Essays in Fiscal Policy and Consumer Finance

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ABSTRACT

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During recessions, fiscal, monetary and other credit provision policies are used together to combat falling consumption levels and stabilize output. Most such counter-cyclical stabilization policies are deemed effective when households use provided credit or cash towards raising consumption. Hence, a deep understanding of consumer finance is central to understanding how and when such counter-cyclical stabilization policies work, and when they do not. In my dissertation, I focus primarily on one set of stabilization policies; namely fiscal stimulus. I provide particular empirical and theoretical insight into how consumers manage their finances and in particular liquidity levels, and how this behavior is connected to the effectiveness of fiscal policy during balance sheet recessions. I also discuss how the definition of effectiveness itself may need to undergo some revisions as applied to a balance sheet recession.

Chapter 1 “Heterogeneity in effectiveness of fiscal stimulus: The Economic Stimulus Payments of 2008” empirically investigates regional heterogeneity in the effectiveness of fiscal rebates during recessions characterized by housing crises. While general estimates of the effectiveness have been measured in previous literature, the state dependence of such effectiveness to the particular type of business cycle state (for example depth of regional housing crisis) is unknown. I first provide a description of the 2008 recession, and the history of recent fiscal policies along with the institutional arrangement of the fiscal stimulus policies enacted during the time. I next review the relevant empirical literature on fiscal policy effectiveness. I then describe the empirical methodology to estimate the effectiveness of fiscal rebate policies in 2008 and their regional heterogeneity. Using a special module of the Nielsen Consumer Panel which surveys households about their 2008 Economic Stimulus Payments, I show that households’ marginal propensity to consume (MPC) out of these rebates was significantly lower in zipcodes with larger
declines in housing prices. This pattern holds for both households with liquid assets and for those without. This highlights a novel finding compared to the previous literature; fiscal policy effectiveness is not explained solely by the behavior of households without liquid assets. These findings are not caused by differences in socio-economic and other observable characteristics and are robust to the use of a topology based instrument for housing price changes. Finally, I show that the results are driven by the difference in reported vs. revealed preference for reported savers and deleveragers in the hardest hit areas.

Chapter 2 “Policy and Theoretical Implications of Regional Heterogeneity in Fiscal Stimulus Effectiveness” investigates how the findings in Chapter 1 square with policy implications and consumption theory. On the policy side, I discuss how this result creates a policy dilemma, where fiscal stimulus may have been least effective in stimulating nondurable consumption in precisely the regions experiencing the worst recession. This underscores potential tradeoffs between the utilitarian and aggregate demand stabilization motives for rebate provision and the need to add nuance to the definition of fiscal policy effectiveness. On the theory side, I revisit the theoretical consumption literature and describe its predictions for MPC in a time of lower incomes and wealth. In particular, I look at how the negative relation between MPC and house price decline is at odds with the predictions of canonical buffer-stock models, which predict a higher MPC in worse affected regions. Next, I build a state of the art heterogeneous agent life cycle model, which features adjustment costs, long term debt and a default option, and calibrate it to regional variation in housing price declines, unemployment risk and income declines. I discuss newer mechanisms which could potentially match the empirical results. In reality, I show that even such a model substantially overestimates the effectiveness of fiscal stimulus in the worst affected regions. I explore the reasons behind such a mismatch, including the lack of marginal deleveraging in the model. Finally, I use data from the Michigan Survey of Consumers to rule out regional variation in permanent expectations
as a key variable which could reconcile the findings in the data. Overall, the findings remain unreconciled with standard consumption theory, even after the augmentation of modern and realistic elements.

Chapter 3 “Evolution of Hand to Mouth Households (2007-09) and Lessons” continues on the theme of household liquidity which has been analyzed significantly to understand fiscal policy. A key parameter in the previous literature has been the proportion of illiquid households with housing wealth (also called wealthy hand to mouth households) who are important in understanding fiscal policy effectiveness. Two separate strands of the literature have emphasized either the role of permanent characteristics or income and wealth shocks (circumstance) in determining such status. In light of this, I document three new and robust findings. First, the overall proportion of such wealthy hand to mouth households stayed constant during the early years of the Great Recession. Second, there was massive underlying movement between various groups underneath the overall numbers. Third, households who built liquidity buffers had significantly larger losses to housing wealth and smaller losses to permanent income expectations. They also achieved this improvement in liquidity through methods other than the extraction of illiquid assets. This implies households who build liquidity buffers during housing crisis recessions do so through cutting consumption sharply. Taken together, these findings imply a) that both circumstantial and characteristics views on household liquidity are important, and b) that consumption models with net illiquid assets cannot match central facts for balance sheet recessions. This is because they predict households building liquidity buffers through extraction of illiquid wealth, which is unavailable during such recessions. In contrast, models with asset valuation effects do a better job of matching the liquidity management decisions of households.

The goal of my research is to inform debates on fiscal policy effectiveness and the linkages to household liquidity. Future recessions with limitations on conventional monetary policy will especially be important times when these debates will play out. I hope
this research provides useful information in the design and analysis of future countercyclical fiscal policies.
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To my parents
1.1 Introduction

The marginal propensity to consume (MPC) out of fiscal stimulus payments during recessions is important for understanding both the determinants of consumption and the effectiveness of fiscal policy. A large empirical literature has estimated a quarterly MPC for nondurables out of fiscal rebates of between 0.2 to 0.35 (Johnson et al. (2006), Johnson et al. (2013)). Beginning with Mian et al. (2013), there has also been significant interest in studying how housing wealth shocks led to higher consumption in the 2003-06 housing boom and then lower consumption during the 2007-2009 recession. We know little, however, about how such declines in wealth affect the MPC out of fiscal rebates. Much of the theoretical literature predicts that fiscal rebates are more effective at stimulating consumption in a housing crisis, as households face tighter borrowing

1Calculated (or Derived) based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

2Fiscal rebates are a key part of the fiscal stimulus policy toolkit and accounted for $100 billion of spending during the Stimulus Act of 2008. Oh and Reis (2012) document that three quarters of the increase in U.S. government expenditures during the 2007-2009 recession were accounted for increases in transfers, rather than government purchases.
constraints and lower net worth, increasing their propensity to consume. Yet in practice, there is widespread concern that in a housing crisis, overleveraged households will use stimulus checks to pay down debt, rather than increase consumption.

Understanding the empirical relation between the MPC out of transitory income and declines in housing wealth is important for two reasons. First, this is a moment which can be used to test a key prediction of existing consumption models, namely that the MPC should be higher when wealth is lower. Second, since the primary goal of fiscal stimulus programs is to raise aggregate consumption during recessions, the MPC out of rebates is a key determinant of these policies’ effectiveness. Understanding how the MPC relates to declines in wealth informs policymakers about when these policies will be effective at the aggregate level, and how they can be best targeted to stimulate spending.

In this chapter, I empirically study regional heterogeneity in the effectiveness of fiscal rebates during recessions characterized by housing crises. I construct a unique dataset by combining Zillow housing price data, the Nielsen Consumer Panel and a supplemental Economic Stimulus Payments survey. The U.S. Treasury scheduled tax rebate payments based on the last two digits of individual Social Security Numbers, which are effectively random. Following the recent literature, I exploit the randomized timing of rebates to estimate the effect of stimulus receipt on household expenditures. The primary result is that the average MPC was lower in zipcodes where housing prices declined more sharply. In particular, households in the bottom third of the housing price decline distribution had a marginal propensity to consume close to zero. This pattern remains when I use housing supply elasticity (Saiz (2010)) as an instrument for house price changes. The result is also robust to controlling for demographic differences between zipcodes and winsorizing the data. The negative correlation between regional housing wealth declines and average MPC exists both among households with substantial liquid assets, and for those with lower levels of liquid wealth. This finding is novel, as recent literature on
MPC has primarily emphasized the role of households without liquid assets. Finally, I show that the difference in average MPC is driven by the variation in difference in reported vs. revealed behavior of self-reported savers/deleveragers in the hardest hit zip codes.

**Related Literature** This chapter is connected to several strands of the literature. The first, a body of empirical papers, highlights the propensity of households to spend a significant proportion of their rebate checks in nondurables. Using the 2001 Consumer Expenditure Survey, Johnson et al. (2006) show households on average spent between 20 to 40% of their tax rebate checks in the quarter of receipt. Agarwal et al. (2007) affirm these findings. In a subsequent study, Johnson et al. (2013) show households on average spent between 20 and 30% of their 2008 stimulus checks on nondurables in the quarter of receipt. Broda and Parker (2014) find similar MPC for 2008 rebate checks in their analysis of Nielsen weekly spending data. In all of these studies, authors use random variation in rebate payments distribution to control for selection effects and address endogeneity concerns. In addition, Shapiro and Slemrod (2009) use the University of Michigan Survey of Consumers to affirm an average MPC of 33% in 2008. This literature establishes an important fact; the quarterly average MPC for nondurables out of stimulus checks is between 20 and 35%.

Concurrently, a related line of research has emphasized the role of household heterogeneity in spending responses to fiscal rebates. In their analysis, Broda and Parker (2014) ask respondents if they have sufficient liquidity to cover two months of income. Households who respond ‘Yes’ have close to zero spending responses to rebates, while households who do not have sufficient liquidity have significantly higher consumption responses. Misra and Surico (2014) find almost 50% of households did not increase consumption after receiving rebates in 2001 or 2008, and around 20% spent a significant amount, with MPC over 50%. They find MPC is heterogeneous across households based on liquidity status and debt. They also find MPC distribution across income is bi-modal.
Poor households and wealthier households with more debt and less liquidity have high MPC, while middle income households have the lowest MPC.

Traditional consumption theory has had difficulty in matching these facts. The rational expectations life cycle model with one risk free asset (Deaton (1991)) implies only net worth constrained households spend large amounts out of transitory income shocks. However, the proportion of households who are net worth constrained is too small (around 8-10% of population in United States) to match the empirical results. In light of this, more recent work by Kaplan and Violante (2014) uses the tradeoff between return and liquidity to generate a group of wealthier but financially constrained households; those who have parked their wealth in illiquid assets such as houses. The presence of these households with higher MPC (around 15 to 20% of the US population\(^3\)) helps match the average MPC. Moreover, this newer model can match the bi-modal correlation of MPC with income, as illiquid households, both poor and wealthier, have higher MPC.

In an influential series of papers, Mian and Sufi (2011) and Mian et al. (2013) show significant response of consumption to positive housing wealth shocks in 2002-06 and to negative housing wealth shocks in 2008-2010. Households in zip codes with large housing wealth increases raised their consumption during the housing boom. During the recession, these households cut their consumption by more. This research has revived interest in the role of housing wealth in consumption. Since then, both empirical and theoretical research has argued housing wealth shocks were the key factor in affecting consumption in the boom and bust periods.

However, there is no consensus on the efficacy of fiscal policy transfers during recessions with large housing wealth falls. Most of the theoretical literature predicts that fiscal transfers are effective at stimulating consumption in recessions with large wealth falls for two reasons. First, as households face tighter borrowing constraints as they go into negative equity on their houses, their propensity to consume increases. This

\(^3\) Kaplan and Violante (2014) use the Survey of Consumer Finances to measure the proportion of hand to mouth households with illiquid assets and find close to 15% of households fall under this category.
logic is familiar from the borrowing constraints literature such as Deaton (1991). Second, the buffer stock theory of life cycle saving in Carroll and Kimball (1996) stipulates consumption as a concave function of wealth due to the precautionary savings motive. When wealth falls, MPC increases. Yet in practice, there is a concern that in a housing crisis, overleveraged households will use their stimulus checks to pay down debt, rather than increasing consumption. Sahm et al. (2015) show that during the payroll tax holiday of 2011, a significant proportion of households (35% of the sample) mostly used the increase in income to improve their balance sheets instead of spending. Sahm et al. (2015) consider them “balance sheet households”, i.e. those whose consumption responses to transitory income changes mimic permanent income hypothesis consumers even though they are anything but. Regions where house prices declined significantly in 2008-10 also had more households with larger negative balance sheets. If more households used the rebates for balance sheet repair, aggregate MPC would be lower in these areas. I am unaware of any prior research that analyzes whether balance sheet repair affected MPC out of fiscal stimulus and if this outweighs these two channels.

In addition, this chapter is connected to research evaluating the regional variation in effectiveness of government policies during the 2008 recession. Beraja et al. (2017) find QE1 elicited much higher refinancing and consumption responses from households in less depressed regions of the country. They argue that variations in housing equity made it easy for households in less depressed areas to refinance, thus helping them smooth consumption. The authors also claim that monetary policy actually exacerbated consumption inequality rather than decreasing it. Given that the stated goal of stabilization policies (whether monetary or fiscal) is to help households in areas hardest hit by the recession, this result is important for future policy considerations. Unlike Beraja et al. (2017), I study regional variation in effectiveness of fiscal policy, but the possible lessons are similar.

The remainder of this chapter is structured as follows: Section 2 discusses the recent
history of counter-cyclical fiscal policy. Section 3 discusses the Great Recession and the Economic Stimulus Act of 2008, which this chapter studies. Section 4 discusses the data and empirical work, including the results. Section 5 concludes.

1.2 Recent History of Counter-cyclical Fiscal Policy

Since John Maynard Keynes’ seminal contributions, counter-cyclical fiscal policy has been recognized as a potential tool for governments to stabilize output during recessions. The pendulum swung away from fiscal policy in the past three decades before the Great Recession, as the policy and academic consensus shifted towards using monetary policy as the key lever in managing business cycles. This reflected doubts on the expertise of fiscal policymakers, the relative insulation of monetary policy from political constraints and theoretical doubts about timeliness and effectiveness of fiscal policy. As Blinder (2016) notes, the primacy of monetary policy as the tool for macroeconomic stabilization was shared by a consensus of economists and policymakers.

Even with this consensus, fiscal policy has been used extensively even before the Great Recession. There are three groups of tools in the counter-cyclical fiscal policy toolbox. The first are automatic stabilizers. As the tax system is progressive, tax receipts go down when incomes fall and unemployment rises during recessions. On the other side, unemployment benefits, food stamps and other transfers rise during recessions. Without any discretionary government action, these elements work to offset fluctuations in output by spending more when output is below trend and vice versa. Ever since the current tax system was set up in 1913, automatic stabilizers have been an important part of counter-cyclical fiscal policy in the United States and remain so. The other two tools are discretionary changes to government spending and discretionary changes to taxes. The first among these, discretionary government spending had been largely disregarded before the Great Recession. Instead, the focus has been on the third tool, discretionary
changes to taxes.

In 1992, facing a recession, George H.W. Bush lowered tax withholding rates with the goal of increasing consumption and stabilizing output. Similarly, Bill Clinton proposed a fiscal stimulus package in 1993 mixing both government spending and tax cuts but was thwarted by Congress. In 2001, George Bush passed a $1.35 billion cut in taxes, which was a mix of stabilization policy and long term tax cuts. This included the provision of fiscal rebates (between $300-$600 per household) between July and September 2001. The 2001 fiscal stimulus policy has been studied extensively (Johnson et al. (2006), Misra and Surico (2014)) and was found to have been effective in stimulating consumption.

Since the Great Recession, limits to monetary policy have become more obvious and the discussion on discretionary fiscal policy has been reignited. As the federal funds rate hit the zero lower bound, the conventional channel of monetary policy became harder to implement. While the Federal Reserve engaged in unconventional monetary policy in the form of quantitative easing, commentators saw discretionary fiscal policy as a key tool to complement monetary policy. As Blinder (2016) argues, the crowding-out costs of fiscal policy would be minimal in a world with zero interest rates, and the fiscal burden placed by such policy would be lower due to the low borrowing costs for the government.

In addition, some economists have questioned even the time-worn view that fiscal stimulus policies would not affect the long term potential output of the economy. DeLong and Summers (2012) argue that if a deep recession lowers future potential output through effects on productivity or labor force skill deterioration, then expansionary fiscal policy can have permanent and larger effects on output. Such possibilities make it even more pertinent to engage in expansionary fiscal policy during large downturns like the Great Recession.

Policymakers indeed took note, as both George Bush and Barack Obama passed two

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4See DeLong and Summers (2012) on the detailed implications of such hysteresis.
fiscal stimulus packages in 2008 and 2009. The first, the Economic Stimulus Act of 2008, was passed in January 2008. It included measures such as tax breaks for equipment purchases by businesses, payments to disabled veterans and some senior citizens, along with tax rebate provision to 130 million US households. In February, the American Recovery and Reinvestment Act of February 2009 (ARRA) was passed. This was a much larger stimulus package of $787 billion, which included $288 billion in tax cuts to households and firms, $275 billion in extra unemployment and other benefits and $275 billion in contracts, loans and grants. Of these various policies, I study the Economic Stimulus Act of 2008.

1.3 The Great Recession and the Economic Stimulus Act of 2008

The Great Recession of 2007-09 was the deepest recession since the Great Depression of the 1930s. Between December 2007, when the recession started and June 2009, the unemployment rate had increased from 5% to 10%. Real GDP fell by 4.3% between peak and trough, and total personal consumption expenditures fell by 2.49%. This period was also characterized by large losses to household and corporate wealth, as house prices fell around 30% on average between mid-2006 to mid-2009 and the S&P 500 index fell by 57% between October 2007 and March 2009. Finally, net worth of households and non profit organizations fell by 20% between 2007 and 2009.

