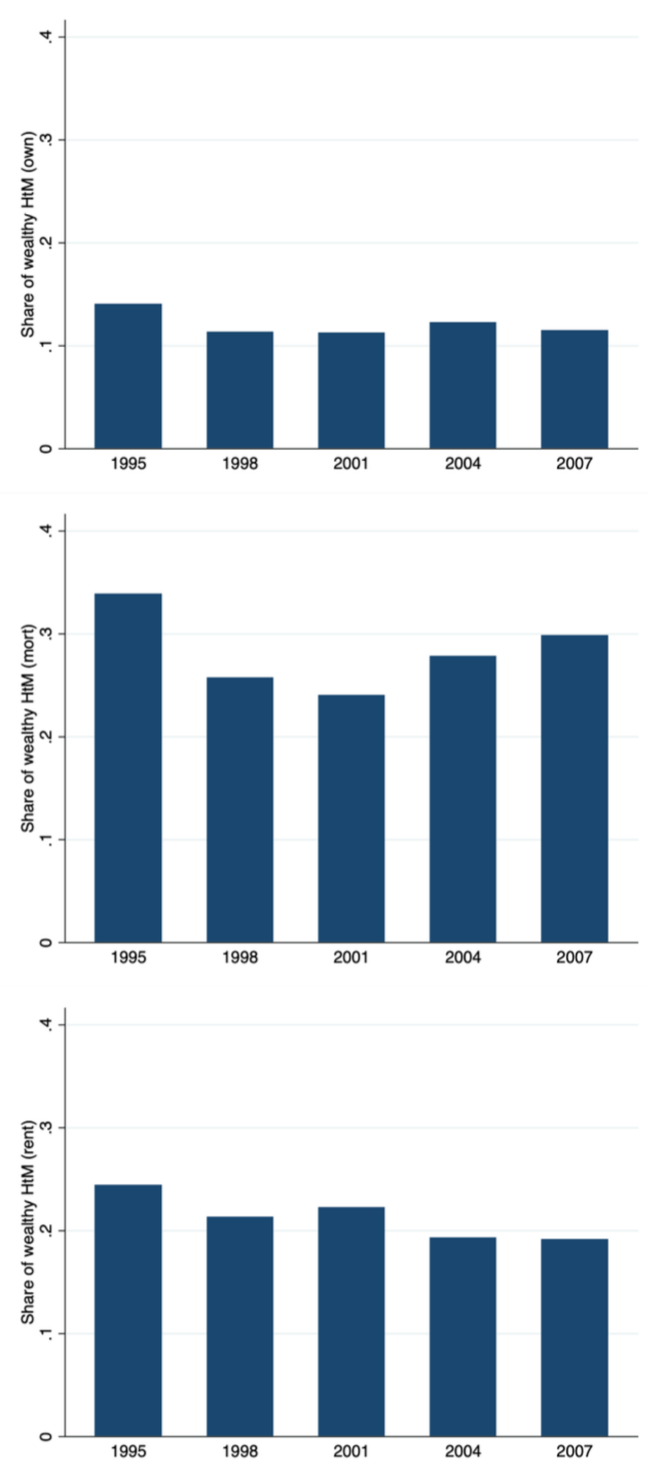

Notes: This figure shows the share of each housing tenure group in the total population (1995 - 2007).

Figure A.7: Share of wealthy hand to mouth by housing tenure group (total population, SCF)




Notes: This figure shows the share of wealthy Hand-to-Mouth (HtM) by housing tenure groups in the total population (1995 - 2007).

Figure A.8: Share of wealthy hand to mouth by housing tenure group (within group, SCF)




Notes: This figure shows the share of wealthy Hand-to-Mouth (HtM) within each housing tenure group (1995 - 2007).

## A.5 Model: First Order Conditions

### A.5.1 Patient Households

$$\theta\left(\frac{s_{P,t}}{c_{P,t}}\right)^{1-\theta}\left[\frac{\upsilon_t}{x_{P,t}}-\beta_P\mu_c E_t\left\{\frac{\upsilon_{t+1}}{x_{P,t+1}}\right\}\right]=(1+\tau_c)\,\lambda_{P,t} \tag{A.5.1}$$

$$\begin{aligned}\left[1+\tau_p\left(1-\tau_{yP}\right)+\kappa_h\left(\frac{h_{P,t}}{h_{P,t-1}}-1\right)\frac{h_{P,t}}{h_{P,t-1}}\right]q_{h,t}&=\frac{\upsilon_t\xi_h}{\lambda_{P,t}h_{P,t}}\\ &+E_t\left[\left(\beta_P\frac{\lambda_{P,t+1}}{\lambda_{P,t}}\right)\left[1-\delta_h+\kappa_h\left(\frac{h_{P,t+1}}{h_{P,t}}-1\right)\left(\frac{h_{P,t+1}}{h_{P,t}}\right)^2\right]q_{h,t+1}\right]\end{aligned} \tag{A.5.2}$$

$$\begin{aligned}\left[1+\tau_p\left(1-\tau_{yP}\right)+\kappa_h\left(\frac{h_{RP,t}}{h_{RP,t-1}}-1\right)\frac{h_{RP,t}}{h_{RP,t-1}}\right]q_{h,t}&=\left(1-\tau_{yP}\right)r_{hP,t}\\ &+E_t\left[\left(\beta_P\frac{\lambda_{P,t+1}}{\lambda_{P,t}}\right)\left\{\left[1-\delta_h+\kappa_h\left(\frac{h_{RP,t+1}}{h_{RP,t}}-1\right)\left(\frac{h_{RP,t+1}}{h_{RP,t}}\right)^2\right]q_{h,t+1}+\tau_{yP}\delta_h\right\}\right]\end{aligned} \tag{A.5.3}$$

$$\begin{aligned}&\left[1+\kappa_k\left(\frac{k_t}{k_{t-1}}-1\right)\frac{k_t}{k_{t-1}}\right]q_{k,t}\\ &=E_t\left[\left(\beta_P\frac{\lambda_{P,t+1}}{\lambda_{P,t}}\right)\left\{\left[1-\delta_k+\kappa_k\left(\frac{k_{t+1}}{k_t}-1\right)\left(\frac{k_{t+1}}{k_t}\right)^2\right]q_{k,t+1}+\left(1-\tau_k\right)r_{k,t+1}+\tau_k\delta_k\right\}\right]\end{aligned} \tag{A.5.4}$$

$$\begin{aligned}\left[(1+\tau_c)+\kappa_s\left(\frac{s_{P,t}}{s_{P,t-1}}-1\right)\frac{s_{P,t}}{s_{P,t-1}}+\frac{\kappa_s}{2}\left(\frac{s_{P,t}}{s_{P,t-1}}-1\right)^2\right]q_{s,t}&=\frac{(1+\tau_c)(1-\theta)}{\theta}\frac{c_{P,t}}{s_{P,t}}\\ &+E_t\left[\left(\beta_P\frac{\lambda_{P,t+1}}{\lambda_{P,t}}\right)\left\{\left[(1+\tau_c)(1-\delta_s)+\kappa_s\left(\frac{s_{P,t+1}}{s_{P,t}}-1\right)\left(\frac{s_{P,t+1}}{s_{P,t}}\right)^2\right]q_{s,t+1}\right\}\right]\end{aligned} \tag{A.5.5}$$

$$\upsilon_t\xi_n n_{P,t}^{\vartheta}=\lambda_{P,t}\Omega_{nP,t}\left(1-\tau_{yP}\right)w_{P,t} \tag{A.5.6}$$

$$\left(\frac{\pi_{wP,t}}{\pi}-1\right)\frac{\pi_{wP,t}}{\pi}$$
$$=E_t\left[\beta_P\frac{\lambda_{P,t+1}}{\lambda_{P,t}}\left(\frac{\pi_{wP,t+1}}{\pi}-1\right)\frac{\pi_{wP,t+1}}{\pi}\frac{\pi_{wP,t+1}}{\pi_{t+1}}\frac{n_{P,t+1}}{n_{P,t}}\right]-\frac{(\eta_w-1)(1-\tau_{yP})}{\kappa_w}(1-\theta_w\Omega_{nP,t}) \tag{A.5.7}$$

where $\theta_w=\dfrac{\eta_w}{\eta_w-1},\ \pi_{wP,t}=\dfrac{W_{P,t}}{W_{P,t-1}}$

$$\frac{\pi_{wP,t}}{\pi_t}=\frac{w_{P,t}}{w_{P,t-1}} \tag{A.5.8}$$

$$1=E_t\left[\left(\beta_P\frac{\lambda_{P,t+1}}{\lambda_{P,t}}\right)\left(\frac{1+(1-\tau_b)R_t}{\pi_{t+1}}\right)\right] \tag{A.5.9}$$

$$1=\Omega_{dP,t}+\Omega_{rP,t}R_t^F \tag{A.5.10}$$

$$\Omega_{dP,t}+\Omega_{rP,t}R_t^M=E_t\left[\left(\beta_P\frac{\lambda_{P,t+1}}{\lambda_{P,t}}\right)\left(\frac{(1-\tau_b)R_t^M+\kappa+(1-\kappa)\left\{\Omega_{dP,t+1}+\Omega_{rP,t+1}R_t^M\right\}}{\pi_{t+1}}\right)\right] \tag{A.5.11}$$

$$\Omega_{rP,t}=E_t\left[\left(\beta_P\frac{\lambda_{P,t+1}}{\lambda_{P,t}}\right)\left(\frac{1-\tau_b+(1-\kappa)\Omega_{rP,t+1}}{\pi_{t+1}}\right)\right] \tag{A.5.12}$$

### A.5.2 Impatient Households

$$\theta\left(\frac{s_{I,t}}{c_{I,t}}\right)^{1-\theta}\left[\frac{\upsilon_t}{x_{I,t}}-\beta_I\mu_cE_t\left\{\frac{\upsilon_{t+1}}{x_{I,t+1}}\right\}\right]=(1+\tau_c)\lambda_{I,t} \tag{A.5.13}$$

$$\left[1+\tau_p(1-\tau_{yI})+\kappa_h\left(\frac{h_{I,t}}{h_{I,t-1}}-1\right)\frac{h_{I,t}}{h_{I,t-1}}-\phi\mu_t\right]q_{h,t}=\frac{\upsilon_t\xi_h}{\lambda_{I,t}h_{I,t}}$$
$$+E_t\left[\left(\beta_I\frac{\lambda_{I,t+1}}{\lambda_{I,t}}\right)\left\{\left[(1-\delta_h)[1-\phi\mu_{t+1}]+\kappa_h\left(\frac{h_{I,t+1}}{h_{I,t}}-1\right)\left(\frac{h_{I,t+1}}{h_{I,t}}\right)^2\right]q_{h,t+1}\right\}\right] \tag{A.5.14}$$

$$\left[1+\tau_p\left(1-\tau_{yI}\right)+\kappa_h\left(\frac{h_{RI,t}}{h_{RI,t-1}}-1\right)\frac{h_{RI,t}}{h_{RI,t-1}}-\phi\mu_t\right]q_{h,t}=\left(1-\tau_{yI}\right)r_{hI,t}$$
$$+E_t\left[\left(\beta_I\frac{\lambda_{I,t+1}}{\lambda_{I,t}}\right)\left\{\left[\left(1-\delta_h\right)\left[1-\left(\phi-\Upsilon\right)\mu_{t+1}\right]+\kappa_h\left(\frac{h_{RI,t+1}}{h_{RI,t}}-1\right)\left(\frac{h_{RI,t+1}}{h_{RI,t}}\right)^2\right]q_{h,t+1}+\tau_{yI}\delta_h\right\}\right]$$
(A.5.15)

$$\left[(1+\tau_c)+\kappa_s\left(\frac{s_{I,t}}{s_{I,t-1}}-1\right)\frac{s_{I,t}}{s_{I,t-1}}+\frac{\kappa_s}{2}\left(\frac{s_{I,t}}{s_{I,t-1}}-1\right)^2\right]q_{s,t}=\frac{(1+\tau_c)(1-\theta)}{\theta}\frac{c_{I,t}}{s_{I,t}}$$
$$+E_t\left[\left(\beta_I\frac{\lambda_{I,t+1}}{\lambda_{I,t}}\right)\left\{\left[(1+\tau_c)(1-\delta_s)+\kappa_s\left(\frac{s_{I,t+1}}{s_{I,t}}-1\right)\left(\frac{s_{I,t+1}}{s_{I,t}}\right)^2\right]q_{s,t+1}\right\}\right] \quad \text{(A.5.16)}$$

$$\upsilon_t\xi_n n_{I,t}^{\vartheta}=\lambda_{I,t}\Omega_{nI,t}\left(1-\tau_{yI}\right)w_{I,t} \quad \text{(A.5.17)}$$

$$\left(\frac{\pi_{wI,t}}{\pi}-1\right)\frac{\pi_{wI,t}}{\pi}$$
$$=E_t\left[\beta_I\frac{\lambda_{I,t+1}}{\lambda_{I,t}}\left(\frac{\pi_{wI,t+1}}{\pi}-1\right)\frac{\pi_{wI,t+1}}{\pi}\frac{\pi_{wI,t+1}}{\pi_{t+1}}\frac{n_{I,t+1}}{n_{I,t}}\right]-\frac{\left(\eta_w-1\right)\left(1-\tau_{yI}\right)}{\kappa_w}\left(1-\theta_w\Omega_{nI,t}\right)$$
(A.5.18)

where $\pi_{wI,t}=\frac{W_{I,t}}{W_{I,t-1}}$

$$\frac{\pi_{wI,t}}{\pi_t}=\frac{w_{I,t}}{w_{I,t-1}} \quad \text{(A.5.19)}$$

$$1-\mu_t=\Omega_{dI,t}+\Omega_{rI,t}R_t^F \quad \text{(A.5.20)}$$

$$\Omega_{dI,t}+\Omega_{rI,t}R_t^M=E_t\left[\beta_I\frac{\lambda_{I,t+1}}{\lambda_{I,t}}\left(\frac{\left(1-\tau_{yI}\right)R_t^M+\kappa+\left(1-\kappa\right)\left\{\Omega_{dI,t+1}+\Omega_{rI,t+1}R_t^M\right\}}{\pi_{t+1}}\right)\right]$$
(A.5.21)

$$\Omega_{rI,t} = E_t \left[ \beta_I \frac{\lambda_{I,t+1}}{\lambda_{I,t}} \left( \frac{1 - \tau_{yI} + (1-\kappa)\,\Omega_{rI,t+1}}{\pi_{t+1}} \right) \right] \tag{A.5.22}$$

### A.5.3 Renter Households

$$\theta \left( \frac{s_{R,t}}{c_{R,t}} \right)^{1-\theta} \left[ \frac{\upsilon_t}{x_{R,t}} - \beta_R \mu_c E_t \left\{ \frac{\upsilon_{t+1}}{x_{R,t+1}} \right\} \right] = (1+\tau_c)\,\lambda_{R,t} \tag{A.5.23}$$

$$p_{hP,t} = \frac{\upsilon_t \xi_t \mu_h}{\lambda_{R,t} h_{RP,t}} \tag{A.5.24}$$

$$p_{hI,t} = \frac{\upsilon_t \xi_t (1-\mu_h)}{\lambda_{R,t} h_{RI,t}} \tag{A.5.25}$$

$$\begin{aligned} &\left[ (1+\tau_c) + \kappa_s \left( \frac{s_{R,t}}{s_{R,t-1}} - 1 \right) \frac{s_{P,t}}{s_{R,t-1}} + \frac{\kappa_s}{2} \left( \frac{s_{R,t}}{s_{R,t-1}} - 1 \right)^2 \right] q_{s,t} = \frac{(1+\tau_c)(1-\theta)}{\theta} \frac{c_{R,t}}{s_{R,t}} \\ &+ E_t \left[ \left( \beta_R \frac{\lambda_{R,t+1}}{\lambda_{R,t}} \right) \left\{ \left[ (1+\tau_c)(1-\delta_s) + \kappa_s \left( \frac{s_{R,t+1}}{s_{R,t}} - 1 \right) \left( \frac{s_{R,t+1}}{s_{R,t}} \right)^2 \right] q_{s,t+1} \right\} \right] \end{aligned} \tag{A.5.26}$$