Unlike other recessions in recent history, the Great Recession was unique, as it involved the housing sector so prominently. As house prices declined severely during the recession, significant proportions of American households were underwater on their mortgages (as of 3Q 2009, 4.5 million homeowners). This led a large number of house-

\[5\] The recession technically ended in June 2009 as per NBER’s Business Cycle Dating Committee, but the negative effects lingered for multiple years.

\[6\] http://www.nytimes.com/2010/02/03/business/03walk.html?pagewanted=all
holds to default on their mortgage (lenders filed 3.8 million foreclosures in 2010, which was 23% increase compared to 2008 according to Realtytrac). Those who were not in foreclosure often were delinquent on their mortgage payments, as the number of households missing at least one payment went up to 5 million by 2009. There were fears the recession would become as deep and painful as the Great Depression.

As the recession was strengthening in 2008, the Economic Stimulus Act (ESA) was passed by United States Congress in January 2008 and signed by President George W. Bush on February 13, 2008 as a “booster shot” for the American economy entering a recession. The most significant part of the Act was the provision of tax rebates to most American households. The Internal Revenue Service (IRS) disbursed $100 billion in rebate checks to over 130 million households. Payments ranged from $300-$600 for singles, $600-$1200 for couples plus $300 in child credit per child. The payments were provided to households with annual income above $3,000 and were phased out for households with incomes above $150,000 (for couples and $75,000 for individuals).

As worries about the financial system were rising, the authorities attempted to distribute the rebate payments as soon as possible. Distribution of the rebates started in mid May and ended by the end of July. Rebates were either sent through direct deposit or through mail, based on whether households had provided the IRS with direct deposit bank account numbers. Figure 1.1 shows the weeks of rebate receipt by method in the sample. Households signed up to direct deposit received their checks mostly in May, while the households with mail receipt received checks throughout late May, June and July.

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8 http://www.cnn.com/2008/POLITICS/02/13/bush.stimulus/
9 The payments equaled the households’ net tax liability.
10 If gross income was higher than $75,000 for individuals and $150,000 for couples, the payments were lowered by five percent of the gap between the gross income and the thresholds.
11 The rebate distribution happened after Bear Stearns had been bought out by JP Morgan in March and before Lehman Brothers filed for bankruptcy in September 2008.
Effective randomization of the rebate disbursement process makes this policy episode attractive for research. Due to administrative difficulties, the Internal Revenue Service (IRS) used the last two digits of the family head’s social security numbers to disburse the rebates. Since these digits are assigned effectively randomly, the receipt date for rebates is also random. Such randomization in the variation in rebate receipt allows for causal estimation of MPC.

1.4 Data, Empirical Strategy and Results

1.4.1 Data

To document how the MPC out of tax rebates is correlated with local house price declines, one requires a dataset that includes three characteristics. The first is high frequency spending data from a large, representative sample of United States households. We also need information on when and how these households learned about and received their tax rebates. Finally, to study how the MPC is related to local house price declines, we need data on local housing price changes. I thus combine i) weekly spending data from the Nielsen Homescan Consumer Panel (NCP), ii) a supplemental Nielsen
survey that records dates when households received fiscal stimulus rebates in 2008 and iii) housing market data from Zillow Inc.\textsuperscript{12}

The NCP is a weekly panel dataset following 60,000 U.S. households uniquely suited to the needs. NCP data is high frequency, as respondent households scan their expenditures through barcodes when they purchase goods from stores. These purchases are recorded daily and then aggregated to weekly spending data. Hence, the NCP suffers much less from memory bias compared to traditional surveys such as the Consumer Expenditure Survey (CEX). The size of the panel (over 5 times as many respondents as the CEX) improves statistical power. Geographic coverage of the NCP data extends to 49 states across the United States. Nielsen attempts to create a balanced sample by using stratified sampling based on demographic variables such as household size, income, race, education and occupation. In addition, NCP provides survey weights, making the data projectable to the US population. Finally, the dataset records demographic variables such as household size, income, age, presence and age of children, employment, education, marital status, occupation and race. These variables allow me to check for sample balance and control for demographic characteristics.

One significant disadvantage of the data is that NCP does not include all consumption goods. It includes household goods and services purchased on trips made to stores. The spending is mostly concentrated in grocery, drugstore and mass-merchandise sectors. Food, alcohol, drug products, health and beauty products, small appliances and electronic goods are covered. The data does not cover spending on apparel, vehicles, housing and health services. The coverage of the NCP only includes around 35\% of all nondurable goods from the CEX. My results are thus scaled to ensure the correct interpretation.\textsuperscript{13}

\textsuperscript{12} The data employed in this study is a combination of data licensed from Nielsen and data available through the Kilts-Nielsen Marketing Data Center at the University of Chicago Booth School of Business. The Kilts-Nielsen data are available at http://research.chicagobooth.edu/nielsen/

\textsuperscript{13} I discuss scaling issues and goods coverage in the Section A of the Appendix.
Following Broda and Parker (2014), I combine the NCP with the 2008 Economic Stimulus Supplementary Survey (run by Nielsen with Broda and Parker (2014)) which surveyed NCP recipients on fiscal rebates. Respondents were asked whether they received stimulus checks in 2008, when they learnt about the checks, when they received them and the amounts. The survey also records the receipt method, whether direct deposit or mail. Questions on liquidity status and financial planning help understand households’ response to the rebate checks. Similar to Broda and Parker (2014), I drop households who do not report receipt of the rebates or report receiving the rebate beyond the reasonable time frame.

Finally, I include data on local housing market conditions from Zillow in order to proxy changes in household housing wealth with local housing price changes. I use Zillow’s House Price Index\textsuperscript{14} to construct a measure of these changes. Zillow’s data is nonproprietary and yet tracks the Case-Shiller indices very well. It also has very good coverage across zipcodes in the United States. Combining all three datasets leaves me with weekly spending and rebate receipt data on 17,000 households for all 52 weeks in 2008 alongside data on local (zipcode level) housing prices.

1.4.2 Empirical Strategy and Results

The empirical strategy uses randomized variation in rebate receipt. I use this to understand how the estimated MPC varies with local house price declines. Significant variation in housing price changes is important for the validity of this exercise. Figure A.4 in the Appendix shows the distribution of housing price changes in zipcodes between December 2005 (the peak of the housing market boom) and May 2008 (when the first rebates were sent). Housing price changes range from a fall of 60% to a rise of 40%. Next, I show the differences in MPC across regions through subsample analysis and polynomial regressions.

\textsuperscript{14} I use Zillow’s Home Value Index (ZHVI) for All Homes (SFR, Condo/Co-op) Time Series.
1.4.2.1 Subsample Results

The baseline regressions are specified to allow estimation of the dynamic causal impact of rebates on weekly household spending in the NCP. I follow Broda and Parker (2014) in using a distributed lag model as in equation (1). I include household and time fixed effects to control for aggregate time specific factors and time invariant personal characteristics.

\[ C_{i,t} = \mu_i + \sum_{k=-1}^{35} \beta_{t-k} \text{REB}_{i,t-k} + \lambda_{m,t} + \epsilon_{i,t} \] (1.1)

where \( C_{i,t} \) is the weekly spending by households in the NCP, \( \mu_i \) denote household fixed effects and \( \lambda_{m,t} \) denote weekly time fixed effects by method of rebate receipt. In the baseline regressions I set \( \lambda_{m,t} = \lambda_t \). I also separate the time fixed effects by method of receipt for robustness checks. The regressions use the maximum possible lags (35 lags) for rebate receipt and one lead as well. \( \text{REB}_{i,t} \) is an indicator variable for rebate receipt that takes the value of 1 if the household \( i \) received a rebate check in week \( t - k \). I only use the indicator variable and not the amount of the rebate, as the rebate amount is based on personal characteristics that are not random, hence the possibility of omitted variable bias.

Households raise their NCP spending significantly in the first four weeks after rebate receipt. Figure 1.2 shows the impulse response function from the week of receipt to the next seven weeks, alongside the confidence bands at the 95% level. Rebate coefficients for the first two weeks are positive and statistically significant, showing strong consumption responses to rebates. Households raise average spending on NCP-measured household goods in the week of receipt by roughly 14 dollars, 12 dollars in the week after. The total cumulative spending in the first four weeks of receipt is higher by 38 dollars and significant at the 5% level. The average marginal propensity to consume NCP goods for the first month is 4.23% of average rebate size. The Nielsen Consumer Panel (NCP) only covers around 35% of nondurable consumption in the CEX. In order to make these
results comparable to CEX estimates, I scale the MPC by multiplying the estimate of MPC for NCP goods by 100/35. Doing this exercise, the average MPC for nondurables in the month of receipt is 12.1%, which is in line with results found by Broda and Parker (2014).

Relative to the previous literature, I focus on MPC heterogeneity by asking the following question: does the average MPC vary by local housing market conditions? To get an initial answer to this question, I split the sample into three different geographic sub-samples. Each sub-sample groups together households in zipcodes where the housing price changes fell into various terciles of the distribution. Figure 1.3 below shows the cutoffs for each tercile. The lowest tercile covers areas where local housing prices had fallen by 9% to 60%. These are the areas that were most severely hit by the housing crisis.

In each sub-sample, I estimate equation 1 separately. This formulation allows the comparison of spending responses within each area between households who had received rebates with those who had not. Next, I sum up the rebate coefficients for the first four weeks after rebate receipt, and scale the cumulative response into MPC by
Finally, I show the cumulative first four weeks’ MPC (in percent) in Figure 1.4 along with 95% confidence bars.

The MPC out of fiscal rebates in the lowest tercile is significantly lower than the MPC for the two higher terciles. In the lowest tercile, average household spent 7 dollars out of their rebates in the first four week of receipt. In contrast, the average household in the top two terciles spent 51 and 52 dollars out of their rebates in the first four weeks of receipt, both significant at the 5% level. Scaling the estimates, the first month spending response is rebates is 2.21% in the lowest tercile, and between 15-16% in the second and third tercile. The gap between the lowest and the other two terciles is statistically significant as well. Running equality of coefficients tests rejects the null hypothesis of no difference between the coefficients at 1% level.

Figure A.5 in the Appendix shows spending responses in the following four weeks of rebate receipt (2nd month). None of the spending responses are statistically significant,

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\[15\] Average rebate amounts in the terciles are very similar, the maximum at $920 and minimum at $890.
but the response in the lowest tercile is again much lower than those in the first two terciles. Table A.3 shows the detailed regression results for the full sample and the three terciles.

### 1.4.2.2 Polynomial Specification

While the subsample analysis gives a flavor of the differences in MPC between areas with large housing price falls and areas without, I am interested in the full correlation between changes in local housing prices and average MPC. In order to measure this, I use the whole sample and run a polynomial regression using a cubic function of the percentage change in housing prices interacted with rebate receipt lags. I choose the cubic form to allow for nonlinear relationships. The regression specification allows the time fixed effects to be different based on the cubic function of zip code level housing price changes, as in equation (2). $\Delta H$ is the percentage change in housing prices in the zip code of household $i$ according to Zillow’s data. Predicted coefficients at each level
of $\Delta H$ along with 95% confidence bands are shown in Figure 1.5. Standard errors are clustered at the zip code level.

$$C_{i,t} = \mu_i + \lambda_{m,t} + \lambda_{m,t} \times \Delta H + \lambda_{m,t} \times \Delta H^2 + \lambda_{m,t} \times \Delta H^3$$

$$+ \sum_{k=-1}^{35} \beta_{t-k} \text{REB}_{i,t-k} + \sum_{k=-1}^{35} \eta_{t-k} \Delta H \times \text{REB}_{i,t-k}$$

$$+ \sum_{k=-1}^{35} \gamma_{t-k} \Delta H^2 \times \text{REB}_{i,t-k} + \sum_{k=-1}^{35} \rho_{t-k} \Delta H^3 \times \text{REB}_{i,t-k} + \epsilon_{i,t} \quad (1.2)$$

**Figure 1.5: Month 1 MPC by Housing Price Change**

The full sample regression provides similar results to the subsample graphs, while adding a few important nuances. Figure 1.5 shows the strong upward sloping correlation between spending responses and local housing price changes after including all the polynomial effects. Spending responses fall as housing prices decline more. Figure A.6 in the Appendix shows the spending response for the second month as well. The responses again show a positive slope. Detailed results of the polynomial regression are shown in Table A.4 in the Appendix. Additionally, I test cumulative coefficients for level and linear effect of $\Delta H$.

**Hypothesis 1.** $H_0 : \sum_{k=0}^{3} \beta_{t-k} = 0$
The Wald test rejects the null hypothesis at 1% level; (p-value = 0.0000). In zipcodes with a zero housing price change, the spending coefficient is 41 dollars, which scales to a MPC of 12.7%.

**Hypothesis 2.** $H_0: \sum_{k=0}^3 \eta_{t-k} = 0$

Similarly, I also reject the null hypothesis of zero linear effect of $\Delta H$ (p-value = 0.0116). A one percentage point increase in the local housing prices change variable (from -10% to -9% for example) is associated with a 1.8 dollar increase in first month NCP spending responses out of the rebates, which is an increase in MPC of 0.6 percentage points.

### 1.4.2.3 Liquidity Status and Robustness Checks

Recent literature has emphasized household liquidity status as a crucial parameter in explaining MPC heterogeneity. Lack of liquid wealth signals borrowing constraints and hence high MPC.\(^{16}\) Kaplan and Violante (2014)'s model of fiscal rebate responses rests significantly on hand to mouth households who have little liquid wealth. Such households have much larger MPC than non hand to mouth households. Behavioral models such as Angeletos (2001) also predict hyperbolic discounter households have low liquid assets as a commitment mechanism and high MPC out of rebates. Empirically, Broda and Parker (2014) find the quarterly MPC of illiquid households in quarter of receipt is 32.1%, significantly higher than 13.5% for liquid households.

Is the negative relationship between MPC and local house price declines driven by the behavior of liquid or illiquid households? To answer this question, I utilize the following question in the dataset: *In case of an unexpected decline in income or increase in expenses, do you have at least two months of income available in cash, bank accounts, or easily accessible funds?* Households answering yes (no) to the question are deemed liquid.

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\(^{16}\) Lack of liquid wealth does not always imply borrowing constraints. For individuals with low incomes and low but stable expectations of permanent income, a small level of liquid assets is enough as an optimum buffer.
(illiquid) households. In equation (3), the polynomial specification is allowed to vary for liquid and illiquid households, including time fixed effects. If liquidity status is a persistent characteristic, separate time fixed effects can control for the difference in persistent spending differences between the liquid and illiquid household groups. LIQ is a dummy variable used to denote households with liquid assets.

\[
C_{i,t} = \mu_i + \lambda_{m,t} + \lambda_{m,t} \times \Delta H + \lambda_{m,t} \times \Delta H^2 + \lambda_{m,t} \times \Delta H^3 + \lambda_{m,t} \times LIQ_i + \lambda_{m,t} \times \Delta H \times LIQ_i + \lambda_{m,t} \times \Delta H^2 \times LIQ_i + \lambda_{m,t} \times \Delta H^3 \times LIQ_i + \sum_{k=-1}^{35} \beta_{t-k} \text{REB}_{i,t-k} + \sum_{k=-1}^{35} \eta_{t-k} \Delta H \times \text{REB}_{i,t-k} + \sum_{k=-1}^{35} \gamma_{t-k} \Delta H^2 \times \text{REB}_{i,t-k} + \sum_{k=-1}^{35} \rho_{t-k} \Delta H^3 \times \text{REB}_{i,t-k} + \sum_{k=-1}^{35} \zeta_{t-k} \text{REB}_{i,t-k} \times LIQ_i + \sum_{k=-1}^{35} \xi_{t-k} \Delta H \times \text{REB}_{i,t-k} \times LIQ_i + \sum_{k=-1}^{35} \chi_{t-k} \Delta H^2 \times \text{REB}_{i,t-k} \times LIQ_i + \sum_{k=-1}^{35} \tau_{t-k} \Delta H^3 \times \text{REB}_{i,t-k} \times LIQ_i + \epsilon_{i,t} \tag{1.3}
\]

These regressions re-affirm a prior result and establish a new one. Figure 1.6 shows spending responses for illiquid and liquid households. Illiquid households always spend more out of their rebates compared to liquid households. This affirms results from prior studies such as Broda and Parker (2014). In addition, I find the negative correlation between housing wealth declines and average MPC across most of the distribution come from both liquid and illiquid households.\(^\text{18}\)

F-tests for the linear slope are rejected at the 10% level for both the liquid and illiquid households groups; Illiquid Households:(p-value = 0.089), Liquid Households:(p-value = 0.062).

\(^{17}\) A recent literature discusses whether people hold low levels of liquidity because of personal characteristics such as impatience or due to circumstances such as unanticipated shocks to wealth or income. For a discussion on this circumstance vs. characteristics views of liquidity status and effect on MPC, Gelman (2016) provides a good summary.

\(^{18}\) Figures A.8 and A.9 in the Appendix show Figure 1.6 with confidence intervals.
There are three interesting parts to this result. First, research has recently focused on illiquid households as the key group for explaining MPCs out of transitory income shocks such as rebates. The results are however not driven by one group or another, but are general across both groups. Any underlying cause that only affected illiquid households was not the reason for the downward sloping relationship. Second, Figure 1.6 also shows the nonmonotonicity at the lower end of the housing price distribution comes primarily from illiquid households, as the results for liquid households show much less nonmonotonicity.\textsuperscript{19} Finally, the aggregate pattern is not driven by variation in the proportion of liquid and illiquid households. Using the actual proportions of liquid households at each $\Delta H$ bin and using the mean proportion for the full sample gives the same pattern, as shown in Figure A.10 in the Appendix.

The main result is also general across other dimensions such as income and age. In order to understand if this pattern is similar for poorer and richer households, I create a

\textsuperscript{19}Why do households with illiquid assets have higher MPC in areas with large housing price declines? I explore this in Subsection 2 of the Appendix.
binary variable separating households with 2006 incomes above $70,000 from those below. Figure A.11 in the Appendix shows poorer and richer groups have similar patterns in their predicted coefficients from the regression. Both groups display the negatively sloped pattern with local housing price declines. As expected, poorer households always have higher MPC compared to richer households. Next, I split the data by the age of the household head, separating older and younger households. Figure A.12 displays the downward sloping pattern for both older and younger households, even as the pattern is much more striking for younger households. In addition, younger households display a more striking nonmonotonicity as the illiquid and young categories have higher correlation.

As a robustness check, I winsorize the data by cutting the top 0.1% of spending. Figure A.13 in the Appendix shows the results remain the same. I also run the baseline regressions in 10 subsamples which include deciles of the housing price change distribution. Figure A.14 in the Appendix affirms the basic results of the parametric regressions. Finally, I add the following control variables to the polynomial regression; high income status, Hispanic and Black dummies, college education dummy and household size. Each of these variables are interacted with the leads and lags of the rebate receipt variable, which controls for dynamic effects of these characteristics on MPC. Figure 1.7 shows that the general result is robust to the addition of household covariates.

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20 I take the maximum of the age of the male and female heads of households, and categorize based on whether this age variable is above or below 55 years.
\[ C_{i,t} = \mu_i + \lambda_{m,t} + \lambda_{m,t} \times \Delta H + \lambda_{m,t} \times \Delta H^2 + \lambda_{m,t} \times \Delta H^3 \]
\[ + \sum_{k=-1}^{35} \beta_{t-k} \text{REB}_{i,t-k} + \sum_{k=-1}^{35} \eta_{t-k} \Delta H \times \text{REB}_{i,t-k} + \sum_{k=-1}^{35} \gamma_{t-k} \Delta H^2 \times \text{REB}_{i,t-k} \]
\[ + \sum_{k=-1}^{35} \rho_{t-k} \Delta H^3 \times \text{REB}_{i,t-k} + \sum_{k=-1}^{35} \zeta_{t-k} \text{REB}_{i,t-k} \times \text{EDUC}_i + \sum_{k=-1}^{35} \psi_{t-k} \text{REB}_{i,t-k} \times \text{HISP}_i \]
\[ + \sum_{k=-1}^{35} \upsilon_{t-k} \text{REB}_{i,t-k} \times \text{BLACK}_i + \sum_{k=-1}^{35} \xi_{t-k} \text{REB}_{i,t-k} \times \text{INC}_i + \sum_{k=-1}^{35} \nu_{t-k} \text{REB}_{i,t-k} \times \text{SIZE}_i + \epsilon_{i,t} \]

Figure 1.7: Regressions with Controls

1.4.2.4 Instrumental Variable Regressions and Sample Balance

Multiple factors can cause the negative correlation between local housing price shocks and average MPC. Imagine a world where housing prices around the country are shocked randomly. Such exogenous fall in housing prices would lower households’ wealth and push a proportion of households to underwater status on their mortgages differentially across the country. This would also affect the budget constraints of these households and force some of them to be more credit constrained than others. Finally, differential shocks
to housing wealth would also push households in different areas differentially towards defaulting on their mortgages, or paying back their debt and deleveraging. All of these changes can affect the marginal propensity to consume out of rebates. I call these the “housing net worth” channel. Importantly, if the housing shocks are large enough, they will also amplify through effects on local economic activity. Mian and Sufi (2014) show this was the case in the Great Recession, as areas with larger fall in housing net worth also experienced larger falls in non-tradable employment. Hence, the housing net worth channel includes direct effects on MPC and indirect effects through effects on the local economy.

A separate issue is if a different shock created the differential downturn across areas, affecting both housing prices and MPC. Recent research has often attempted to guard against this concern by using an instrumental variable approach. A topography based housing supply elasticity variable created by Saiz (2010) has been used extensively as an instrument for measuring exogenous variation in the boom and bust cycle of housing prices between 2002-2009. Areas with inelastic housing supply due to terrain respond much more through prices when housing demand goes up, compared to areas with elastic housing supply where it is easier to build. Importantly, if a third factor is affecting both housing prices and MPC, it is not clear why counties with more or less elastic housing supply would be shocked more or less by an income or employment shocks that are uncorrelated to the housing market. Mian et al. (2013) make this point in their analysis of the impact of housing wealth shocks on consumption.

The housing supply elasticity instrument measures random variation in housing prices in the boom years, but is not exogenous for the 2006-09 period. As counties with inelastic housing supplies saw larger increases in housing prices between 2002 and 2005, households also took more debt and had higher leverage than in elastic counties. As of 2006, low elasticity areas were different from high elasticity areas in other ways aside from the level of house prices as they had higher LTVs. As seen in Figure A.16,
areas that had large booms in housing prices in 2002-05 also had large busts in housing prices in 2005-08. This means that the usage of the housing supply elasticity instrument provides exogenous variation in the full boom-bust cycle. In essence, using the instrument allows the researcher to compare how the MPC differed between areas which did not go through the boom-bust cycle and those that did.

I use the housing supply elasticity as an instrument for changes in housing prices and estimate equation (2) as a 2SLS regression. If the empirical results are all coming from a third factor that caused both the lower MPC and higher drops in local housing prices, and is exogenous to the instrument, then one should see a very different pattern in the 2SLS regressions. In the first stage, I get a F-statistic of 44, meeting the strong instrument criteria as specified by Stock and Yogo (2002). Figure 1.8 shows that both i) the first month MPC out of rebates through the housing price change variable predicted by the instrument (along with the 95% confidence bands) and ii) the first month MPC in the OLS regressions from Section 4.2.2 for comparison. It is worth remembering that the instrument only predicts a subset of the actual $\Delta H$ variable, hence the IV results cut off at these ends rather than at the full extremes of the $\Delta H$ distribution.

Figure 1.8 shows that the upward sloping relationship between local housing market price changes and average MPC remains true in the 2SLS regressions. Compared to the OLS regressions, MPC in the 2SLS regressions are slightly larger (although not statistically different) and the slopes are very similar.\(^{21}\) This suggests that larger boom-bust cycles in local house prices caused certain regions to have lower MPC out of rebates. I can rule out differences in local conditions unrelated to the boom-bust cycle which caused both a fall in house prices and low MPC. These include, for example, dependence on the construction sector.

Finally, I turn attention to a separate channel that may cause an endogeneity problem. The baseline regressions include time and household fixed effects. The worry is

\(^{21}\)As the instrument is at the MSA level, the regressions lose power, and standard error bands are larger.
the following: are there certain household characteristics which push households to live in housing boom/bust zipcodes? If these characteristics also change their spending patterns throughout the sample, household fixed effects will control for such characteristics. However, if the characteristics do not influence spending on average, but affect MPC out of a rebate, household fixed effects cannot control for such factors. While I am not aware of any such factor, I check the sample balance across covariates. Figures 1.9 and 1.10 show i) 20 bins of mean levels of covariates along with ii) quadratic fits after regressing the covariate on \( \Delta H \) through a bin scatter plot. The key covariates used are household income in 2006, household size, age of the oldest head of the family, liquidity status, black and hispanic status, average weekly spending, and work status.

On most dimensions, there are no large differences across the distribution of \( \Delta H \). The subsamples are also balanced on other statistics, such as the timing of receipts, the method of receipt and average rebate amounts. To provide more detailed information, I also show mean covariate levels across deciles of the \( \Delta H \) distribution. These statistics are shown in Tables A.1 and A.2 in the Appendix and affirm these results.
The only covariate with large differences is ethnicity. The concentration of the housing crisis in particular states explains racial differences across the subsamples. California, Florida, Arizona and Nevada constitute the states with the largest average fall
in housing prices during this period. The same states also have the largest proportion of Hispanic populations in the nation. Figure A.17 in the Appendix shows all of the counties in the Nielsen dataset by which decile of the $\Delta H$ distribution they belong to. Crucially, counties in various deciles are spread out instead of being clustered in one state, hence the results are not being driven by one state.

### 1.4.3 Reported vs. Revealed Preference

Parker and Souleles (2017) discuss the difference between reported preferences in surveys and revealed preference in actual human behavior. They also show that households who said they mostly spent their ESA payments spent twice as much in reality compared to other households. Is it possible that households who wanted to and tried to save/deleverage did so much more strictly in harder hit areas? Were the proportions of such savers/deleveragers higher in those areas? In order to understand if these differences account for the regional heterogeneity in MPC, I utilize a question on what the households were using the rebates for. Available answers to this question included; “Mostly to increase spending”, “Mostly to increase saving”, “Mostly to pay off debt” and “Not sure/don’t know”. I look at the geographical heterogeneity across spenders (those who use the rebate to mostly increase spending) and savers/deleveragers (those who use the rebate to mostly pay down debt or increase savings). The proportion of households who are reported savers/deleveragers vs. spenders is stable across the local housing price change distribution. This suggests it was not the difference in proportion of these groups which led to lower MPC in the hardest hit areas.

Figure 1.11 and 1.12 show the discrepancy between hard hit areas and other areas comes instead from the behavior of reported savers and deleveragers. In the hardest hit tercile, savers and deleveragers truly do not spend out of the rebate at all as their MPC is zero. However, in other areas, they spend around 10-20% of the rebates on nondurables in the month of receipt. On the other hand, the MPC of reported spenders is similar.
Figure 1.11: Savers and Deleveragers

across the three terciles. Spenders spend around 30% of their rebate in the first month, with all estimates statistically significant.

Figure 1.12: Spenders
These results suggest the role of debt salience in driving differences in responses to the ESA payments. In the hardest hit areas, the gap between reported and revealed preferences are the lowest while in other areas, this gap is much higher. If households were really debt salient in the hardest hit areas, they would possibly follow through much more seriously on their plans to save/deleverage out of the rebates, while those who were less debt salient would do this less strictly.

1.5 Conclusion

In this chapter, I have shown empirically how the effectiveness of fiscal rebates varied with local housing price declines in 2008. Using a combination of Zillow housing price data, the Nielsen Consumer Panel and a supplemental Economic Stimulus Payments survey, I analyzed the local average MPC out of rebates provided in the 2008 Economic Stimulus Act. The randomization of the 2008 rebates allows me to causally estimate MPC using a distributed lag regression framework. I establish the primary result: average MPC out of 2008 fiscal rebates was smaller in areas where local house prices declined more sharply. These results are robust to the exact specification of the regression, including the use of housing supply elasticity as an instrumental variable. I also show this trend is general across households with and without liquid assets, and across households with higher and lower incomes. I also show that households in areas where housing prices fell by different levels were similar in terms of socio-economic characteristics. Finally, I show that this is driven by the relative difference in behavior of reported savers and deleveragers.
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Chapter 2

Policy and Theoretical Implications of Regional Heterogeneity in Fiscal Stimulus Effectiveness

2.1 Introduction

The results in Chapter 1 present a dilemma for the design of targeted transfer policies. Prior research on MPC heterogeneity by income or cash on hand has found that financially constrained households have a higher MPC. In this case, targeted transfers to such households may be desirable both because they stimulate aggregate demand, and because such redistribution is beneficial from a utilitarian perspective: there is no tradeoff between the utilitarian and aggregate demand stabilization motives for targeted transfers. Results in Chapter 1 suggest, however, that transferring resources to regions most affected by a recession characterized by a collapse in housing wealth - who arguably need financial support the most - may be less effective in stimulating aggregate demand. In this sense, there is a tradeoff between utilitarian and aggregate demand stabilization motives for rebate provision.

These results also pose a puzzle for consumption models. In a canonical buffer stock model of consumption and saving, consumption is a concave function of net wealth:

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1 Based on work co-authored with Keshav Dogra at the Federal Reserve Bank of New York. I acknowledge computing resources from Columbia University’s Shared Research Computing Facility project, which is supported by NIH Research Facility Improvement Grant 1G20RR030893-01, and associated funds from the New York State Empire State Development, Division of Science Technology and Innovation (NYSTAR) Contract C090171, both awarded April 15, 2010.
households whose wealth declines more, because of a fall in local house prices, should have a higher propensity to consume out of a tax rebate. To the extent that borrowing constraints are linked to house prices, a fall in house prices should also tighten borrowing constraints, increasing the MPC further. Thus the canonical model predicts a positive relation between the size of local house price declines and MPC. Empirical results in Chapter 1 indicate precisely the opposite.

The recent literature on household consumption has gone beyond the buffer stock model by incorporating a distinction between liquid and illiquid assets, and a richer treatment of housing, mortgage debt, and default. A priori, these features might reverse the counterfactual predictions of the buffer stock model. To understand whether this is possible quantitatively, I develop a heterogenous agent, life cycle, partial equilibrium model featuring illiquid houses, long term mortgage debt, a refinance option, and a default option. The model allows for three channels which might in principle generate a lower MPC in regions with a larger housing crisis. First, the model features wealthy hand to mouth households (Kaplan and Violante (2014)) who hold substantial illiquid wealth, but generally do not adjust wealth in response to transitory income shocks, thus acting like hand-to-mouth households with a high MPC. Large aggregate shocks might force these households to adjust, making them effectively unconstrained and reducing their MPC. Second, households can use a fiscal rebate to pay down long term debt, as suggested by the literature on balance-sheet households (Sahm et al. (2015)); if they are more willing to do so in crisis-affected regions, these regions would have a lower MPC. Finally, rebates can discourage households from making discrete adjustment decisions (such as default) which increase their consumption in the short term, giving these households a strongly negative MPC. To quantify the effect of these channels, I simulate two regional economies, calibrated to the average region in tercile 1 and tercile 2 of the distribution of house price declines. I subject each model economy to exogenous falls in house prices
and income in line with each region’s experience during the Great Recession. I then calculate the MPC out of a temporary cash rebate in each model economy, and study how these vary with the decline in local house prices.

Quantitatively, the channels described above fail to reverse the predictions of a buffer stock model: the model generates a slightly higher MPC in regions experiencing a larger decline in house prices, contrary to the empirical results. This is for three reasons. First, large falls in housing wealth do not directly force homeowners to pay the transaction cost of moving house or refinancing their mortgage. If anything, cash-out refinancing becomes harder to engage in during a housing crisis, due to stricter collateral requirements. Thus households in the more crisis-affected region do not end up with much higher liquid wealth, and do not have a much lower MPC. Second, the model does feature substantial deleveraging in the aggregate, especially in the more crisis-affected region. But while the average homeowner does use some of the rebate to pay down the debt at the margin, this marginal deleveraging effect is weaker in areas with larger house price declines. Finally, the model does feature “default switchers” who default without a rebate, but not if they receive a rebate. Default switchers do have a strongly negative MPC, as they keep making mortgage payments if they do receive a rebate, reducing their consumption. But with a $1,000 rebate, there are simply not enough of them to substantially affect the aggregate MPC, much less to generate the regional differences in MPC observed in the data. Overall, the buffer stock intuition remains a good guide to the predictions of a richer model of housing and consumption: households experiencing a larger decline in wealth should have a slightly higher MPC. The empirical results are sharply at odds with this class of models.

In buffer-stock models, a fall in permanent income reduces the MPC out of transitory income. If households’ expected future income fell more in regions experiencing a deeper housing crisis, this would decrease the MPC in those regions. The baseline

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2Importantly, I allow for the decline in aggregate income and increase in unemployment to be correlated with the decline in local house prices, as observed in the data.
experiment allows this channel to some extent, by assuming perfect foresight regarding
average future income, implying that households in the worst affected regions expected
a slightly lower path of future income, in line with the data. This was not enough to
generate the low MPC observed empirically. An alternative hypothesis is that house-
holds in the worst-hit regions expected their future income to fall even more than it did
ex post. Using regional data on income expectations from the Michigan Survey of Con-
sumers, I rule out this possibility. The 2008-10 period was characterized by a general
fall in income expectations, but there was no substantial differential decline for areas
with larger decline in housing prices. This suggests a fall in expected permanent income
cannot explain the empirical findings quantitatively.

The remainder of this chapter is structured as follows: Section 2 discusses the pol-
icy implications of the empirical results in detail. Section 3 discusses the theoretical
implications of the results. Section 4 concludes.