$$\upsilon_t \xi_n n_{R,t}^{\vartheta} = \lambda_{R,t} \Omega_{nR,t} (1-\tau_{yR})\, w_{R,t} \tag{A.5.27}$$

$$\begin{aligned} &\left( \frac{\pi_{wR,t}}{\pi} - 1 \right) \frac{\pi_{wR,t}}{\pi} \\ &= E_t \left[ \beta_R \frac{\lambda_{R,t+1}}{\lambda_{R,t}} \left( \frac{\pi_{wR,t+1}}{\pi} - 1 \right) \frac{\pi_{wR,t+1}}{\pi} \frac{\pi_{wR,t+1}}{\pi_{t+1}} \frac{n_{R,t+1}}{n_{R,t}} \right] - \frac{(1-\tau_{yR})(\eta_w - 1)}{\kappa_w} (1 - \theta_w \Omega_{nR,t}) \end{aligned} \tag{A.5.28}$$

where $\pi_{wR,t} = \dfrac{W_{R,t}}{W_{R,t-1}}$

$$\frac{\pi_{wR,t}}{\pi_t} = \frac{w_{R,t}}{w_{R,t-1}} \tag{A.5.29}$$

### A.5.4 Non-residential, Residential investment, and Rental services Producers

$$q_{k,t} - \kappa_{ik} q_{k,t} \left( \frac{i_{k,t}}{i_{k,t-1}} - 1 \right) \frac{i_{k,t}}{i_{k,t-1}} - q_{k,t} \frac{\kappa_{ik}}{2} \left( \frac{i_{k,t}}{i_{k,t-1}} - 1 \right)^2 + E_t \left[ \beta_P \frac{\lambda_{P,t+1}}{\lambda_{P,t}} \kappa_{ik} q_{k,t+1} \left( \frac{i_{k,t+1}}{i_{k,t}} - 1 \right) \left( \frac{i_{k,t+1}}{i_{k,t}} \right)^2 \right] = 1 \tag{A.5.30}$$

$$q_{s,t} - \kappa_{\tilde{c}} q_{s,t} \left( \frac{\tilde{c}_t}{\tilde{c}_{t-1}} - 1 \right) \frac{\tilde{c}_t}{\tilde{c}_{t-1}} - q_{s,t} \frac{\kappa_{\tilde{c}}}{2} \left( \frac{\tilde{c}_t}{\tilde{c}_{t-1}} - 1 \right)^2 + \beta_P E_t \left\{ \frac{\lambda_{P,t+1}}{\lambda_{P,t}} \kappa_{\tilde{c}} q_{s,t+1} \left( \frac{\tilde{c}_{t+1}}{\tilde{c}_t} - 1 \right) \left( \frac{\tilde{c}_{t+1}}{\tilde{c}_t} \right)^2 \right\} = 1 \tag{A.5.31}$$

$$q_{h,t} - \kappa_{ih} q_{h,t} \left( \frac{i_{h,t}}{i_{h,t-1}} - 1 \right) \frac{i_{h,t}}{i_{h,t-1}} - q_{h,t} \frac{\kappa_{ih}}{2} \left( \frac{i_{h,t}}{i_{h,t-1}} - 1 \right)^2 + E_t \left[ \beta_P \frac{\lambda_{P,t+1}}{\lambda_{P,t}} \kappa_{ih} q_{h,t+1} \left( \frac{i_{h,t+1}}{i_{h,t}} - 1 \right) \left( \frac{i_{h,t+1}}{i_{h,t}} \right)^2 \right] = 1 \tag{A.5.32}$$

$$\left( \frac{\pi_{hj,t}}{\pi} - 1 \right) \frac{\pi_{hj,t}}{\pi} = E_t \left[ \beta_P \frac{\lambda_{P,t+1}}{\lambda_{P,t}} \left( \frac{\pi_{hj,t+1}}{\pi} - 1 \right) \frac{\pi_{h,t+1}}{\pi} \frac{\pi_{hj,t+1}}{\pi_{t+1}} \frac{h_{Rj,t+1}}{h_{Rj,t}} \right] - \frac{\eta_h - 1}{\kappa_{ph}} \left( 1 - \theta_h \frac{r_{hj,t}}{p_{hj,t}} \right) \tag{A.5.33}$$

where $\theta_h = \frac{\eta_h}{\eta_h - 1}$ for $j \in \{P, I\}$

$$\frac{\pi_{hP,t}}{\pi_t} = \frac{p_{hP,t}}{p_{hP,t-1}} \tag{A.5.34}$$

$$\frac{\pi_{hI,t}}{\pi_t} = \frac{p_{hI,t}}{p_{hI,t-1}} \tag{A.5.35}$$

### A.5.5 Non-housing Goods Producers

$$\Omega_{n,t} (1 - \alpha) \psi_P \left( \frac{y_{n,t} + f_{n,t}}{n_{P,t}} \right) = w_{P,t} \tag{A.5.36}$$

$$\Omega_{n,t}\left(1-\alpha\right)\psi_I\left(\frac{y_{n,t}+f_{n,t}}{n_{I,t}}\right)=w_{I,t} \tag{A.5.37}$$

$$\Omega_{n,t}\left(1-\alpha\right)\psi_R\left(\frac{y_{n,t}+f_{n,t}}{n_{R,t}}\right)=w_{R,t} \tag{A.5.38}$$

$$\Omega_{n,t}\alpha\frac{y_{n,t}+f_{n,t}}{k_{t-1}}=r_{k,t}+\frac{\kappa_u}{1+\varpi}\left(u_t^{1+\varpi}-1\right) \tag{A.5.39}$$

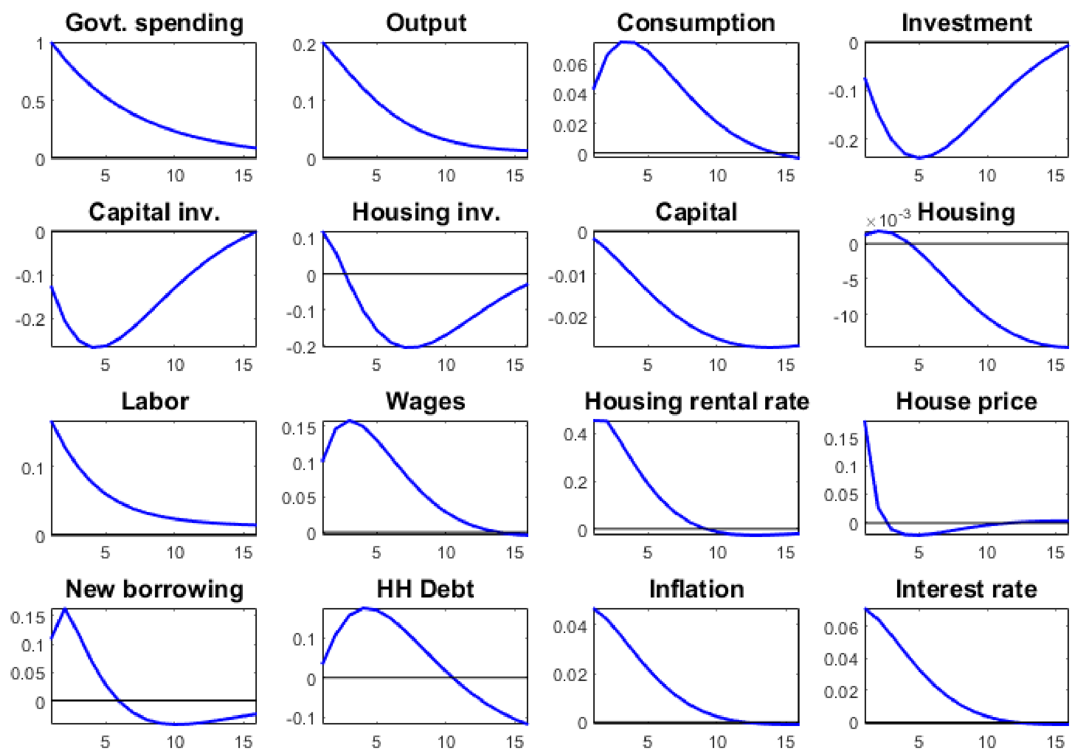
$$\begin{aligned}&\Omega_{n,t}\alpha\frac{y_{n,t}+f_{n,t}}{u_t}=\kappa_u u_t^{\varpi}k_{t-1}\\&\text{where } u=1,\ \kappa_u=\frac{\alpha}{k/y_n}\end{aligned} \tag{A.5.40}$$