2.2 Policy Implications

In the presence of MPC heterogeneity, targeted transfers which redistribute from one
group in the population to another can potentially boost employment and output (Oh
and Reis (2012), Jappelli and Pistaferri (2014a)). The results in Chapter 1 suggest a
dilemma for policymakers attempting to design such targeted transfer programmes.
Prior research on MPC heterogeneity such as Broda and Parker (2014) has found that
financially constrained households have a higher MPC out of fiscal rebates. In such a
scenario, targeted rebates to such households achieve a dual purpose; they stimulate
aggregate demand more through the higher MPC, and they are provided to households
who are more in need of financial support. While I do not take a stand on what the util-
itarian benchmarks are, it is safe to say that most policymakers would want to provide
financial support to people who have lost more wealth or income and are struggling
financially during a recession. In this scenario, there is no tradeoff between utilitarian and aggregate demand stabilization motives for targeted transfers; rebates can achieve both goals.

The empirical results suggest, however, that transferring resources to the regions most affected by a recession - who arguably need financial support the most - may have been less effective in stimulating aggregate demand during the Great Recession. If policymakers want to provide financial support to the individuals and regions worst affected by the recession, they might have to forego the possibility of a high aggregate MPC out of the rebates. While this could mean that many of these households pay their debts and stay current on mortgages, the aggregate demand stabilization goal becomes harder to meet. In this sense, there is a tradeoff between the utilitarian and aggregate demand stabilization motives for rebate distribution.

In order to fix ideas, it is useful to consider a stylized general equilibrium model that highlights the tradeoffs between the various motives for redistribution. A closed national economy consists of \( I \) regions which share a common currency and monetary policy. Households in region \( i \) spend some fraction \( \alpha \) of their income on locally produced goods, and the remaining \( 1 - \alpha \) on nationally produced goods. To create a role for fiscal policy in stabilizing aggregate demand, it is necessary to assume that prices are not fully flexible (otherwise there would be no role for aggregate demand stabilization at all) and monetary policy is constrained (otherwise monetary policy would be able to fully stabilize demand, without the need for fiscal intervention). Suppose for simplicity that nominal wages are fixed in the short run (date 1) and flexible in the long run (dates \( t > 1 \)). Thus at date 1 (which represents the recession), households may potentially be rationed in the labor market. Monetary policy is constrained by the zero lower bound; at dates \( t > 1 \), monetary policy is unconstrained, and targets a given level of inflation.

At date 1, a government raises a fixed amount of resources via lump sum taxes, and can choose how to distribute these resources to households in various regions via
nonnegative fiscal transfers. Appendix B.1 presents a full description of the model, and shows that under an optimal allocation of transfers across regions, in each region which receives positive transfers, you have

\[ g^j \left( 1 + \tau^j \frac{\alpha m^j}{1 - \alpha m^j} \right) + \frac{m^j}{1 - \alpha m^j} \sum_k g^k \tau^k \frac{1}{1 - \alpha} - \sum_k \frac{1}{1 - \alpha m^k} = 1 \]  

(2.1)

where \( g^j \) denotes the social marginal utility of the representative household in region \( j \), relative to the marginal value of public funds for the government; \( \tau^j \) denotes the labor wedge in region \( j \), which is positive if that region is in a recession; and \( m^j \) denotes the average MPC in region \( j \). This equation states that the government is more willing to make transfers to region \( j \) under three conditions. First, transfers to \( j \) are more desirable if that region has a high social marginal utility \( g^j \) (i.e. low consumption). Indeed, if all labor wedges were equal to zero, so there was no motive for aggregate demand stabilization, this formula would reduce to \( g^j = 1 \), stating that the government seeks to smooth social marginal utility across regions. Second, to the extent that labor wedges are positive (indicating a recession), transfers to \( j \) are more desirable if that region has a higher MPC \( m^j \), so the recipients will spend more on both local and nationally produced goods, increasing output and employment and closing labor wedges. Finally, to the extent that there is home bias in consumption (\( \alpha > 0 \)), transfers to a region are more desirable if that region experiences a more severe local recession (\( \tau^j > 0 \)), since households will spend some of those transfers locally and reduce the local labor wedge.

Clearly then, if the same regions have high social marginal utility \( g^j \), high MPC \( m^j \), and deep local recessions \( \tau^j \), the policymaker faces no tradeoff: she should simply target all transfers to these regions, which need the most, spend the most, and benefit the most from higher spending. The empirical results suggest, however, that regions with larger declines in house prices - which faced deeper local recessions\(^3\) - had the

\(^3\)Whether these regions had higher or lower social marginal utility is less obvious, even abstracting the possibility that a policymaker might assign different welfare weights to households in different re-
lowest MPC out of fiscal rebates. In this scenario, regionally targeted transfers are a less effective tool. Directing transfers towards regions experiencing the largest fall in house prices helps mitigate the most severe local recessions, but has a limited effect (especially at the aggregate level) because households in these regions are unwilling to spend. Targeting transfers to regions without a severe housing crisis, on the other hand, stimulates aggregate demand to a greater extent, but fails to direct help to the regions most affected.

2.3 Theory

In order to analyze MPC in a data analogous environment, I develop a heterogeneous agent, partial equilibrium, life cycle model of consumption, housing and default choice. Next, I subject the model to a recession similar to the one observed in 2008 in which housing prices fell and unemployment rose. The model robustly predicts that the MPC is, if anything, slightly higher in regions experiencing a larger decline in house prices - contrary to the empirical findings in Chapter 1.

The model contains four additions relative to a standard life-cycle consumption model: illiquid houses, long term mortgage debt, a refinancing option, and a default option. Households can save either in the form of liquid wealth or illiquid houses. They can only borrow against their home equity relative to a loan to value constraint, in the form of long-term debt with a schedule of minimum required mortgage payments. Households must pay a transaction cost either to increase their mortgage debt relative to their payment schedule (i.e. to refinance), or to move house. Finally, households can default on their mortgage, in which case they lose their home, they no longer have to

regions. On average, the regions with the lowest third of house price changes were slightly richer than the middle third of regions, which would suggest higher consumption and lower marginal utility. However, households in these regions were likely more likely to be financially constrained, which would indicate temporarily high marginal utility. In either case, the tradeoff between making transfers to regions with a high MPC versus regions with a deep local recession remains.
make a mortgage payment, and they suffer a utility cost. This cost captures the sum of both pecuniary costs associated with defaulting on a mortgage\(^4\) and the moral and social stigma associated with default.\(^5\)

Since households can save in either a liquid or an illiquid asset, model features both households with very low net worth and households with high illiquid wealth but little liquid wealth, who behave as hand to mouth consumers. As in Kaplan and Violante (2014), the presence of these \textit{wealthy hand to mouth} households allows the matching of steady state MPC observed in the data without a counterfactually large number of households with low net worth. When subjected to an exogenous fall in house prices and income and an increase in unemployment risk, calibrated to the Great Recession, the model matches several important features of this episode - a tightening of loan to value constraints, a fall in house prices which pushed many homeowners underwater, a fall in refinancing activity, and a spike in defaults.\(^6\)

In order to see whether the model can explain the relation between house price declines and MPC out of fiscal rebates observed empirically, I simulate two regional economies, calibrated to the average region in tercile 1 and tercile 2 of the distribution of house price declines, respectively. I subject each model economy to a fall in house prices and income, and an increase in unemployment risk, in line with each region’s experience during the 2008-2012. I then calculate the MPC out of a $1,000 lump sum transfer in each model economy (that is, the average difference in consumption between a household who receives the rebate, and an identical household who never receives the rebate).

\(^4\)In nonrecourse mortgages, defaulting does not lead to garnishing of wages, but credit scores are demolished, and borrowing in the future becomes much more difficult.

\(^5\) Guiso et al. (2013) argue that the majority of homeowners have moral concerns about defaulting on their mortgage.

\(^6\)In this regard, the results are also related to a recent literature (e.g. Ganong and Noel (2016)) which argues that a combination of negative income shocks and negative housing wealth shocks is necessary to generate default. Bhutta et al. (2010) find that median homeowners only started strategically defaulting purely based on home equity losses after equity fell to -62 \% of home’s value. See also Foote et al. (2008).
The canonical buffer stock model of consumption predicts that consumption is a concave function of total financial resources (Carroll and Kimball (1996)). Thus all else equal, a fall in net worth should lead to a higher MPC out of transitory income. Clearly, the empirical result would be hard to explain within such a benchmark model. Importantly, the model allows for three channels which might in principle reverse the counterfactual predictions of the buffer stock model.

First, the model features a significant number of wealthy hand-to-mouth (WHTM) households in the sense of Kaplan and Violante (2014). These households hold substantial illiquid wealth, yet have the high MPC associated with liquidity constrained households, because they hold little liquid wealth and generally prefer not to adjust illiquid wealth in response to transitory income shock. In principle, WHTM households may have a smaller MPC out of transitory income when faced with a larger recession; this shock forces them to pay the transaction cost and withdraw from their liquid asset, making them effectively unconstrained, and so less responsive to rebates. Whether households facing a deeper recession actually have a higher MPC, though, depends on whether they are able to withdraw from their illiquid asset. In the model, withdrawals take the form of cash out refinancing: if households facing a deeper recession cashed out more of their housing equity, they would be flush with liquidity and would have a lower MPC out of fiscal stimulus. However, during the Great Recession, collateral constraints (both Loan-to-Value ratio and Debt-to-Income Ratio) tightened, making it difficult for homeowners to take remaining equity from their houses. This was especially hard for households in areas with larger housing price declines, who were more likely to have negative equity and so to be unable to take advantage of cash out refinancing. Once I impose that loan to value constraints tighten during the recession, in line with the U.S. experience, households in areas with large housing crisis actually have less liquid assets

---

7 Appendix B.2 revisits this result in detail.

8 This is a point argued by Beraja et al. (2017) who show QE1 primarily helped households in areas with less severe local recessions to refinance.
and a higher MPC. Overall, this effect pushes the MPC higher in regions with a larger decline in house prices.

The counterfactual predictions of the buffer stock model could also be reversed if households in regions experiencing a larger decline in house prices were more likely to use their rebate checks to pay down debt (and so less likely to use the checks to finance current spending). Indeed 47% of households in the NCP sample say they were planning to mostly pay off debt with their rebates. To allow for this possibility, the model features long-term mortgages and allows free prepayment of mortgages relative to the amortization schedule. As housing prices fall, a significant proportion of homeowners become underwater on their mortgages. As the interest costs of mortgages are relatively high, some homeowners have an incentive to use rebates to pay back their debt. If the marginal deleveraging effect becomes stronger with a larger fall in housing prices, the average MPC can be smaller, matching the pattern observed in the data.

Finally, the model could in principle generate a lower MPC in more crisis-affected regions through the interaction between household default decisions and rebate receipt. Most households will either default whether or not they receive a rebate, or will never default; but there will be some small fraction of ‘default switchers’ who default if they do not receive a rebate (because the benefit of higher consumption today outweighs the utility cost of default), but do not default if they receive a rebate. While these households have higher welfare if they receive a rebate and are dissuaded from defaulting, they have significantly lower current consumption, since they keep making mortgage payments. Thus these households can have a significantly negative MPC if their mortgage payment is large relative to the size of the rebate. If the proportion of default

---

9Details of such behavior is expanded in a model in Appendix B.3.

10Empirically, it seems reasonable to assume that relatively small changes in cash on hand can affect default decisions. Fuster and Willen (2015) show that cutting mortgage payments in half reduced the probability of delinquency by 55% during the crisis of 2008.

11Here by MPC I mean the treatment effect of rebate receipt, i.e. the difference between a household’s consumption with the rebate and without, divided by the size of the rebate. Since the household’s con-
switchers is much larger in regions with a more severe housing crisis, this mechanism can drive down the average MPC in these regions.

Whether all of these mechanisms actually allow the model to match the relation between MPC and housing price declines observed in the data, though, is a quantitative question. I use the calibrated version of the model to understand how significant all of these mechanisms can be in a data-analogous environment, and how they interact.

2.3.1 Model Setup

**Demographics and preferences:** Households live for $J$ periods and retire at age $J’ < J$. A household $i$ born at time $t$ maximizes expected discounted utility given by

$$
E \left\{ \sum_{j=1}^{J} \beta^{j-1} [U(c_{i,t+j}, h_{i,t+j}) - \chi Ud_{i,t+j}] + \beta^{J} B(m_{i,t+J+1}) \right\},
$$

where $\beta$ is the discount factor, $c_{i,t+j}$ denotes nondurable consumption, $h_{i,t+j}$ housing services, $d_{i,t+j}$ is an indicator variable equal to 1 if the household defaults on a mortgage at date $t + j$ and 0 otherwise, and $m_{i,t+J+1}$ denotes cash bequests. Preferences are Cobb-Douglas over nondurable consumption and housing services (to match the fact that households mostly spend a fixed proportion of income on either of these categories) with a weight of $\alpha$ on nondurables relative to housing services in period utility. The utility function is CRRA with elasticity of intertemporal substitution $1/\sigma$. Thus,

$$
U(c_{i,t+j}, h_{i,t+j}) = \left( \frac{c_{i,t+j}^\alpha h_{i,t+j}^{1-\alpha}}{1-\sigma} \right)^{1/(1-\sigma)}
$$

**Income process:** Household’s income during working years ($j \leq J$) $y_{i,t}$ contains life-cycle, idiosyncratic and aggregate components:

$$
\ln y_{i,t} = \begin{cases} 
  u & \text{with probability } \gamma_t \\
  \ln Z_t + \psi_j + z_{i,t} & \text{with probability } (1 - \gamma_t)
\end{cases}
$$

The consumption function is neither differentiable nor even continuous in the present of discrete choices such as default, it is not possible to define the MPC as the derivative of the consumption.
and

\[ z_{i,t} = \rho z_{i,t-1} + \eta_{i,t}, \]

where \( \psi_j \) is a deterministic age profile common to all households, \( z_{i,t} \) is the idiosyncratic component of income, \( \rho \) is the persistence of the idiosyncratic component and \( \eta_{i,t} \) is the idiosyncratic income shock. The idiosyncratic shock is normally distributed with standard deviation \( \sigma_\eta \). With probability \( \gamma_t \), household income is equal to a low value \( u \), which I interpret as the value of unemployment insurance.\(^{12}\) When solving the model numerically, I discretize income shocks using Tauchen’s method with 10 nodes. Finally, retired households \((j > J_r)\) receive a constant benefit \( y' \).

**Housing and other assets:** Households can hold three assets. The first asset is a one period bond \( m \) which pays a constant return of \( r \) every period. Households cannot borrow in this bond. The second asset is housing. In any period, a household is either a house owner or a renter. Owners must hold an amount of housing equal to the flow of housing services that they consume. I use \( h_{i,t} \) to denote both the quantity of housing owned and the flow of services it provides. The price of one unit of owner-occupied housing is \( p_t \). Owners can choose from a finite set of possible house sizes, \( \mathcal{H} = \{h_1, ..., h_N\} \). Renters must hold a house which delivers a smaller flow of housing services, \( h_0 < h_1 \).

Households can also take out mortgages. Given a mortgage of size \( b_{i,t} \), a household must make a minimum payment \( \phi b_{i,t} \) each period. Debt accumulates at an interest rate \( r_m \). When the household makes only the minimum payment, debt evolves according to

\[ b_{i,t+1} = (1 + r_m - \phi)b_{i,t} \]

If \( \phi = r_m \), the mortgage is unamortized; if \( \phi > r_m \), it is amortized.

When households adjust their level of \( h_{i,t} \), the level of their housing asset, they must pay a fixed cost \( \kappa_h \). This cost captures both the closing costs of buying a new house and

\(^{12}\)When a household exits the low income state, which happens with probability \( 1 - \gamma_t \), they draw the idiosyncratic component of productivity \( z_{i,t} \) from its stationary distribution.
getting a new mortgage. When households increase debt, choosing \( b_{i,t+1} > (1 + r_m - \phi) b_{i,t} \) (which I interpret as cash-out refinancing), they must pay a fixed cost of \( \kappa_b \). This cost captures the closing costs of cash out refinance. However, households can pay down debt ahead of schedule without incurring any cost. This allows for the possibility that households use their rebates to pay down debt, as prepayment of mortgage is the only possible deleveraging channel in the model. In reality, costs of buying a new house are larger than cash out refinancing costs, hence I impose \( \kappa_h > \kappa_b > 0 \). If households pay \( \kappa_h \) and adjust their house, they can adjust their mortgage for free.

When households adjust their mortgage or house, their borrowing must respect a loan-to-value (LTV) constraint: \( b_{i,t+1} \leq \theta_b p_{t+1} h_{i,t+1} \) if they adjust only the mortgage, and \( b_{t+1} \leq \theta_h p_{t+1} h_{i,t+1} \) if they adjust their housing. I allow \( \theta_b \) to be greater than \( \theta_h \) as most refinancing LTV constraints are less strict compared to initial downpayment rules. If households rent, they pay \( \rho^R \) each period.

**Default:** Households have the option to default on their mortgage. If they default, they lose their debt and house immediately. I potentially allow for a one-off utility cost of default \( \chi_U \). As is standard in models of default, \( \chi_U \) is intended to capture both the pecuniary costs of defaulting on a mortgage, and the stigma associated with this decision.