$$\left(\frac{\pi_t}{\pi}-1\right)\frac{\pi_t}{\pi}=E_t\left\{\beta_P\frac{\lambda_{P,t+1}}{\lambda_{P,t}}\left(\frac{\pi_{t+1}}{\pi}-1\right)\frac{\pi_{t+1}}{\pi}\frac{y_{n,t+1}}{y_{n,t}}\right\}-\frac{\eta_n-1}{\kappa_{pn}}\left(1-\theta_n\Omega_{n,t}\right) \tag{A.5.41}$$

where $\theta_n=\dfrac{\eta_n}{\eta_n-1}$

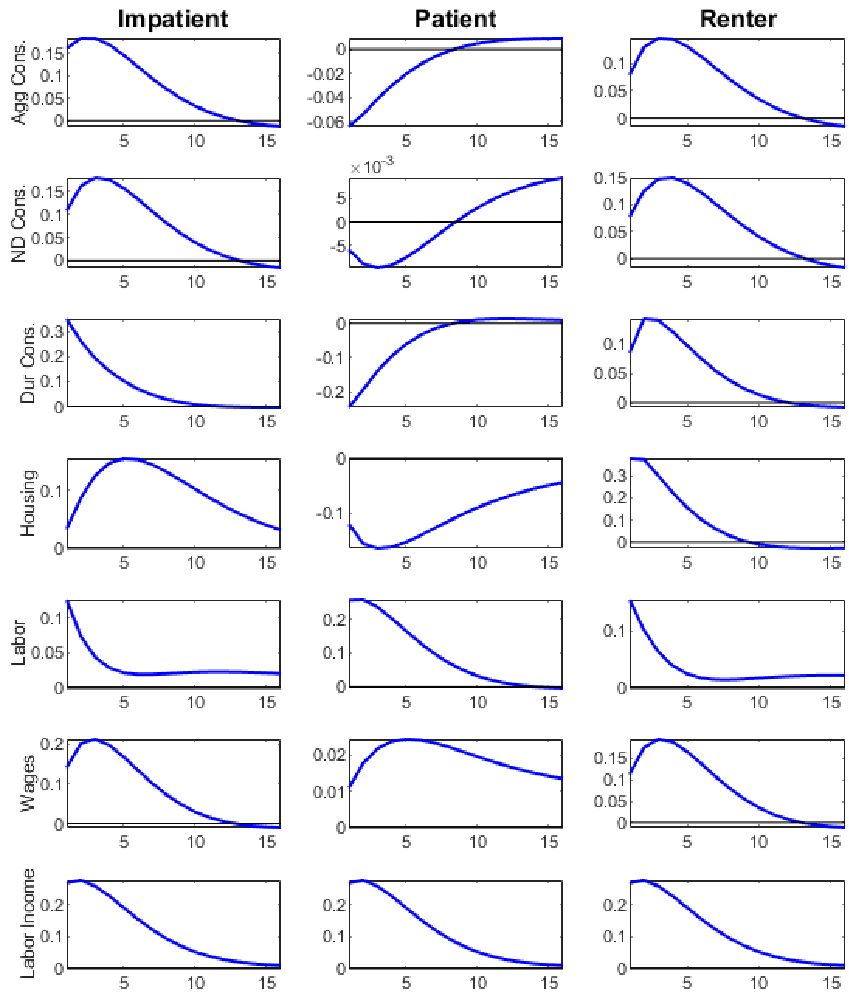
## A.6 Model Results

Figure A.9: Impulse responses for aggregate variables in the model




Notes: This figure shows the impulse response functions of aggregate variables in response to a positive government spending shock in the baseline model with durable goods.

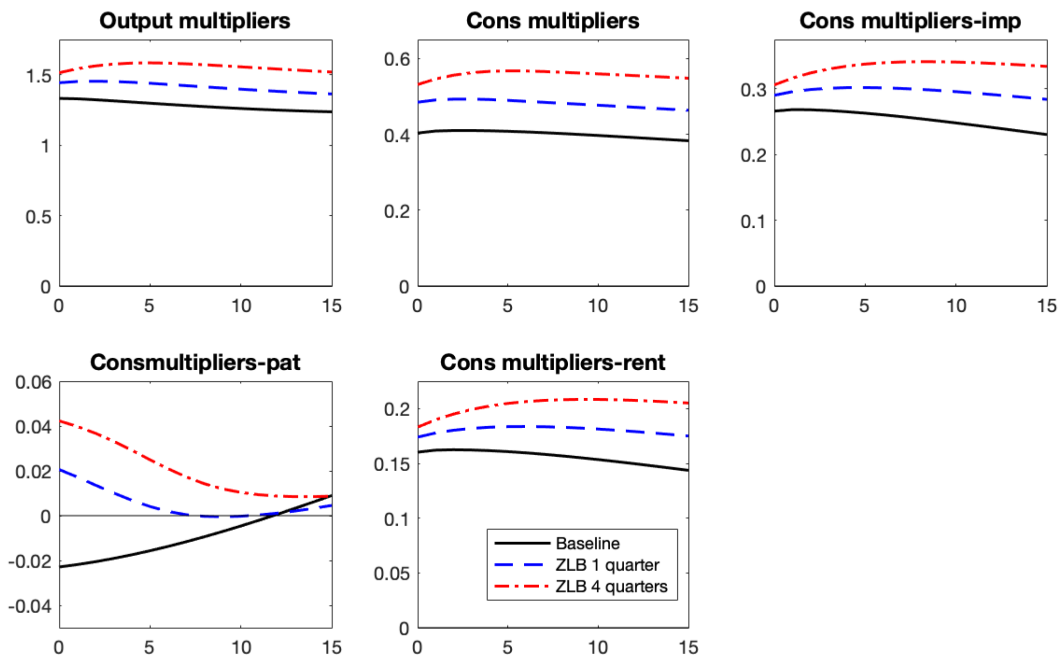
Figure A.10: Impulse responses for disaggregate variables in the model




Notes: This figure shows the impulse response functions of disaggregate variables in response to a positive government spending shock in the baseline model with durable goods.

## A.7 Multipliers in Normal Times and during ZLB Periods

Figure A.11: Cumulative output and consumption multipliers




Notes: This figure plots the cumulative output and consumption multipliers in and out of ZLB periods. The black solid line represents multipliers during normal times. The Blue dashed line is the cumulative multipliers under ZLB binding for one quarter and the red dash-dotted line indicates multipliers under ZLB for four quarters.

# APPENDIX B

# APPENDIX TO CHAPTER 3

## B.1 Literature Review

Please refer to the table (Table B.1) on the next page.

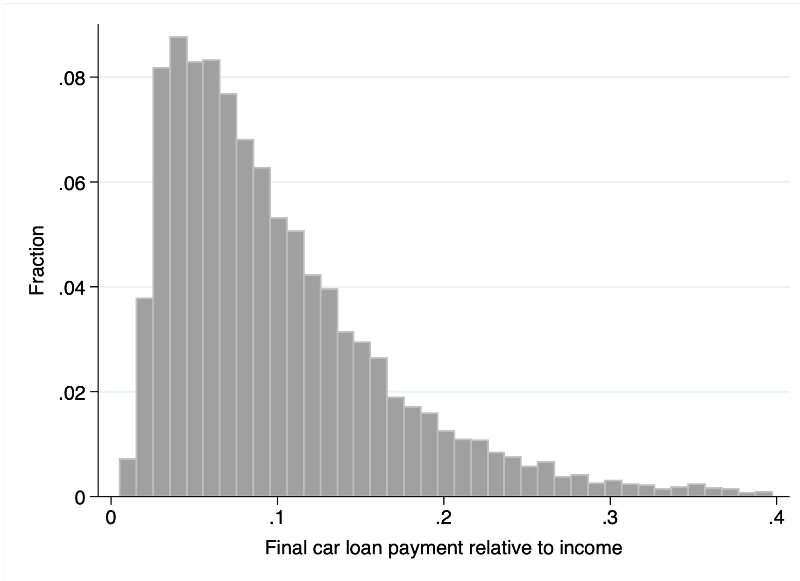
Table B.1: Overview of the marginal propensity to consume using natural experiment

| 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)<br>2008 Economic stimulus payments ($900) | CEX interview survey; 2000 - 2002<br>2007 - 2008 | 0.43 (2001)<br>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: This table reports the overview of the marginal propensity to consume (MPC) in response to an anticipated income increase based on natural experiments for each study. 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.

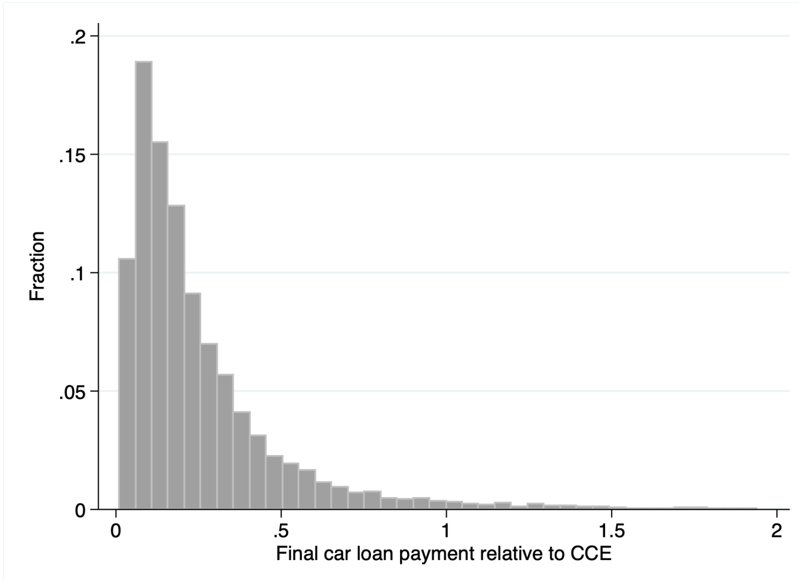
## B.2 Distribution of Sample

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



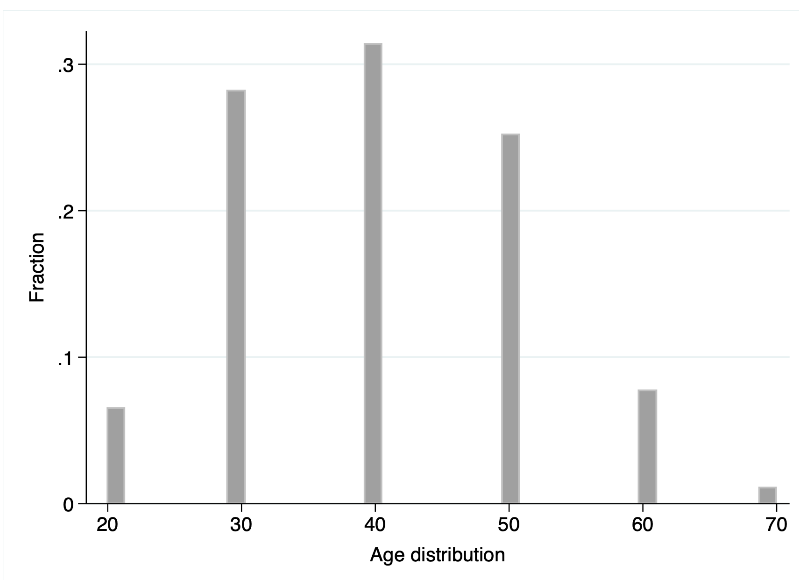

*Notes*: This figure plots the distribution of the final car loan payment size relative to income ratio for sample period from 2012 to 2016.

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




*Notes*: This figure the distribution of the final car loan payment size relative to consumption expenditure ratio for sample period from 2012 to 2016.

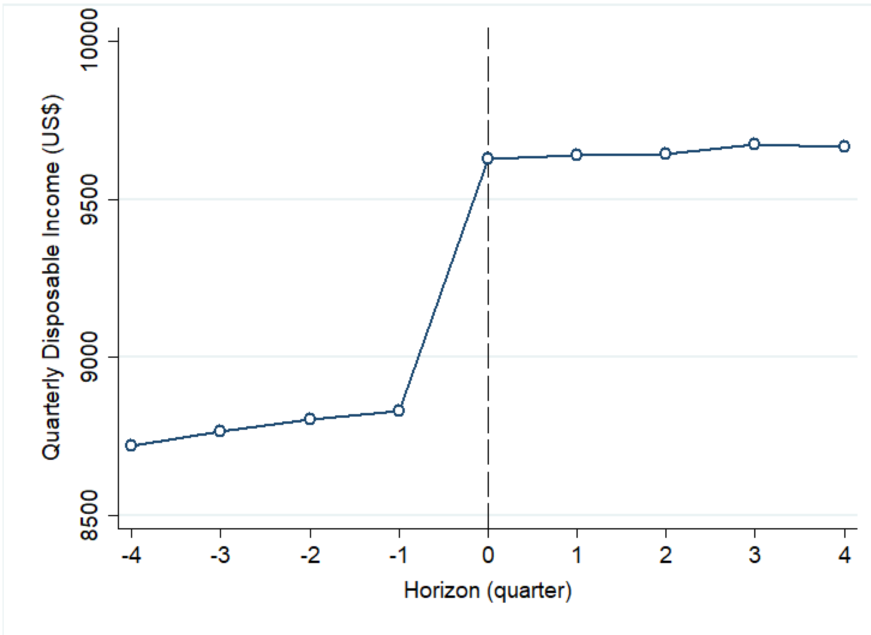
Figure B.3: Distribution of age, 2012-2016




*Notes*: This figure plots the distribution of age groups (from 20 to 70) for sample period from 2012 to 2016.

### B.3 Income process

Figure B.4: Income dynamics




*Notes*: This figure 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.

## B.4 Marginal Propensity to Consume by Relative Magnitudes

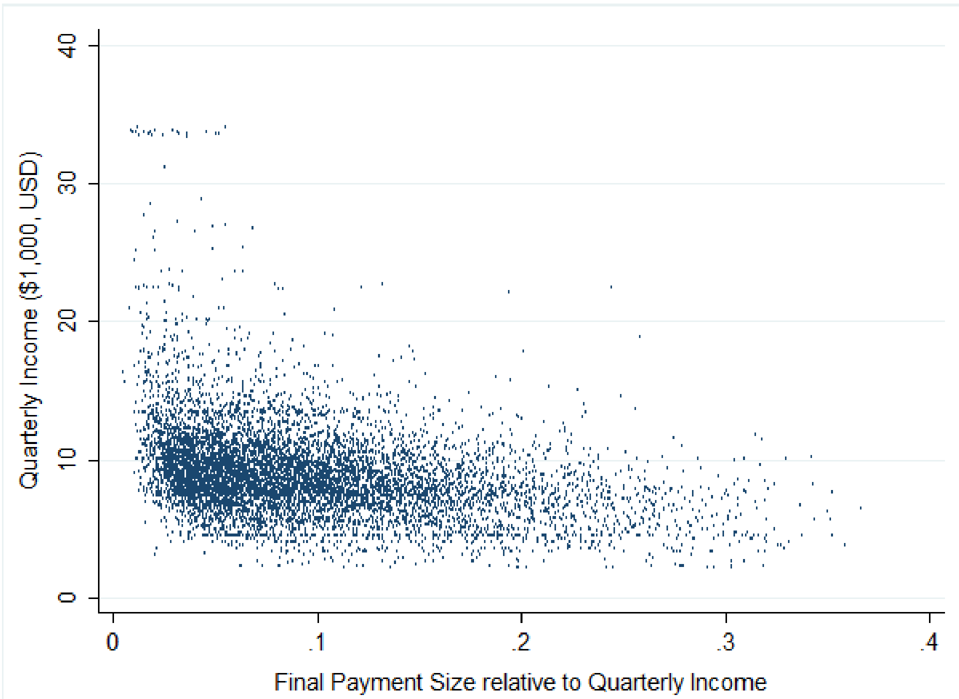
Table B.2: Consumption response by relative magnitudes

| Dep. Var: $\Delta c_{it}$ | (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.