**Bequest motive:** Finally, households receive ‘warm glow’ utility from cash bequests, of the following form: where \( \psi_0 \) is the parameter that regulates the warm glow from such bequests. I assume homeowners sell their houses and rent in the final year of life and leave all bequests in liquid assets.

\[
B(m_{i,t+J+1}) = \frac{\psi_0 [m_{i,t+J+1} h_0^{1-a}]^{1-\sigma}}{1-\sigma}
\]
The household budget constraint is therefore given by
\[ c_{i,t} + \frac{m_{i,t+1}}{1+r} + p_t(h_{i,t} - h_{i,t-1}) - \frac{b_{i,t+1}}{1+r_m} = y_{i,t} + m_{i,t} - b_{i,t} - \delta \{h_{i,t} = h_0\} \]
\[ - \kappa_h \{h_{i,t} \neq h_{i,t-1}\} \]
\[ - \kappa_b \{b_{i,t+1} > (1 + r_m - \phi) b_{i,t} \text{ and } h_{i,t} = h_{i,t-1}\} \]
for households who do not receive a moving shock, and
\[ c_{i,t} + \frac{m_{i,t+1}}{1+r} + p_t(h_{i,t} - h_{i,t-1}) - \frac{b_{i,t+1}}{1+r_m} = y_{i,t} + m_{i,t} - b_{i,t} - \delta \{h_{i,t} = h_0\} - \kappa_h \]
for homeowners who receive a moving shock.

The household problem can be written recursively as a collection of seven value functions. For \( j < J \), these are defined recursively as follows:

- The value of not owning a house at the start of a period is the maximum of a)
The value of keeping on renting against b) the value of adjusting into being a homeowner.

\[ V^0_j(m,z) = \max \{V^R_j(m,z), V^A_j(m,0,0,z)\} \]

1. The value of continuing to rent today:

\[ V^R_j(m,z) = \max_{c,x'} U(c,h_0) + \beta E_z V^0_{j+1}(m',z') \]
\[ \text{s.t. } c + \delta p_j h_0 + m' \leq (1 + r)m + y_j(z) \]
\[ m' \geq 0 \]

2. The value of adjusting one’s house (transitioning from renting to owning):

\[ V^A_j(m,b,h,z) = \max_{c,x',b',h'} U(c,h) + \beta E_z V^H_{j+1}(m',b',h',z') \]
\[ \text{s.t. } c + p_j h' + m' - b' \leq (1 + r)m - (1 + r_m)b + p_j h + y_j(z) - \kappa_h \]
\[ m' \geq 0 \]
\[ b' \leq \theta p_{j+1} h'; h' \in \mathcal{H} \]
• The value of having a home at the start of the period is the maximum of a) the value of adjusting the house level (from owning a house to owning a different size of house), b) the value of selling home and becoming a renter, c) the value of cash out refinancing, d) the value of not adjusting, and e) the value of defaulting.

\[ V^H_j(m, b, h, z) = \max \{ V^A_j(m, b, h, z), V^S_j(m, b, h, z), \] 
\[ V^B_j(m, b, h, z), V^N_j(m, b, h, z), V^D_j(m, z) - \chi U \} \]

1. The value of adjusting one’s house (transitioning from renting to owning):

\[ V^A_j(m, b, h, z) = \max_{c, x', b', h'} U(c, h) + \beta \mathbb{E}_z V^H_{j+1}(m', b', h', z') \]

\[ \text{s.t. } c + p_j h' + m' - b' \leq (1 + r)m - (1 + r_m)b + p_j h + y_j(z) - \kappa_h \]

\[ m' \geq 0 \]

\[ b' \leq \theta p_{j+1} h' \]

\[ h' \in H \]

2. The value of selling one’s home and becoming a renter:

\[ V^S_j(m, b, h, z) = \max_{c, x'} U(c, h_0) + \beta \mathbb{E}_z V^0_{j+1}(m', z') \]

\[ \text{s.t. } c + \delta p_j h_0 + m' \leq (1 + r)m - (1 + r_m)b + p_j h + y_j(z) - \kappa_h \]

\[ m' \geq 0 \]

3. The value of refinancing (adjusting mortgage, but not the house):

\[ V^B_j(m, b, h, z) = \max_{c, x', b'} U(c, h) + \beta \mathbb{E}_z V^H_{j+1}(m', b', h, z') \]

\[ \text{s.t. } c + m' - b' \leq (1 + r)m - (1 + r_m)b + y_j(z) - \kappa_b \]

\[ m' \geq 0 \]

\[ b' \leq p_{j+1} h' \]
4. The value of not adjusting:

\[ V^N_j(m, b, h, z) = \max_{c, x'} U(c, h) + \beta \mathbb{E}_z V^H_{j+1}(m', (1 + r_m - \phi)b, h', z') \]

s.t. \( c + m' \leq (1 + r)m + y_j(z) \)

\( m' \geq 0 \)

5. The value of defaulting:

\[ V^D_j(m, z) = \max_{c, x'} U(c, h_0) + \beta \mathbb{E}_z V^D_{j+1}(m', z') \]

s.t. \( c + (1 + \chi_R)\delta p_j h_0 + m' \leq (1 + r)m + y_j(z) \)

\( m' \geq 0 \)

At date \( J \), I impose that owners must sell their house and become a renter, so \( V^H_j(m, b, h, z) = V^S_j(m, b, h, z) \) and \( V^0_j(m, z) = V^R_j(m, z) \). Finally, I have

\[ V^0_{j+1}(m, z) = V^H_{j+1}(m, z) = V^D_{j+1}(m, z) = \frac{\psi_0 m^a h_0^{1-a}[1 - \sigma]}{1 - \sigma} \]

A solution to the household problem is computed by starting at the last period of life \( j = J \) and optimally choosing between consuming all their assets and leaving some bequests. I then solve for policies and values in prior periods by backward induction. In the steady state simulation of the model, I simulate 10,000 households.

### 2.3.2 Calibration

Externally calibrated parameters are reported in Table 2.1. The model period is one year, and I calibrate steady state to 2005-2006 data. I set \( J = 55 \) and \( J' = 35 \): households enter the labor market at age 25, retire at age 60, and die at age 80. I set \( \rho = 0.91 \) and \( \sigma_\eta = 0.21 \) following Floden and Linde (2001). I also follow Kaplan and Violante (2010) to capture the annual life cycle component of earnings \( \psi_j \) using PSID data. I scale up average income so that the median income of 45-54 year olds is consistent with median
income of households whose head was 45-54 years old in 2005. After converting to 2008 dollars, and assuming a 20% flat tax rate, this gives a median income of $53,333 for 45-54 year olds. I set the fixed retirement income at $28,000 in 2008 nominal dollars to match the median income of households whose head was 65+ in 2005.\footnote{While this is a simplification, the analysis is mostly focused on non-retirees.} Finally, I set the intertemporal elasticity of substitution $1/\sigma$ equal to 0.5, similar to much of previous literature. I set the real return on the liquid asset to $-1.5\%$ following Kaplan and Violante (2014) and derive the average interest rate on mortgages from the data. All of these are real, risk adjusted after-tax returns. I set the LTV constraint $\theta_h$ at 0.8 for a new house, and allow households to borrow up to house price with $\theta_b = 1$.\footnote{This assumption is especially important as I am attempting to understand the balance sheets of US households between 2006 and 2008.} I set the amortization rate $\phi$ at 4\% of principal every year to match the half life of a regular 30-year fixed rate mortgage (which describes the majority of the US mortgage market). The households in the model are provided with initial wealth in the form of liquid assets. I measure initial wealth in the SCF for individuals at age 22, and select 10 bins which receive different levels of initial wealth at age $j = 1$ in the model. I allow for three different sizes of owner-occupied houses.

Table 2.1: Externally calibrated parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$J$</td>
<td>55</td>
<td>$\phi$</td>
<td>0.04</td>
</tr>
<tr>
<td>$J^r$</td>
<td>35</td>
<td>$\alpha$</td>
<td>0.8</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>2</td>
<td>$r$</td>
<td>-1.5%</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.91</td>
<td>$r_m$</td>
<td>2%</td>
</tr>
<tr>
<td>$\sigma_n$</td>
<td>0.21</td>
<td>$\rho^R$</td>
<td>0.09</td>
</tr>
<tr>
<td>$\psi_j$</td>
<td>PSID</td>
<td>$\theta_n$</td>
<td>0.85</td>
</tr>
<tr>
<td>$\gamma_j$</td>
<td>0.25</td>
<td>$\theta_b$</td>
<td>1</td>
</tr>
</tbody>
</table>

This leaves us with six free parameters: the discount factor $\beta$, the cost of adjusting...

\footnote{I set the utility cost of default $\chi = 0$ in steady state. In the recession experiments, I choose $\chi$ in order to match default rates in the data, as I describe below.}
houses and mortgages $\kappa_h, \kappa_b$, the probability of exogenous ‘moving shocks’ $p_{\text{move}}$, the housing services provided by a rental apartment $h_0$, and $\psi_0$, which affects the utility of bequests. I calibrate these parameters to match six moments. Average rebate efficacy depends on proportion of constrained households in the population and the general level of wealth. Hence I target the percentage of households with houses but with less than 2 months of income in liquid assets, which is 32.2% according to the 2007 SCF. The ratio of median illiquid wealth to average income is used to match the wealth to income distribution. I choose median over mean illiquid wealth to target the bottom 80% of the income distribution, whose moments are better proxied by medians than means. I use SCF 2007 and set the target statistic at 1.605. Frequency of mortgage adjustment (cash out refinancing) is both a significant method for consumption smoothing for homeowners and is restricted during housing recessions. I follow Bhutta and Keys (2016) who find around 12.5% of borrowers already had a mortgage and extracted equity from their houses in 2001. On the frequency of housing sales, I use data from the CPS which shows 6.6% of homes were sold in 2007. Finally, I target homeownership rates. Homeownership rate is based on 2007 data from the Census Bureau. I target the total bequest wealth to total wealth (the bequest transfer ratio) for the bottom 80% of the US population. De Nardi (2004) finds the wealth transfer ratio for the bottom 80% is 0.148.

These six parameters are chosen to match aggregate US data when house prices, average income, and unemployment risk are calibrated to the aggregate US economy. In these experiments, however, I simulate two model economies, one corresponding to the lowest tercile of the distribution of house price changes (tercile 1) and the other corresponding to the middle tercile (tercile 2). I allow the path of house prices, average income, and unemployment risk to vary across the two economies in line with 2005 data. This gives us a steady state median house price of $393,000 in 2008 nominal dollars for tercile 1, and $257,000 for tercile 2 (based on Zillow data). Median income is $60,000 for

\footnote{https://www.census.gov/prod/2013pubs/acsbr12-20.pdf}
tercile 1 and $59,000 for tercile 2; I set $\gamma = 0.05$ in both regions to match the average 2005 county-level unemployment rate. I also allow the utility from housing services to differ between the two regions: this allows us to match home ownership rates in the two regions, given the difference in steady state house prices. All remaining parameters are set to the same values for both model economies.

Table 2.2: Targeted moments

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Target</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount factor $\beta$</td>
<td>0.955</td>
<td>Median illiquid wealth/income</td>
<td>1.61</td>
<td>1.56</td>
</tr>
<tr>
<td>Cost of adjusting house $\kappa_h$</td>
<td>0.09</td>
<td>% of WHTMs</td>
<td>0.32</td>
<td>0.29</td>
</tr>
<tr>
<td>Cost of increasing mortgage $\kappa_b$</td>
<td>0.07</td>
<td>% borrowers who refinanced</td>
<td>0.13</td>
<td>0.12</td>
</tr>
<tr>
<td>Probability of moving shock $\xi$</td>
<td>0.0075</td>
<td>Frequency of housing sales</td>
<td>0.06</td>
<td>0.07</td>
</tr>
<tr>
<td>Utility from bequests $\psi_0$</td>
<td>1.6</td>
<td>Bequest to wealth ratio</td>
<td>0.15</td>
<td>0.15</td>
</tr>
<tr>
<td>Utility from rental apt $h_0$</td>
<td></td>
<td>Home ownership rate</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Terceile 1</td>
<td>2.6</td>
<td>Tercile 1</td>
<td>0.66</td>
<td>0.68</td>
</tr>
<tr>
<td>Terceile 2</td>
<td>4.0</td>
<td>Tercile 2</td>
<td>0.67</td>
<td>0.69</td>
</tr>
</tbody>
</table>

Parameters: Table 2.2 summarizes the estimated parameters and targeted moments in the data and in the model. I obtain discount factor $\beta = 0.955$, in line with the literature. The fixed cost of adjusting housing ($\kappa_h$) is chosen to be 9,000 in 2008 dollars, while the fixed cost of cash out refinancing $\kappa_b$ is set to 6,000 dollars. The moment matching procedure gives a moving shock probability of 0.75% per year.

Fit for Non-Targeted Moments: The model matches some key moments of the data that were not used in the calibration exercise. Table B.2 in the Appendix reports both the distribution of liquid assets for renters and homeowners and LTV for homeowners. The model reproduces lower end percentiles of the liquid asset distributions for homeowners well. It undershoots the 75th percentile. For renters, the model is close to matching the 10th and 25th percentiles well and I overshoot the median. While the model overshoots the median LTV in the data, it matches the 75th, 90th and 95th percentiles of LTV pretty well.

The model also matches the consumption smoothing motive which is key to a life-cycle model. Panel A of Figure 2.1 shows that steady state mean life cycle patterns of
several variables in the model are realistic. Consumption is hump shaped as households save for retirement. Consumption is less volatile compared to income, which matches the standard consumption smoothing result. Housing wealth peaks at retirement and slowly gets used by households at the end of their lives. Liquid wealth builds up close to retirement as in the data. In the model liquid wealth builds up at the end of life, as I force households to only provide bequests in liquid assets. Panel B of Figure 2.1 shows home ownership rate goes up to 90% at age 50 and stays at that level, and I see the same trend in the data.

Figure 2.1: Mean Life Cycle and Home Ownership Rate over Life Cycle

Figure B.1 in the Appendix shows an example of a simulated life cycle in the model. The individual starts work life at age 25, buys a house initially with some liquid assets provided by her parents with a downpayment. She takes out housing equity at various points in her life. The income graph moves around due to stochastic shocks to the individual’s income. The wealth built up throughout working life is then used for smoothing consumption during the retirement period, which starts at age 60 and goes till age 80.

I match the variation in the proportion of wealthy hand-to-mouth households (defined as households with homes who have limited amount of liquid assets) by age when compared to the SCF in 2007 (Figure B.2 in the Appendix). The model has on average slightly more wealthy hand to mouth households (WHTM) in their middle age compared to the data and slightly lower poor hand to mouth households (PHTM). The
model does not allow for bequests in illiquid assets, hence individuals decumulate housing equity in their final years of life. Because of this, the hand to mouth statistics do not match the data in the final years of life. The model matches the distribution of housing loan-to-value ratios (LTVs) in steady state well (Figure B.3 in the Appendix). The distribution of housing LTV is a crucial predictor of default probabilities. The model generates a trend in housing LTV very similar to LTV for households in the 2007 SCF. Housing LTVs are around 80-100% in the earliest years of life. As amortization depletes mortgage values and households gain more housing equity, LTV ratios get smaller.

**MPC in Steady State:** I simulate the provision of a $1,000 rebate to households in the model at steady state.\(^{17}\) Rebate is provided to 10,000 simulated households while no rebates are provided to 10,000 identical households. I measure the MPC out of rebates as the difference in their consumption in the period as a % of the rebate size. In steady state, the average MPC is 20% of the rebate amount, which is close to the estimates from previous empirical literature and the results. Similar to Berger et al. (2015), average MPC is decreasing in income, housing size, liquid wealth and age (these correlations are all assuming other variables are kept constant).

### 2.3.3 Recession Experiments

In order to reproduce the main empirical findings in the model, I analyze the dynamic response after the two steady state economies (terciles 1 and 2) are shocked with both housing wealth and income shocks. At \( t = 1 \), households become aware that the economy is entering a recessionary period. More specifically, they learn that their housing prices have fallen permanently, the probability of unemployment shocks \( \gamma_t \) will be higher for the next 4 years and their mean income for the next 4 years will fall as well (I use 4 periods of recession to mimic the 2008-2013 period; after 4 years, the income

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\(^{17}\) The average rebate size in the empirical sample was $898.
shocks revert to steady state values).\textsuperscript{18} In addition, I tighten the down-payment (from 85% to 80%) and refinancing (from 100% to 85%) LTV constraints during the period of the recession. The timeline of the recession is shown in the following figure. Period $t = 0$ corresponds to the steady state, and $t = 1$ is the first period in which agents realize the recession has started. At $t = 1, 2, 3, 4$, the economy stays in recession and moves to the new steady state in $t = 5$. In the new steady state, the probability of unemployment rates go back to initial steady state.

In order to mimic the variation in recession depth across the country, I allow the two economies to have separate paths for housing prices, unemployment and median incomes. I get the path of housing prices for both terciles from Zillow data, unemployment rates from the BEA local unemployment rate series and median incomes from the Census Bureau. Figure 2.2 shows the path for housing prices and unemployment. Housing price levels were higher in tercile 1 in 2005-06, and fell much more than in tercile 2 during the recession. The unemployment rate also rose by more in these areas. Figure B.5 in the Appendix shows the path for median incomes, where the differences are present, but weaker.