### B.5 Consumption Response by Relative Magnitudes

Figure B.5: Relative payment size and quarterly income



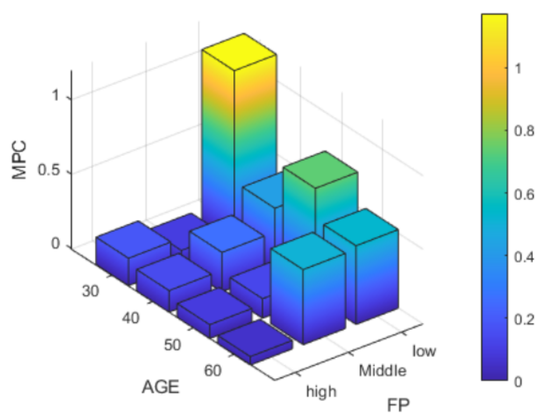

*Notes*: This figure plots the relative size ratio against quarterly income for the full sample. The solid line indicates the fitted line for two variables in each panel.

## B.6 Conditional MPC Heterogeneity by Absolute Payment Size

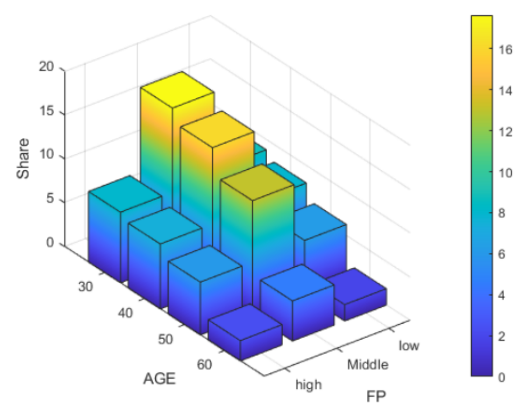
### B.6.1 Consumption Response by the Absolute Payment Size

Figure B.6: MPC heterogeneity by payment size (Level)

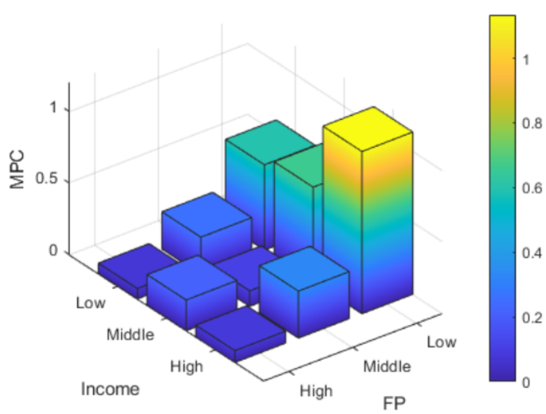
(a) MPC distribution, age, size



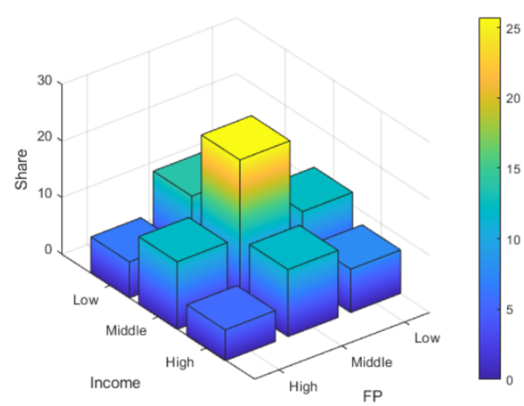

(b) Population share, age, size




(c) MPC distribution, income, size



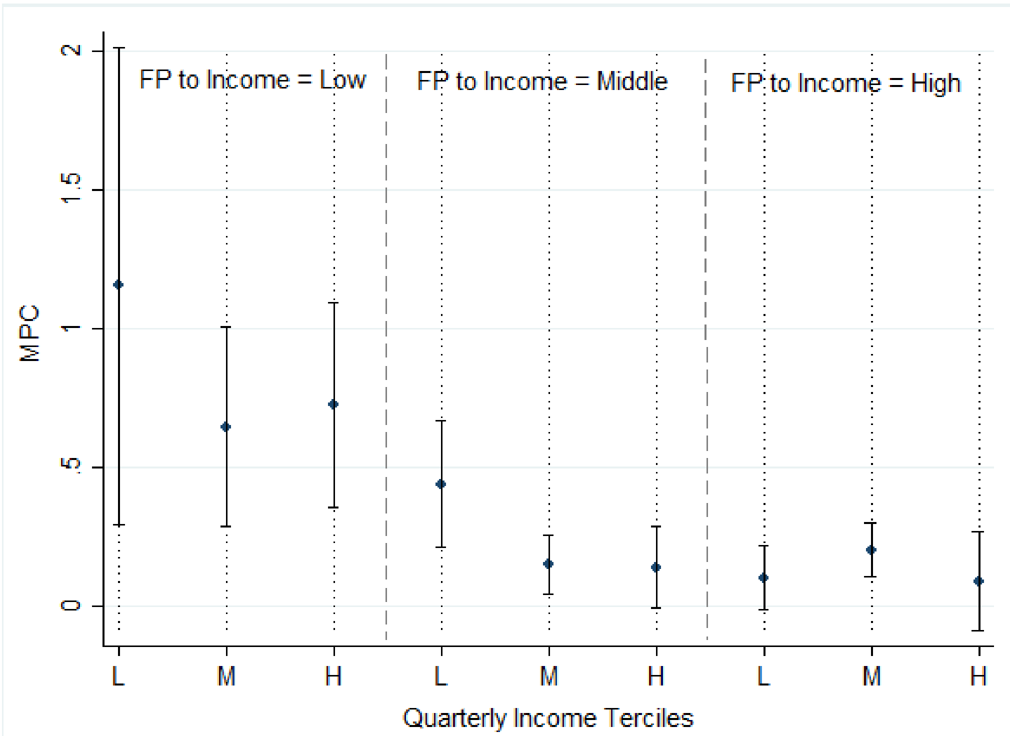

(d) Population share, income, size




*Notes*: This figure shows the conditional MPC heterogeneity (and the population share) among age, income, and the absolute size of the car loan payment.

### B.6.2 Marginal Propensity to Consume by Relative Size conditional on Income

Figure B.7: Conditional MPC heterogeneity by relative size



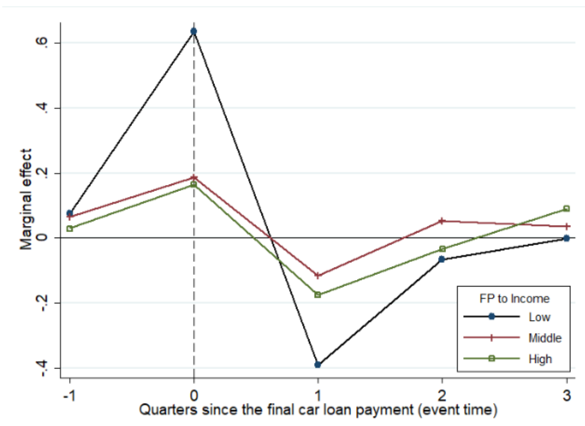

*Notes*: This figure displays the spending responses by income terciles conditional on the final payment size relative to quarterly income (*FP to Income*). Bars and lines show the estimated coefficients and 95 percent confidence intervals, respectively. Standard errors are clustered at the individual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