Further, I raise the cost of selling houses $\kappa_h$ by a factor of 3 during the recession period in both economies, in order to capture the fact that it became harder to sell a house during the 2008 recession. By raising the cost of selling houses, I avoid potentially counter-factual implications, such as a significant proportion of households moving house in response to a fall in house prices. The main result - the difference in MPC between regions - remains identical whether I increase $\kappa_h$ during the recession, or keep

\begin{flushright}
\textsuperscript{18}I choose fat tailed unemployment shocks in addition to fall in average incomes based on recent research by Guvenen et al. (2014). The authors find that recessions are driven by left skewness of income shocks, as both large upward income shocks do not happen and left tailed unemployment shocks become much more likely.
\end{flushright}
Finally, I utilize the last free parameter $\chi_U$ to match default rates in both economies. I measure the default rate in the data as the proportion of mortgages that are more than 90 days delinquent in the fourth quarter of 2008, provided by Freddie Mac. I set $\chi_U = 4$ in order to match default rates in model in data, averaging across both terciles, as shown in Figure B.4. As expected, default rates in tercile 1 (7%) are higher than default rates in tercile 2 (3%), in line with the data.

In both of these economies, I provide an unanticipated $1,000 in rebates to one set of households and no rebates to a set of identical households. After solving for their
optimal responses, I study the differences in consumption between the two groups, and calculate the MPC out of the rebate checks. The MPC across the two regions is shown in Figure 2.4. The central result is that the MPC in tercile 1 is slightly higher than that of tercile 2 (17.6% against 15.5%). As in a one asset buffer stock model, a richer model of consumption and housing delivers a slight positive correlation of MPC with housing price declines. This stands in sharp contrast with the empirical finding that the MPC was substantially lower in tercile 1.

Figure 2.4: Average MPC by Tercile

As discussed above, a canonical buffer stock model would predict a higher MPC in tercile 1, which experiences a larger decline in house prices. The richer model of housing and default allows for a number of channels that could in principle reverse this prediction and match the pattern I documented empirically. Quantitatively though, these channels fail to reverse the predictions of the buffer stock model.

The first channel that could in principle lower the MPC in tercile 1, relative to tercile 2, is associated with households who switch from defaulting to servicing their debts when they receive their rebates. These “default switcher” households have a strongly negative MPC, as they are induced to keep on making mortgage payments by the rebate. Such households are present in the model, and have a significantly negative MPC. However, when the model is calibrated to generate a level of default in line with that observed
during the Great Recession (around 7% of homeowners in tercile 1), there are simply not enough households who would change their default decisions based on a $1,000 rebate. In the simulations, fewer than 0.1% of households are default switchers in either tercile 1 or tercile 2; this reduces the average MPC for the full sample by less than a percentage point. The contribution of default switcher households to changes in average MPC between terciles 1 and 2 is close to zero, as shown in Figure 2.5.

Figure 2.5: **Offsetting Channels**

![Offsetting Channels](image)

Figure 2.5 also shows offsetting effects due to refinancing switcher households. Similar to the default switcher households, some households choose to take cash out of their housing equity when not provided a rebate. These households (refinance switchers) have a very large negative MPC. However, as housing prices fall, collateral constraints bind tighter and the proportion of these households gets smaller. This pushes the average MPC higher. This channel is analogous to the traditional borrowing constraints channel in the literature. Figure 2.5 shows the contribution of this channel is also below a percentage point. The largest contribution to the change in MPC between terciles 1 and 2 comes from the traditional buffer stock channel. A loss in wealth moves households to a slightly more concave part of their consumption function, hence leading to a slightly higher MPC.

The model is also useful in understanding the role of deleveraging in balance sheet
recessions, and its effect on the MPC. Aggregate deleveraging is present and strong in recession experiments. Figure 2.6 shows levels of total debt in the two economies as they go through the recession. Both economies deleverage significantly. A large majority of this is through default (debt gets charged off) and collateral constraints (down-payment constraints are tighter, and new houses have lower debt). Deleveraging through prepayment of mortgages is present, but very weak. Kennedy et al. (2014) document that around 70 percent of the 2007-2014 decline in mortgage debt in the United States occurred as a consequence of charge-offs.

Do the households in the model use their rebates to pay down debt? Figure 2.7 shows the marginal propensity to deleverage out of rebates for households (who do not default, refinance or move) in the two economies. Marginal deleveraging is present in both economies. This is because of the interest differential, as mortgage rates have a high interest rate. However, this marginal deleveraging effect is actually stronger in tercile 2 compared to tercile 1. The average household in tercile 1 only spends around 25 cents on the dollar to prepay debt, while the household in tercile 2 spends over 50 cents on the dollar to prepay debt.

For households who do not take discrete adjustment decisions, the following identity approximately holds true. Any transitory income provided to the household has
to be either spent in nondurables (MPC), used for prepaying debt (MPD), or used to accumulate liquid asset balances (MPM).

\[ MPC + MPD + MPM \approx 1 \]

In the experiments, as housing prices fall, the MPC stays relatively constant, but the households shift from deleveraging towards accumulating liquid assets. This is because of the option value of accumulating liquid assets. For a given level of net worth, one can either have high liquid assets and high levels of debt, or low liquid assets and low debt. Having high levels of liquid assets and high levels of debt has costs in terms of the interest differential. However, it has a key benefit, which is its option value. Having higher checking account balances means one has more options to respond to shocks in the future. This insurance benefit leads to a lower marginal deleveraging as housing wealth gets more negative.

One key reason for why deleveraging does not significantly reduce the MPC is because there is no extra benefit to deleveraging for anyone moderately underwater beyond the interest differential. A moderately underwater household in the model can wait it out and pay off mortgage payments until they regain positive equity in the house. However, DiMaggio et al. (2014) find that in response to Adjustable Rate Mortgage (ARM)
resets that reduced households’ mortgage payments, borrowers with low or intermediate LTV ratios paid off other debt more quickly than deeply underwater homeowners. Households in the model do not behave in this way, because achieving slightly positive equity is not an important goal for them. Since they must pay an adjustment cost of $\kappa_b$ in order to extract equity, households must at least reach a value of home equity greater than $\kappa_b$ for equity extraction to even potentially be worthwhile; and since equity extraction is costly, in practice homeowners will only pay the transaction cost if they can extract a significant amount (Bhutta and Keys (2016) find homeowners on average extracted $23,000 in home equity when they took a cash-out refinance.) This suggests the bar for positive home equity is much larger than $\kappa_b$. With fully rational agents, $1,000 cannot push moderately underwater agents to strongly deleverage.

2.3.4 Shift in Permanent Income Expectations

We have seen that both a canonical buffer stock model and a richer model of housing and default fail to match the empirical finding that the MPC out of transitory income is lower in areas experiencing a deeper local recession. I now consider the possibility that more pessimistic expectations of permanent income in regions experiencing a deeper housing crisis could resolve this puzzle.

In the canonical buffer stock consumption model, (see Carroll (2000)), the MPC out of transitory income is increasing in a household’s permanent income. The ratio of consumption $C$ to permanent labor income $P$ is a concave function of the ratio of current resources $X$ (defined as the sum of financial wealth and current income) to permanent labor income. That is,

$$C = c \left( \frac{X}{P} \right) P,$$

where $c(x)$ is an increasing, concave function. It follows that the MPC out of transitory income is increasing in $P$:

$$\frac{\partial}{\partial P} \left( \frac{\partial C}{\partial X} \right) = -c'' \left( \frac{X}{P} \right) \frac{X}{P^2} > 0$$
Thus to the extent that permanent income falls more in regions with a deeper housing crisis, this should tend to reduce the MPC out of transitory income in these regions. In fact, the model experiments described above already allowed for this possibility. These experiments assumed that agents have perfect foresight regarding the path of average income during the recession and recovery. Thus, in line with the data, average income falls more in the areas with a deeper house price fall. Quantitatively, this difference was not enough to generate a significantly lower MPC in these regions.

However, an alternative hypothesis is that households in counties experiencing a housing crisis had more pessimistic expectations about the path of future income than were borne out in the data ex post. Within the model, this translates into a larger fall in permanent income for households in tercile 1. Qualitatively, this should lead to a lower MPC, bringing the model closer in line with the data (to the extent that the buffer-stock intuition applies to the richer model). The question is how much heterogeneity in households’ expectational errors we need in order to match the data, and whether this degree of heterogeneity is plausible.

I test this hypothesis using expectations data from the Michigan Survey of Consumers. The Survey asks a sample of American households about their expectations of future house price changes, future income changes and future unemployment risk. I utilize responses from 2005 to 2010, and combine this with the Zillow dataset on local housing price declines. In particular, I take counties in the various terciles of the $\Delta H$ distribution and find the average value of responses from the Michigan Survey. As the survey does not directly ask households what they expect their future income to be, I use three other questions; a) What do you think the chances are that your income will increase by more than the rate of inflation in the next five years or so?; b) During the next 5 years, what do you think the chances are that you (or your husband/wife) will lose a job you wanted to keep? and c) By about what percent do you expect your income to (increase/decrease) during the next 12 months?
Figure 2.8: Mean Responses to Q.a.: Probability income goes up in next five years

Figure 2.8 shows mean responses for three groups of counties to question a). Confidence that real income will rise in five years goes down across all groups between 2007 and 2010. On average, respondents believed that their real income would rise in five years with a probability of 40% in 2005, and this probability drops to 33% in 2010. However, this drop in expectations is not larger for tercile 1 compared to terciles 2 and 3.

Next, I look at question b) on the probability of unemployment in five years. Figure 2.9 shows the expectations of an unemployment spell also went up across all areas between 2005 and 2009. The full sample average increased from a low of 17% in 2007 to 21% in 2009. However, again, there is no differential trend in tercile 1 compared to the others.

Figure 2.9: Mean Response to Q.b.: Five year probability of getting unemployed
Finally, Figure 2.10 shows how much the average respondent in each group believed income will go up/down in a year. Average expected changes in income drop from 5% in 2005 to 1% in 2009. Again, these trends are similar across all three terciles.

Figure 2.10: Mean Expectations of income increase in 12 months

For a fall in expected permanent income to explain the empirical results, there needs to be a very strong difference on future income expectations between the groups. There is no support for this hypothesis in the Michigan Survey data. This suggests that the empirical results in Chapter 1 are not driven by a very large differential fall in permanent income expectations in areas where housing prices declined more.

2.4 Conclusion

In this chapter, I highlight the implications for policy and theory from the results of Chapter 1. These results highlight a problem for policymakers, suggesting that fiscal stimulus may have been least effective in stimulating nondurable consumption in the regions experiencing the worst recession. This highlights the tradeoffs between the utilitarian and aggregate demand stabilization motives for rebate provision.

I also discuss how these results pose challenges to consumption theory. To understand these challenges in a realistic setting, I develop a heterogenous agent, life cycle, partial equilibrium model featuring housing, mortgages and realistic collateral constraints. With such a model, I simulate various elements of a recession such as the one
observed in 2008, including higher unemployment probability shocks, tighter downpayment and refinancing constraints. Such a model delivers a stable correlation of MPC with housing wealth shocks. I argue this is due to three reasons: the dependence of MPC on liquid assets which do not change significantly, the quantitative weakness of the mechanism by which rebate pushes households to avoid default and continue mortgage payments and finally the lack of incentives to sharply deleverage in a model with long term mortgages. I also extend the analysis to other possibilities, such as differential shift in expectations about permanent income. By getting regional income expectations data from the Michigan Survey of Consumers, I rule out the role of differential shift in permanent income expectations in explaining the findings. Overall, I find a discrepancy between household behavior and consumption theory in this dimension. I leave it for future research to reconcile this discrepancy.
Evolution of Hand to Mouth Households (2007-09) and Lessons

3.1 Introduction

Heterogeneity in household liquidity is an important topic for both academics and policy practitioners. Studies consistently show such heterogeneity is highly correlated to how households respond to transitory income changes. In particular, households with low cash in hand (hand to mouth households) spend much more out of transitory income changes. As most countercyclical stabilization policies (whether fiscal, monetary or other credit supply policies) attempt to provide households with extra liquidity during recessions, their effectiveness is clearly linked to household liquidity decisions. This makes the study of household liquidity not just an interesting topic in consumer finance, but a key issue for business cycle macroeconomics.

It is hence essential that we both measure the distribution of household liquidity status well and understand the reasons behind the distribution. Is liquidity status a reflection of deeper habits and preferences? Are low-cash households prone to persist as low-cash in the future or is such status due to pure circumstance and hence unlikely to persist? How do households manage their liquidity when they are going through a large recession characterized by housing crisis and large negative shocks to their balance sheets? These are all important questions which remain unanswered. This chapter studies the final question, and provides suggestive evidence for the others.

These questions are important both for policy purposes and consumption theory.

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1I use the terms housing crises recessions and balance sheet recessions interchangeably.
Recent empirical literature has linked effectiveness of various countercyclical policies on liquidity status. In particular, an extensive set of papers show fiscal policy effectiveness depends on the proportion of households without significant cash in hand. Johnson et al. (2006) use the Consumer Expenditure Survey to show households with low levels of liquid assets had much larger marginal propensities to consume (MPC) out of the 2001 tax rebates. Johnson et al. (2013) repeat the findings from the 2008 rebates. In subsequent analysis, Broda and Parker (2014), using the Nielsen Homescan Panel, ask respondents if they have sufficient liquidity to cover two months of income. Households who respond ‘Yes’ have close to zero spending responses to rebates in 2008, while households without sufficient liquidity show significantly higher spending responses. Misra and Surico (2014) refine the Johnson et al. (2006) analysis by looking at the heterogeneity in consumption responses across various groups. They use quantile regressions instead of the OLS framework used by JPS. They find substantial heterogeneity in response to stimulus checks. While half of the households do not change their consumption after receiving the tax stimulus checks both in 2001 and 2008, around 20% of the families spend above half of the stimulus checks. The group that spends the most out of rebate checks has high mortgage debt and low liquidity. Similarly, Fagereng et al. (2016) show that Norwegian lottery winners spend much more significantly out of lottery winnings if they have low levels of liquid assets. Finally Jappelli and Pistaferri (2014b) use the 2010 Italian Survey of Household Income and Wealth to show households with low cash in hand have significantly larger MPC out of transitory income changes.

A recent literature has also argued that monetary policy effectiveness relies on the heterogeneity of household behavior. Auclert (2017) shows that if the MPC of those who gain from accommodative monetary policy is larger than those who lose, then such monetary policy has a larger effect on overall output. Again, MPC of households is correlated to their liquidity status. DiMaggio et al. (2014) measure consumption responses for homeowners whose ARM mortgage resets led to lower mortgage rates during the
recession. They find homeowners with low incomes and liquidity spend more out of the
the loosening of liquidity constraints caused by the mortgage rate resets.

While there are many reasons why households hold the liquidity levels they do, the
theoretical literature has generally followed two paths. I follow Gelman (2016) in dis-
tinguishing between studies that focus on circumstantial factors and those that focus
on persistent characteristics. The circumstance view has traditionally focused on a se-
ries of negative income shocks as the primary driver of hand to mouth status. In the
rational expectations life cycle model with one risk free asset as in Deaton (1991) or
Carroll (1997), households who receive such shocks are unable to consumption smooth
due to the lack of perfect credit markets. Such models imply the existence of one group
of hand to mouth households; those with very little net worth. These net worth con-
strained households spend large amounts out of transitory income shocks. However,
the proportion of households who are net worth constrained is too small to match the
empirical results on average MPC out of fiscal stimulus payments. Kaplan and Violante
(2014) use the tradeoff between return and liquidity to generate a group of wealthier
but financially constrained households; those who have parked their wealth in illiquid
assets such as houses. They call such households “Wealthy Hand to Mouth"(WHTM)
households. The presence of these households with higher MPC (around 15 to 20% of
the US population) along with traditional financially constrained households ("Poor
Hand to Mouth"(PHTM)) helps match the average MPC. Moreover, this newer model
can match bi-modal correlation of MPC with income, as illiquid households, both poor
and wealthier, have higher MPC. Another set of studies such as Hercowitz et al. (2009)
argue the presence of large consumption commitment concerns (such as future educa-
tion expenses for children) drives households to become WHTM. In all of these studies,

While consumer preferences and characteristics can change over their life cycle, the literature generally ignores this possibility.

Kaplan and Violante (2014) use the Survey of Consumer Finances to measure proportion of hand to mouth households with illiquid assets and find close to 15% of households fall under this category.
low liquidity status is often temporary for the WHTM group, as households either become illiquid while they are initially buying houses, or saving in illiquid assets for other consumption commitments.

A second group of studies focuses on persistent preference or behavioral characteristics of households. Campbell and Mankiw (1989) argue for the existence of two types of consumers; patient and impatient. Impatient consumers always have low cash in hand, and also have a high MPC out of transitory income changes. Laibson et al. (2003) highlight self-control problems, where consumers often fail to achieve their optimal financial outcomes, and remain hand to mouth. The same households spend significantly out of transitory income changes. Reis (2006) is another paper in the same vein that focuses on limited attention. Households with limited attention find it costly to acquire and process information, hence choose to update their consumption plans infrequently. In all of these examples, low liquidity is a sign of a deeper behavioral characteristic which also causes stronger consumption responses to transitory income changes.