## B.7 Robustness Analysis

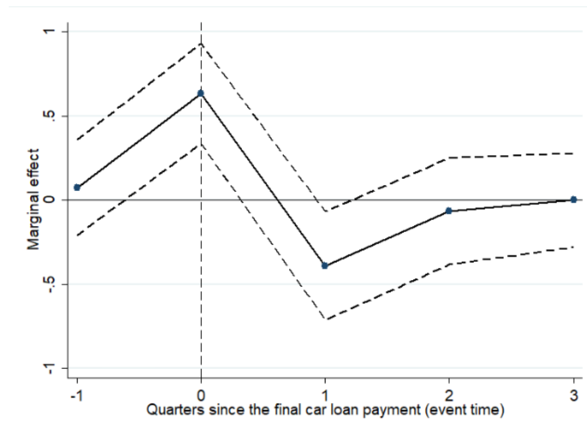
### B.7.1 Heterogeneity in Consumption Dynamics

Figure B.8: Consumption dynamics (marginal) by payment size relative to income

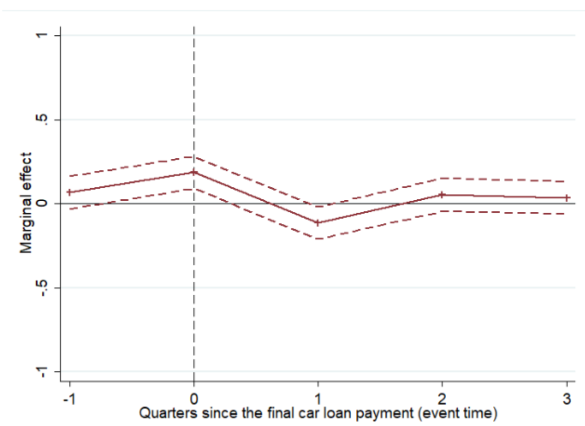
(a) Consumption responses by *FP to Income*



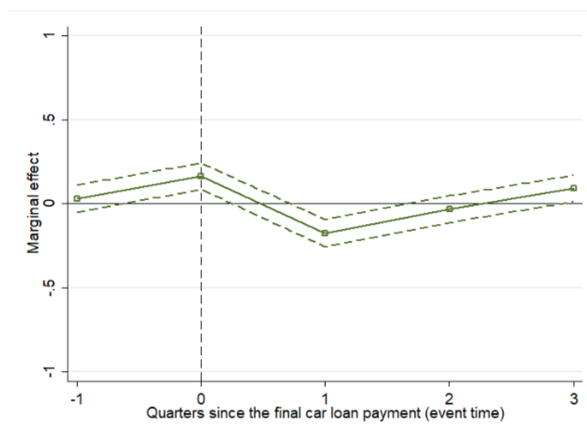

(b) *FP to Income* = Low




(c) *FP to Income* = Middle

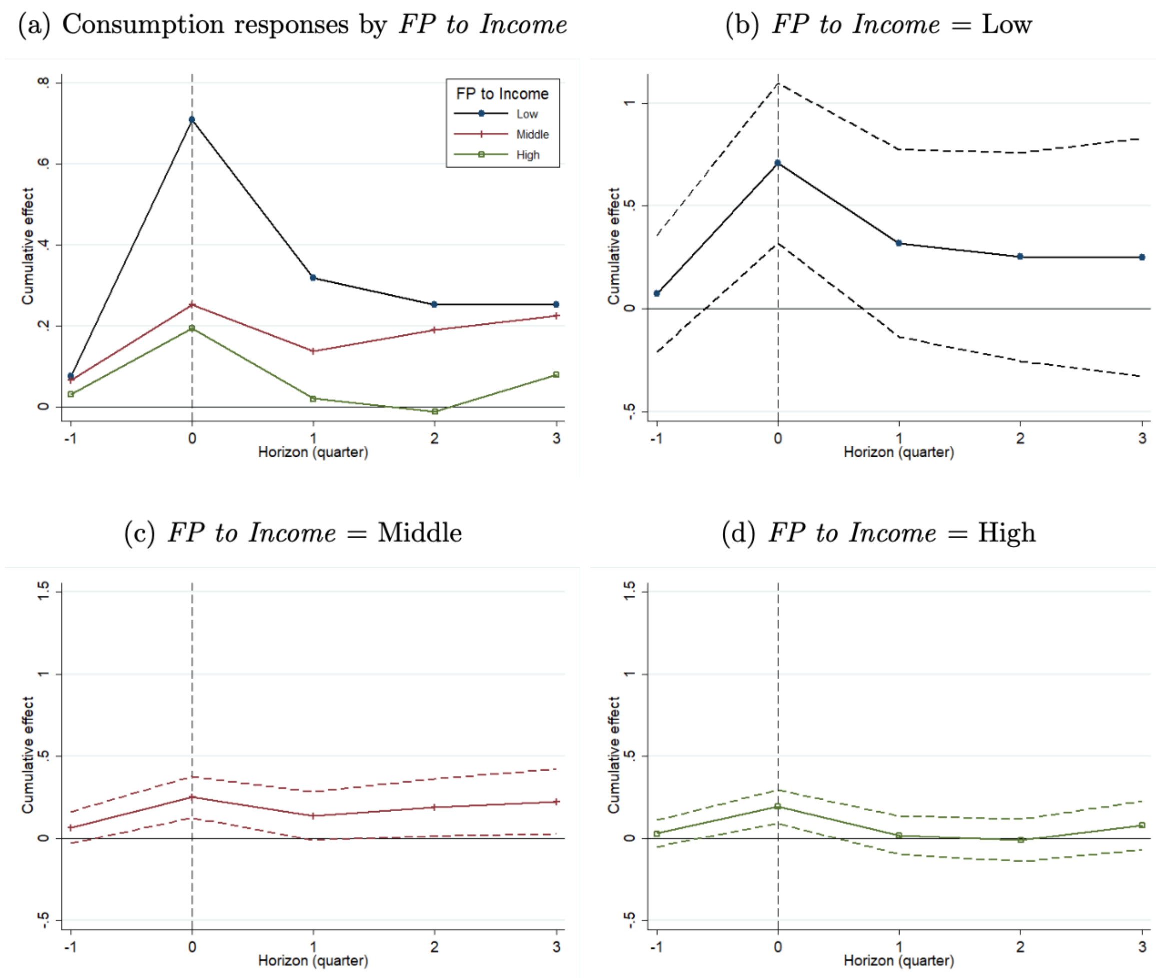



(d) *FP to Income* = High




*Notes*: This figure 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.

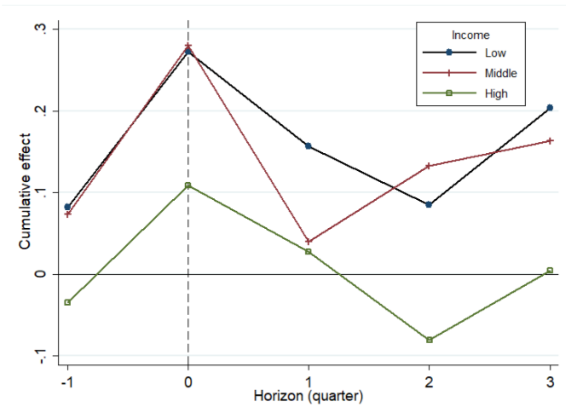
Figure B.9: Consumption dynamics (cumulative) by payment size relative to income



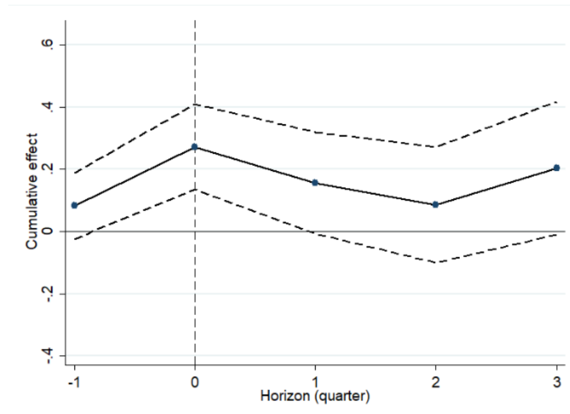

*Notes*: This figure displays the cumulative effects on consumption by the payment size relative to income (*FP to Income*) terciles. Solid lines indicate the marginal response and the dashed lines indicate the 95 percent confidence intervals.

Figure B.10: Consumption dynamics (cumulative) by income

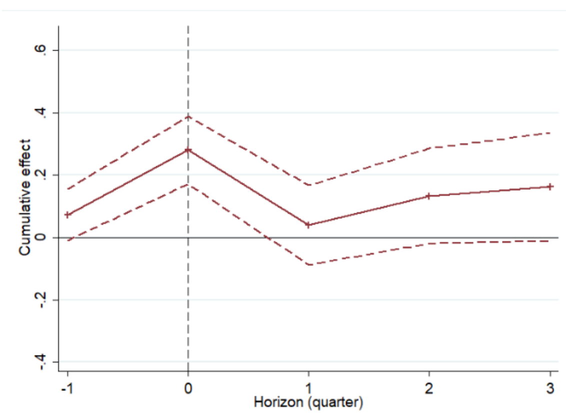
(a) Consumption responses by *Income*



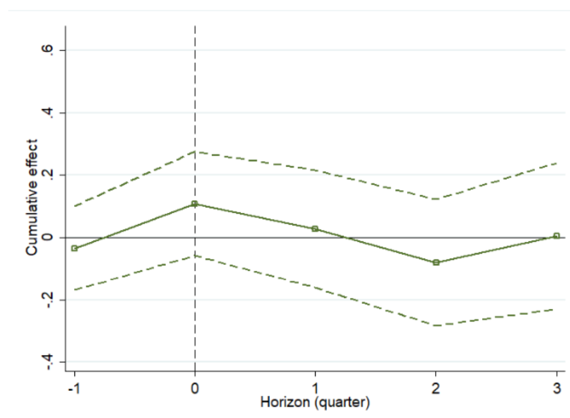

(b) *Income* = Low




(c) *Income* = Middle




(d) *Income* = High




*Notes*: This figure 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.

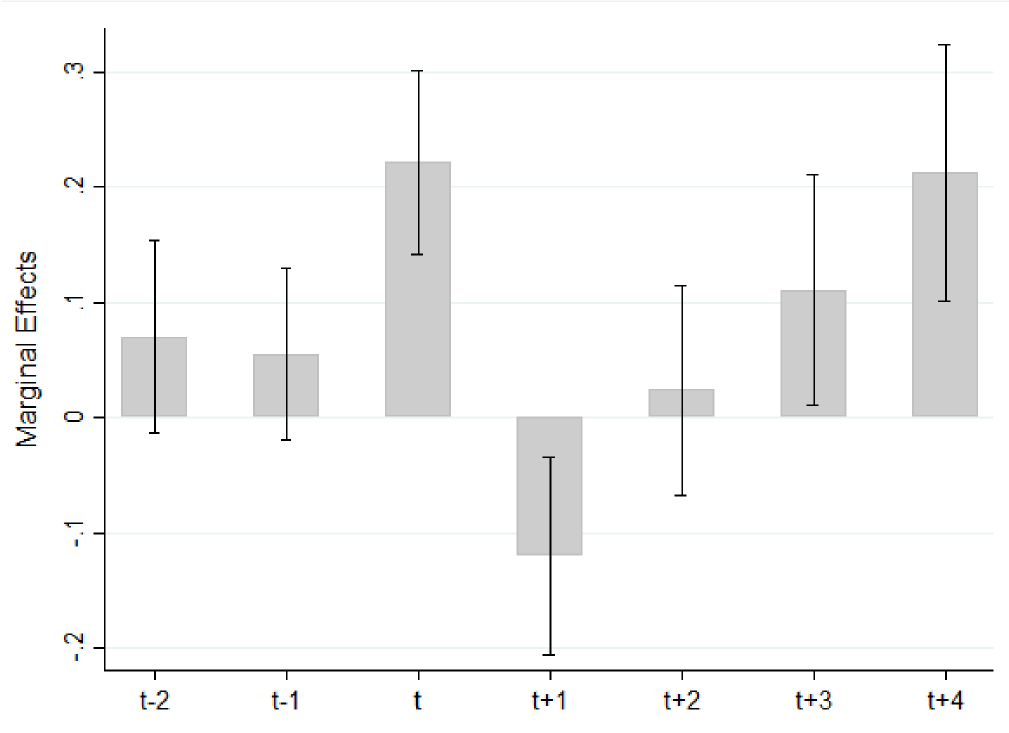
### B.7.2 Estimation Results in Korean WON

Table B.3: 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 indicate 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 B.11: Marginal effects on marginal propensity to consume




*Notes*: This figure shows leads and lags of the regression coefficients based on original currency (Korean won) estimated by the standard parametric regression equation (Equation 3.1). $t$ 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.

### B.8 Permanent Income Hypothesis (PIH)

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

$$\max_{\{c_{i,t+s}\}_{s=0}^{\infty}} E_t \sum_{s=0}^{\infty} \beta^s u\left(c_{i,t+s}\right) \tag{B.8.1}$$

subject to

$$\sum_{s=0}^{\infty} \left(\frac{1}{1+r}\right)^s c_{i,t+s} = \bar{a}_{i,t} + \sum_{s=0}^{\infty} \left(\frac{1}{1+r}\right)^s y_{i,t+s} \tag{B.8.2}$$

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 $t$. $\beta$ 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,

$$\Delta c_{i,t} = \frac{r}{1+r}\left[E\left(\sum_{s=0}^{\infty}\left(\frac{1}{1+r}\right)^s y_{i,t+s}|\Omega_{i,t}\right) - E\left(\sum_{s=0}^{\infty}\left(\frac{1}{1+r}\right)^s y_{i,t+s}|\Omega_{i,t-1}\right)\right] \tag{B.8.3}$$

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 (B.8.3) 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.

### B.9 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:

$$c^{pih}_{i,w_t} = arg\ max_{c_t}\{U(c_t) \text{ s.t. } p_{t+1}c_t \leq w\} \tag{B.9.1}$$

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

$$U(c^{pih}_w) - U(c^{deviate}_w) \approx -\frac{1}{2}\gamma^t \cdot \frac{\partial^2 u(c^{pih}_t)}{\partial c^2} \cdot (c^{pih}_t)^2 \cdot \left(\frac{c^{deviate}_t - c^{pih}_t}{c^{pih}_t}\right)^2 \tag{B.9.2}$$

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:

$$U(c^{pih}_w) - U(c_{\tilde{w}}{}^{pih}) \approx -\left(\frac{\tilde{w} - w}{w}\right) \sum_t \gamma^t \cdot \left(\frac{\partial u(c^{pih}_t)}{\partial c} \cdot c^{pih}_t\right) \tag{B.9.3}$$

For simplicity, we consider $\gamma = 1$. Then, combining above two equations gives the potential welfare loss function (i.e. equation 3.11).

$$Welfare\ loss\ (c^{deviate}_i, c^{pih}_i) \approx \frac{\delta}{2} \cdot \sum_t \zeta_t \left(\frac{c^{deviate}_t - c^{pih}_t}{c^{pih}_t}\right)^2 \tag{B.9.4}$$

where $\delta$ captures the curvature of the utility function. $\zeta_t$ 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

$$c_t = \begin{cases} c^{pih} & \text{without predictable income changes} \\ c^{pih} + MPC \cdot FP & \text{with predictable income changes} \end{cases} \tag{B.9.5}$$

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 $c_t^{deviate}$ where

$$\frac{c_t^{deviate} - c_t^{pih}}{c_t^{pih}} = \begin{cases} 0 & \text{without predictable income changes} \\ \frac{(1-MPC)\cdot FP}{c^{pih}} & \text{with predictable income changes} \end{cases} \tag{B.9.6}$$

and therefore, the welfare loss from deviation becomes

$$Welfare\ loss\ (c_i^{deviate}, c_i^{pih}) \approx \frac{\delta}{2} \cdot \left( \frac{(1 - MPC) \cdot FP}{c^{pih}} \right)^2 \tag{B.9.7}$$

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