Distinguishing between the relative importance of either of the factors is very difficult. Ideally, one would require a large representative sample of households with full information on financial balance sheets along all dimensions (liquid and illiquid assets, debt, income) and panel features to control for household specific fixed effects. Traditional datasets on consumption (such as the CEX, PSID) either do not have panel features, or do not have required information on financial balance sheets. Gelman (2016) is a recent paper which uses data from a personal finance website to answer this question. He finds that empirically, the characteristics view is as important as the circumstantial view of household finances, and uses the empirical results to calibrate a model with discount factor heterogeneity. Parker (2017) uses the panel element of the Nielsen Homescan Consumer Panel to ask if any prior characteristics can predict low liquidity. He finds that households with low incomes two years in the past respond strongly to tax refund payments compared to other households. He interprets this finding as suggestive of the
importance of persistent characteristics such as preferences, and argues low permanent
income drives lack of consumption smoothing, not transitory income shocks, or trans-
action costs on illiquid wealth. Olafsson and Pagel (2016) use information from another
financial data management website to argue significant proportion of households spend
heuresitically. They argue this shows persistent behaviors for some households, which
suggests the importance of the characteristics view of hand to mouth households.

In light of this broader literature, measuring the proportion of hand to mouth house-
holds in an economy is an important topic. Kaplan et al. (2014) explore the historical
evolution of hand to mouth status in the United States using the Survey of Consumer
Finances. They analyze both poor and wealthy hand to mouth status between 1989 and
2010. The analysis shows between 25 and 40% of households in hand to mouth sta-
tus, with two thirds of such households being wealthy hand to mouth. Wealthy hand
to mouth households are generally richer than the PHTM, are slightly older (peaking
at above 40 years), hold significant illiquid wealth (median of 50,000 dollars) and have
higher education levels. They are however poorer and younger than the NHTM group.
Finally, Kaplan et al. (2014)’s demonstrate the stability in the proportion of hand to
mouth households between 1989 and 2010. Their analysis however mostly ignores hand
to mouth status during the Great Recession, which this chapter focuses on.

The first contribution of this chapter is to empirically measure how households man-
aged their finances and liquidity status during the Great Recession of 2008-10. Using
the panel version of the Survey of Consumer Finances panel data (2007 and 2009), I find
the overall proportion of HTM (both WHTM and NHTM) did not change between 2007
and 2009. I also find that this finding is robust to different definitions of liquid assets,
iliquid assets and hand to mouth status. While this result hints at the importance of
the characteristics view, the trends underneath the overall statistics tell a different story.
The panel feature of the 2007-09 SCF allows me to follow each household. Using this
feature, I find that there was significant movement between the NHTM and WHTM cat-
egories. Almost half of the WHTM households in 2007 (7% of the sample in baseline) gained liquidity buffers and switched to NHTM in 2009. Similarly, the same percentage of the sample who were NHTM in 2007 switched to WHTM status in 2009. This result is robust to defining the liquid, illiquid asset definitions and cutoffs for hand to mouth in multiple ways.

The main contribution of the chapter is a deeper analysis of these results. I find households who have larger losses to housing wealth and smaller losses to permanent income expectations are more prone to building liquidity buffers in this period. While this suggests the importance of circumstance (as in a traditional buffer stock model), I argue a certain class of circumstantial models, those with net illiquid assets, are ill-equipped to explaining such transitions. The Great Recession was a period with both a) the largest changes in household wealth and b) largest increase in unemployment risk since the Great Depression. Kaplan and Violante (2014), using a model with net illiquid assets, argue that in a deep recession, households with money parked in illiquid assets will find it worth the transaction costs to pull their money out. This is because the utility loss from the large fall in consumption outweighs the transaction costs of taking wealth out of illiquid assets. This effect should increase the amount of liquid assets across the population distribution and lower the number of WHTM households.4 I however find that this group did not change their status by actively liquefying their illiquid asset. Instead they did so while the valuations of their illiquid asset fell massively, which points to them cutting consumption significantly. Hence, I argue; adding valuation effects on the illiquid asset (such as houses) by separating housing wealth from mortgages is key to match these facts.5 As housing valuations fell deeply, and a significant proportion of households only held housing wealth as illiquid assets, refinancing constraints became more binding. Hence, accessing illiquid wealth became much harder. Households

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4 This should also lower the overall MPC out of transitory income changes such as fiscal rebates.
5 Along with Keshav Dogra, I use such a model to study MPC in the other chapters.
attempting to build liquidity buffers hence had only one margin to change in consumption. On the other hand, I show that for households who lose liquidity buffers, past income, age and education are better at predicting behavior than changes in income, which suggests the role of characteristics based factors.

These results suggest a few lessons. First, there are roles for both circumstantial and characteristics based theories on household liquidity and hand to mouth status when analyzing deep recessions with housing crises. Second, understanding housing crisis recessions require at the very least circumstantial models with assets and liabilities separated; as valuation effects and their impact on borrowing constraints are key for a significant proportion of households. Finally, these effects mean the largest margin of adjustment for such households is through consumption.

The rest of this chapter is organized as follows. Section 2 discusses the Great Recession and the dataset. Section 3 discusses the main empirical results and lessons. Section 4 concludes.

### 3.2 Background and Data

The Great Recession of 2007-09 was the deepest recession since the Great Depression of the 1930s. Between December 2007, when the recession started and June 2009, the unemployment rate had increased from 5% to 10%. Real GDP fell by 4.3% between peak and trough, and total personal consumption expenditures fell by 2.49%. This period was also characterized by large losses to household and corporate wealth, as house prices fell around 30% on average between mid-2006 to mid-2009 and the S&P 500 index fell by 57% between October 2007 and March 2009. Finally, net worth of households and non-profit organizations fell by 20% between 2007 and 2009.

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6 The recession technically ended in June 2009 as per NBER’s Business Cycle Dating Committee, but the negative effects lingered for multiple years.
Unlike other recessions in recent history, the Great Recession was unique, as it involved the housing sector so prominently. As house prices declined severely during the recession, significant proportions of American households were underwater on their mortgages (as of 3Q 2009, 4.5 million homeowners). This led a large number of households to default on their mortgage (lenders filed 3.8 million foreclosures in 2010, which was 23% increase compared to 2008 according to Realtytrac). Those who were not in foreclosure often were delinquent on their mortgage payments, as the number of households missing at least one payment went up to 5 million by 2009. There were fears the recession would become as deep and painful as the Great Depression.

The Survey of Consumer Finances (SCF) allows me to take a detailed look at household finances during the Great Recession. The SCF is a triennial survey conducted by the Federal Reserve Board (FRB) which records a vast range of information about the financial health of households. The SCF interviews around 5,000 households in detail about their incomes, assets, debt, pension along with demographic variables such as education, race, family status. The survey first creates a geographically based random sample with an eye on coverage of important population characteristics. The second step involves creating an additional sample to include wealthy households, who are harder to reach and hold disproportionately large shares of certain assets such as businesses and bonds. Unlike some of the other datasets that have been used to study household liquidity, the SCF is based on structured sampling of households, with appropriate survey weights designed during the sampling procedure. This makes it a more representative sample of all Americans compared to personal finance website data, which have larger self selection issues (skewed towards younger, more educated and single consumers). On the flipside, the SCF has a smaller sample size and is undertaken every few years when compared to high frequency data from other sources such as personal finance

7http://www.nytimes.com/2010/02/03/business/03walk.html?pagewanted=all
While most versions of the SCF do not follow the same households, the SCF 2007-09 is unique in its panel design. As up to date information was key during the recession, the FRB ran a follow-up survey of participants in the 2007 SCF, hence creating a panel dataset. The first version of the 2007-09 SCF was conducted first in 4Q 2007. The second part of the survey took place between July and December 2009. This unique timing provides us with a window into the financial conditions of households while the Great Recession was strengthening. Between early 4Q 2007 and July 2009, S&P500 index fell by 40.3% and fell by 27.92% between early 4Q 2007 and December 2009. Between the two surveys, a multitude of events occurred, including the passage of the Economic Stimulus Act of 2008, the sale of Bear Sterns to by JP Morgan, the bankruptcy of Lehman Brothers and the start and strengthening of the deepest recession in decades.

With any panel survey, it is important to check nonresponse and other potential biases. Bricker et al. (2011) show the response rates for the 2009 survey was around 87% of the 2007 sample. In addition, there was no large difference between respondents and nonrespondents showed in important characteristics, minimizing fears of nonresponse bias.

I restrict the SCF sample in two ways; by taking out families where the head is not between 22 and 79 years of age and families where all income originates from self-employment. The final sample for analysis after these restrictions is a balanced panel on 2,921 households.

### 3.3 Empirical Method and Findings

In order to understand the evolution of household finances during the Great Recession, I first define income, liquid and illiquid wealth in the data.

**Asset Measurement:** I measure assets in the SCF similar to Kaplan et al. (2014).
Liquid assets are the sum of cash, checking, savings, money market, call account, mutual fund, stocks, corporate and government bond holdings. Cash holdings are not available in the SCF, and are imputed based on the median cash to checking account ratio data from the Survey of Consumer Payment Choice in 2010. I subtract credit card balances to get net liquid wealth. Illiquid assets are measured as the sum of retirement accounts, insurance policy cash values, longer term bonds and housing asset prices. I subtract mortgage debt to measure net illiquid wealth.

**Income Measurement:** I include both labor income and government transfers. Income is defined as gross wages and salaries, self employment income, child support and alimony, unemployment benefits, food stamps, and Social Security Income (SSI). Investment income is not included. All values are reported before taxes.

**Descriptive Statistics:** Table 3.1 summarizes the various asset and incomes of the sample in both 2007 and 2009 surveys. The median household held around $2,900 in cash, checking and savings account in both years, while holding no stocks, bonds and credit card debt. The median net illiquid wealth was around $95,000 in 2007 and dropped to $79,500 in 2009. Housing wealth dominated for the median household, as they held only around $10,000 in non-housing illiquid wealth. Median incomes were around $45,000 in 2007 and $49,000 in 2009.

**Hand to Mouth Status** A survey with data on liquid wealth balances at the end of every pay period would be ideal in measuring hand to mouth status. Such hand to mouth households (HTM) include two groups; households who hold zero net liquid wealth \( m_{it} = 0 \) and households who are at their credit card limit \( m_{it} \leq 0, m_{it} \leq -\bar{m}_{it} \).  

The SCF however measures average balances \( \bar{m}_{it} \) through the period. This introduces some measurement error. I use the criterion used by Kaplan et al. (2014) and perform two cutoffs. In the first, households can be hand to mouth if their average

---

9 The households who are at their credit card limit are a small minority of the sample (around 2-3%).
Table 3.1: Descriptive Statistics: Median Levels of Assets, Liabilities and Income

<table>
<thead>
<tr>
<th></th>
<th>2007</th>
<th>2009</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cash, Checking and Savings</td>
<td>2919.755</td>
<td>2924.462</td>
</tr>
<tr>
<td>Directly held stocks and bonds</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Credit Card Debt</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Net Illiquid Wealth</td>
<td>95369.8</td>
<td>79522.88</td>
</tr>
<tr>
<td>Net Non-Housing Illiquid Wealth</td>
<td>9223.388</td>
<td>10162.08</td>
</tr>
<tr>
<td>Retirement Account Wealth</td>
<td>0</td>
<td>73.4412</td>
</tr>
<tr>
<td>Income</td>
<td>44800</td>
<td>48600</td>
</tr>
</tbody>
</table>

liquid wealth balance is greater than zero, and is less than half their earnings per pay period. This cutoff proxies for households who have zero liquid assets at the end of the pay period.

\[
\bar{m}_{it} \geq 0, \bar{m}_{it} \leq y_{it}/2
\]

The second cutoff includes households with negative net liquid wealth which is smaller than the half their earnings per pay period minus their credit limit. This is proxying for households who are at their credit limit at the end of each pay period. \(^{10}\)

\[
\bar{m}_{it} \leq 0, \bar{m}_{it} \leq y_{it}/2 - \bar{m}_{it}
\]

Finally, I assume in my benchmark analysis that most households are paid bi-weekly. This follows data from the Consumer Expenditure Survey which shows around 50% of individuals get paid on a bi-weekly basis.

\(^{10}\)These are conservative definitions, as households may consume resources faster than at a constant rate.
Using this method, I define poor hand to mouth households (PHTM) as households with zero net illiquid wealth who meet the cutoff for HTM status as described above. Similarly, wealthy hand to mouth households (WHTM) are households with positive illiquid wealth who meet the cutoff for HTM status. Finally non hand to mouth households (NHTM) have positive net illiquid wealth and have net liquid wealth balances above the cutoffs.

Table 3.2 summarizes the relative characteristics of the three groups as discussed in Kaplan et al. (2014). WHTM households have a larger median income than the PHTM but lower than the NHTM households. They are slightly older compared to PHTM households, but younger than NHTM households. They also have intermediate levels of normal income, defined as income the household would expect to receive in a "normal" year.

### Table 3.2: Characteristics by hand to mouth status

<table>
<thead>
<tr>
<th></th>
<th>NHTM</th>
<th>WHTM</th>
<th>PHTM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income</td>
<td>52000</td>
<td>37000</td>
<td>18000</td>
</tr>
<tr>
<td>Normal Income</td>
<td>61769</td>
<td>42599</td>
<td>24494</td>
</tr>
<tr>
<td>Age</td>
<td>49</td>
<td>44</td>
<td>40</td>
</tr>
<tr>
<td>Education</td>
<td>14</td>
<td>12</td>
<td>12</td>
</tr>
</tbody>
</table>

3.3.1 Hand to Mouth Trends

Figure 3.1 shows the evolution of constrained groups in the SCF sample between 2007 and 2009. Overall proportion of WHTM or PHTM households did not change between

---

11Households with negative illiquid wealth are also considered to PHTM. These are households who are underwater on their mortgages. They are only 0.4% of the sample in 2007 and 2.9% of the sample in 2009.
2007 and 2009. The baseline proportion of WHTM households was 14.1% in 2007 and 13.4% in 2009. Similarly, the baseline proportion of PHTM households was 10.8% in 2007 and 10.7% in 2009.

**Figure 3.1: Proportion of Hand to Mouth Households in the United States**

![Hand to Mouth Proportion](image)

In order to understand whether this result is specific to the definition of hand to mouth status, I define both WHTM and PHTM status in alternative ways. Table 3.3 shows the finding is robust to various definitions. Using a stricter definition of both liquid and illiquid asset cutoffs changes the proportion of WHTM and PHTM households, but does not affect the finding that the proportions do not change over the period. As there are some costs to liquidating directly held mutual funds, stocks and bonds, another measure includes them as illiquid assets. This raises the proportion of WHTM households and lowers the proportion of PHTM households, but the trends remain the same. Some households use financial equity in vehicles for consumption smoothing purposes. Hence, I also use a definition of illiquid assets which includes vehicle wealth and get the same result. Since retirement accounts are more liquid for retired households\(^\text{12}\), I use an alternative definition where retirement account values are included in liquid assets for

\(^{12}\)Households in retirement do not need to pay taxes when pulling cash out of their retirement accounts.
those above sixty years. Next, I do not include households with large credit card debt in the measure of hand to mouth status to check if the trends are dominated by such households. I find that the trends remain even after discarding such households. Finally, I also include two other measures of hand to mouth status, defining financially fragile households as households with up to 2,000 dollars in liquid assets and defining households with up to 2 months of income in liquid assets as hand to mouth households. The results remain the same in these cases as well.

Table 3.3: Robustness of HTM household proportions

<table>
<thead>
<tr>
<th></th>
<th>WHTM</th>
<th>PHTM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2007</td>
<td>2009</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.14</td>
<td>0.13</td>
</tr>
<tr>
<td>Higher Illiquid Asset Thresholds a</td>
<td>0.12</td>
<td>0.11</td>
</tr>
<tr>
<td>Higher Illiquid Asset Thresholds b</td>
<td>0.11</td>
<td>0.10</td>
</tr>
<tr>
<td>Stricter Liquid Asset Categories c</td>
<td>0.15</td>
<td>0.14</td>
</tr>
<tr>
<td>Vehicles in Illiquid Assets d</td>
<td>0.21</td>
<td>0.20</td>
</tr>
<tr>
<td>Retirement Accounts for Older Households e</td>
<td>0.13</td>
<td>0.13</td>
</tr>
<tr>
<td>Credit Card Users not included f</td>
<td>0.15</td>
<td>0.15</td>
</tr>
<tr>
<td>Financially Fragile Households g</td>
<td>0.26</td>
<td>0.24</td>
</tr>
<tr>
<td>Broad Liquidity Status h</td>
<td>0.39</td>
<td>0.39</td>
</tr>
</tbody>
</table>

a Illiquid assets threshold is set at 3,000 dollars.
b Illiquid assets threshold is set at 6,000 dollars.
c Liquid assets do not include directly held mutual funds, stocks and bonds.
d Vehicle values are now included in illiquid assets.
e Retirement accounts for respondents over 60 years is included in liquid assets.
f People with credit card balances over 1,000 dollars are not included in the calculations.
g These include households with upto 2,000 dollars in liquid assets.
h These include households with upto 2 months of income in liquid assets.
These findings however mask tremendous instability of these groups within them. The panel element of the SCF data allows me to follow each household and analyze transitions between groups in the two year period. There are large movements between the WHTM and NHTM groups between 2007 and 2009. Table 3.4 shows the WHTM status is very transitory and half of the group become NHTM (7.32%) and a similar number of households join WHTM from NHTM (6.89%) between 4Q 2007 and later half of 2009. In contrast, the PHTM status is more stable, as a majority of PHTM households in 2007 remain in the same status in 2009.

Table 3.4: Percentage of Households in each category in 2007 (row) and 2009 (column)

<table>
<thead>
<tr>
<th>Status</th>
<th>NHTM</th>
<th>PHTM</th>
<th>WHTM</th>
</tr>
</thead>
<tbody>
<tr>
<td>NHTM</td>
<td>65.51</td>
<td>2.66</td>
<td>6.89</td>
</tr>
<tr>
<td>PHTM</td>
<td>3.13</td>
<td>6.35</td>
<td>1.37</td>
</tr>
<tr>
<td>WHTM</td>
<td>7.32</td>
<td>1.65</td>
<td>5.12</td>
</tr>
</tbody>
</table>

These two findings hold true when assets and hand to mouth cutoffs are defined in different ways. Table 3.5 shows the % of households switching from WHTM into NHTM and vice versa with the different definitions. In all the cases, half of WHTM households turn into NHTM and a similar proportion of NHTM households turn into WHTM. Even when using the broadest definition of illiquid households, I find that around 13% of the sample gains enough liquidity buffers and a similar percentage loses its liquidity buffers.

These results show that the WHTM status is quite transitory, while the PHTM status is more persistent. They also point towards a significant role for circumstance in how households become wealthy hand to mouth during deep recessions. If the characteristics view solely determined liquidity status, wealthy hand to mouth status ought to be more persistent. However, the transitory behavior of WHTM households suggests circumstantial factors such as losses to income, housing wealth are key in driving decisions on liquidity. Why and how do households change their liquidity status? I turn to this question next by focusing on two groups; households who build liquidity buffers
Table 3.5: Robustness of HTM household transitions

<table>
<thead>
<tr>
<th></th>
<th>WHTM into NHTM</th>
<th>NHTM into WHTM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>7.3</td>
<td>6.9</td>
</tr>
<tr>
<td>Higher Illiquid Asset Thresholds (^a)</td>
<td>6.3</td>
<td>6.2</td>
</tr>
<tr>
<td>Higher Illiquid Asset Thresholds (^b)</td>
<td>6.1</td>
<td>5.8</td>
</tr>
<tr>
<td>Stricter Liquid Asset Categories (^c)</td>
<td>8.1</td>
<td>7.3</td>
</tr>
<tr>
<td>Vehicles in Illiquid Assets (^d)</td>
<td>9.6</td>
<td>8.5</td>
</tr>
<tr>
<td>Retirement Accounts for Older Households (^e)</td>
<td>6.9</td>
<td>6.6</td>
</tr>
<tr>
<td>Credit Card Users not included (^f)</td>
<td>5.5</td>
<td>5.7</td>
</tr>
<tr>
<td>Financially Fragile Households (^g)</td>
<td>10.9</td>
<td>8.4</td>
</tr>
<tr>
<td>Broad Liquidity Status (^h)</td>
<td>13.1</td>
<td>13.2</td>
</tr>
</tbody>
</table>

\(^a\) Illiquid assets threshold is set at 3,000 dollars.
\(^b\) Illiquid assets threshold is set at 6,000 dollars.
\(^c\) Liquid assets do not include directly held mutual funds, stocks and bonds.
\(^d\) Vehicle values are now included in illiquid assets.
\(^e\) Retirement accounts for respondents over 60 years is included in liquid assets.
\(^f\) People with credit card balances over 1,000 dollars are not included in the calculations.
\(^g\) These include households with up to 2,000 dollars in liquid assets.
\(^h\) These include households with up to 2 months of income in liquid assets.

between 2007 and 2009 (turn from WHTM to NHTM) and households who lose liquidity buffers between 2007 and 2009 (turn from NHTM to WHTM).

### 3.3.2 Households building liquidity buffers

The first group turn from WHTM to NHTM status by building liquidity buffers they did not have in 2007. The median household in this group increases liquid asset holdings by 1200 dollars, while households in the 75th percentile increase liquid asset holdings by 5000 dollars.\(^{13}\) Figure C.1 in the Appendix shows a majority of this happens through

\(^{13}\)There is a minority in this group that are characterized as NHTM in 2009 because their credit limits rose significantly while they lost liquidity. That subgroup is not included in this analysis.
increases in the checking accounts, although there is a substantial increase in the savings accounts as well.  

### 3.3.2.1 Why?

Households may work hard to build liquidity buffers for a few reasons. First, they might have been hit by transitory income shocks, which may have depleted their liquid asset buffers, and they may have been building liquidity buffers as a result. They may also have personality characteristics which may lead them to shift to NHTM. Finally, they may have learnt something about their wealth or permanent income. I quantitatively analyze how each of these factors affects the probability of a WHTM household switching to NHTM between the survey periods. I use the difference in income between 2007 and 2009 as the measure of short term income changes. In addition, the survey includes a question on "normal" income for the households, which has been used previously as a proxy for permanent income (see Kennickell and Lusardi (2004)). I use this variable to generate the difference in permanent income expectations for each household between 2007 and 2009.  

Finally, I also utilize the changes in housing price values as the wealth shock. Following Kennickell and Lusardi (2004), I run regressions accounting for both multiple imputations and sampling variance issues. Table 3.6 shows the results of regressions where the dummy variable for switching to NHTM status is regressed on all of these factors, as well as socio-economic and demographic variables. Columns 1 and 2 use the linear probability model, while Columns 3 and 4 use a probit regression model.

---

14Data limitations on cash holdings however make it impossible to ascertain if these increases are accompanied by increase in cash holdings as well.

15As expected, around 50% of the group has negative changes to permanent income, as the recession gained strength between 2007 and 2009.

16In order to deal with missing values, FRB creates a set of sample replicates using bootstrap techniques and computes analysis weights independently for each replicate. I use the Stata command `scfcombo` which handles both issues.
The results are qualitatively consistent for both the linear probability models and probit regressions. Decreases in income are associated with a lower probability of building liquidity buffers, as are decreases in permanent income. On the other hand, loss of housing wealth is positively correlated to the probability of building liquidity buffers in this period. While other controls such as age are mostly insignificant, being African American is associated with a significantly lower probability of building liquidity buffers. Finally, having higher education levels is also associated with a higher probability of switching under some regression specifications.
Results from the regression are mostly consistent with buffer stock models of consumption, which specify a target wealth to permanent income ratio. In the canonical buffer stock consumption model, (see Carroll (2000)), the ratio of consumption $C$ to permanent labor income $P$ is a concave function of the ratio of current resources $X$ (defined as the sum of financial wealth and current income) to permanent labor income. That is,

$$C = c\left(\frac{X}{P}\right)P,$$

where $c(x)$ is an increasing, concave function. Here, if the actual wealth to permanent income ratio is below the target ratio, then precautionary savings motives push households to save to get back to the target ratio. However, if the ratio is above the target, households dis-save. In this framework, a fall in permanent income expectations leads to a rise in the actual wealth to permanent income ratio compared to the target, which makes it likely that the households dis-save. This matches the result from the regressions. On the other hand, if illiquid wealth is lost through valuation effects, the need to acquire liquid wealth to meet the target wealth to permanent income ratio becomes more important. 17

In addition, larger permanent income in 2007 and higher education levels are also associated with a higher probability of building liquidity buffers during the recession. Overall, these results show that while there is some room for characteristics, the predictions of traditional circumstance based buffer stock theories are important. Significant parts of the population built buffer stock liquid wealth during the Great Recession. They were more prone to doing so when they had lost wealth in their houses, but did not have a large drop in normal income expectations. An interesting unanswered question is; how did these households build up their liquid asset buffers?

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17This assumes liquid and illiquid wealth is treated similarly when it comes to consumption smoothing plans. This assumption is generally true apart from the fact that households face transaction costs when attempting to use illiquid wealth for consumption smoothing purposes.
3.3.2.2 How?

There have been previous explanations for how households in deep recessions may build liquidity buffers. Kaplan and Violante (2014) argue that in a deep recession, households with illiquid assets find it worth the transaction costs to pull their money out of such assets. A substantial proportion of households leave WHTM status and join NHTM status in this process. In the panel SCF data, households who left WHTM status by building liquidity buffers did have lower illiquid wealth balances in 2009. The median change in illiquid wealth in this group was a fall of $4,100 while the 75th percentile had a fall of $45,000. At first glance, it is plausible that this fall in illiquid wealth was caused by households liquefying their illiquid wealth. In such a scenario, while the illiquid wealth drops, the liquid wealth levels rebound, as in the data. However, I show that this is not a major driver of the liquidity status transitions in this period. The households who gained liquidity buffers did not do so by actively withdrawing from their illiquid wealth. Instead, the large majority of their balance sheet changes were valuation losses on their illiquid assets. I show this in two ways. First, I analyze the cumulative changes for each component of the net illiquid wealth account across all households in the subsample and show the changes were dominated by the valuation effects on housing. Second, I focus on cross-sectional data and argue that for a large majority of the group, housing wealth was the dominant wealth, and the households did not extract housing wealth between the two surveys. Both methods use the following decomposition of the changes in the NIW (net illiquid wealth) account into its various components (Equation 3.1).

\[ \Delta \text{NIW} = \Delta \text{Housing Value} - \Delta \text{Mortgage Value} + \Delta \text{Retirement Account} + \Delta \text{Savings Bonds} + \Delta \text{CDs} + \Delta \text{Insurance Cash Value} \]

Cumulative Analysis

In Figure 3.2, I add up changes in each part of the NIW account across the subsample that changes its status from WHTM to NHTM between 2007 and 2009. This measure allows me to analyze contributions of various components for the whole group.
ΔHousing Value accounts for 70% of the changes in the NIW account for the overall group. The next largest contributors are changes in mortgage values and retirement accounts.

Figure 3.2: Changes in NIW 2007 - 2009 for WHTM households

![Chart showing changes in NIW for WHTM households]

**Housing Values:** Housing values contribute the largest share of the fall in the net illiquid asset accounts by far, accounting for 70% of total changes in the NIW. While changes in housing values can come both from valuation changes and illiquid asset withdrawals (coming from house sales), I find that the withdrawals only contribute 4.5% of ΔHousing Value and 3.3% of the total fall in NIW. I separate changes in housing values into withdrawals and valuation effects by utilizing questions regarding residence changes. The SCF includes variables which denote whether people switched houses, and the reasons behind the decision. Only 3.3% of the group move away from their principal residences between 2007 and 2009 due to cost or income pressures. As a conservative estimate, I assume that all residence changes are due to economic pressures. Even then, only 13.3% of the group change their principal residences between the two surveys. In addition, the total contribution of such moves on ΔHousing Value is 4.5%. More than
95% of $\Delta$Housing Value is coming from the valuation change rather than from active sale decisions by households.

**Mortgage Values:** Traditional methods of withdrawing money from the housing asset include cash out refinancing, borrowing on existing HELOCs, undertaking new HELOCs, and taking out a second mortgage. All of these raise housing liability and do not affect the level of the housing asset. Only around 1% of the fall in the NIW account comes from an increase in the mortgage value in the SCF data. This includes the payment of mortgage balance which is hidden in the SCF data. For a 30 year fixed rate mortgage (which I consider an average mortgage), the amortization schedule is 30 years as well. The homeowner pays back all of it in 30 years, which means a homeowner would pay back around 6.6% of the mortgage in two years, the period between the two SCF panel surveys. This would mean that naturally, the mortgage size should have gone down by around 6.6%. Figure 3.2 adds this to the increase in mortgage values seen in the data, the sum of which accounts for 1% of the total change in the NIW account.

**Retirement Accounts:** another large contributor to the change in NIW is through the retirement account ($\Delta$Retirement Account). Around 25% of the fall in NIW is explained by retirement account differences. Again, the value of the retirement account could have gone down because a) the money was invested in the stock market, where fall in stock market prices led to a fall in the value of the retirement account or b) the households actively withdrew their money out of their 401k and IRA accounts. As the SCF does not include data on actual withdrawals, it is difficult to distinguish between the two causes. As a back-of-the-envelope analysis, I add up the retirement account levels for the group in 2007 and 2009 and find that the total retirement account balance dropped by 20% in the two year period. Considering the stock market dropped by more than 27% in this same period \(^{18}\), I argue a majority of this change came from the fall in the stock market rather than from withdrawals.

\(^{18}\)Between early 4Q 2007 and July 2009, S&P500 index fell by 40.3% and fell by 27.92% between early 4Q 2007 and December 2009.
Others: $\Delta$Savings Bonds, $\Delta$CDs, $\Delta$Insurance Cash Value are very small in proportion to $\Delta$NIW. Both changes in savings bonds and life insurance values are responsible for less than a percentage of the changes in the NIW balances. Changes in CDs are responsible for around 6% of the changes in the NIW balances. A large reason for this is that most WHTM households do not hold much savings bonds, CDs and insurance cash values (median WHTM households have 0 in these accounts in 2007).  

Cross-Sectional Analysis: WHTM households who built liquidity buffers between 2007 and 2009 owned very little in non-housing illiquid assets in 2007, as shown in figure 3.3. The median household in this group owned less than $3,500 in non-housing illiquid assets in 2007. In contrast, the median household owned around $32,000 in housing equity at the same time. Figure C.2 shows non-housing illiquid wealth was all concentrated in retirement accounts, as these households did not own CDs, savings bonds, or life insurance equity.

Figure 3.3: Non-Housing Illiquid Assets for WHTM Households

For these households, most changes in the illiquid accounts between 2007 and 2009.

---

19 Table .15 in the appendix compares median values of various variables in 2007 between the group that switches to NHTM and finds they are richer, and have more more housing wealth in 2007.
came from valuation effects on the house, not adjustment of illiquid assets. There are four ways of accessing illiquid housing wealth; selling, cash out refinances, second mortgages and home equity lines of credit (HELOC). Selling for income pressure reasons was very rare in this period, as 3.3% of the group moved away from their principal residences between 2007 and 2009 due to cost or income pressures. Cash out refinances are reflected in increases in the mortgage value for households who own the same houses as in 2007. I find that the median household does not increase housing debt at all in this period. Only around ten percent of the group have increases in mortgage above 20,000 dollars, which suggests very limited usage of cash out refinancing. 20 As for second mortgages, the proportion of households who take a second mortgage to get home equity in the house is only 2.23% of the group. Finally, the proportion of households who take a new HELOC loan (did not have HELOCs in 2007 but had HELOCs in 2009) is 3.86% of the group. For households with existing HELOCs, households between 10th percentile to the 90th percentile had no change in HELOC usage, which suggests HELOC usage between 2007 and 2009 only increased for a very small subsample of the group. This provides further evidence to the assertion that traditional methods of withdrawing money from the housing asset were not significant reason for changes in NIW. On the other hand, the median household lost around $9,000 in home values. Figure 3.4 shows the change in home prices was heavily skewed negative for the whole group, as household in the 75th percentile of losses lost $43,000 in housing wealth. 21

I perform robustness checks by analyzing the proportion of the group for whom \( \Delta \text{NIW} \) is dominated by \( \Delta \text{Housing Value} \). 66% of the group with a fall in NIW show a fall in \( \Delta \text{Housing Value} \). For 54% of the group, fall in housing asset value contributes to more than half of the fall in the NIW.

---

20 This is after adjusting for imputed principal payments between the two survey periods. Bhutta and Keys (2016) show households take out a median of $23,000 in housing equity every time they cash out refinance on their mortgage.

21 This analysis does not include households who change residence between 2007 and 2009.
All of these facts reinforce the idea that a) for the households who switched from WHTM to NHTM status between 2007 and 2009 a majority of the contribution in the fall of NIW came from fall in house prices, b) traditional methods of pulling liquidity from the house operate through raising mortgage size and this did not contribute to a majority of changes in the NIW accounts. The mechanism where WHTM households ignore the fixed costs of illiquid assets and actively withdraw wealth from their illiquid accounts in a deeper recession does not appear to be important in the SCF data.

This leaves consumption as the only margin of adjustment for such households. If there are no withdrawals from illiquid asset accounts, then changes to liquid assets have to come from consumption. I calculate the lower bound of this consumption change for households who did not change residences, and did not engage in cash-out refinancing, or taking a second mortgage or using HELOCs. I find the median household cut cumulative consumption over the period by around $1,100 while the lowest 10th percentile cut consumption by $16,000.

\[22\] These results are supported by regression tables .16 and .17 in the appendix, where I regress the changes in various illiquid and liquid accounts on whether a household that is WHTM in 2007 changed its status to NHTM in 2009 or not. I control for log of labor income, age and education.
3.3.3 Households losing liquidity buffers

6.89% of the households in the sample change status from NHTM to WHTM status between 2007 and 2009. The median in this group lost $1,300 in liquid assets, and the 75th percentile lost $5,600. C.5 demonstrates a majority of such losses were in checking accounts, while households lost some liquidity from savings accounts as well. As in the case of households building liquidity buffers, households may lose liquidity buffers as a temporary reaction to income losses. Large losses to permanent income expectations can also cause households to keep lower cash in hand. I regress wealthy hand to mouth status in 2009 on all of these factors, and Regression 3.7 shows the results. Columns 1 and 2 show results of the linear probability model regressions while Columns 3 and 4 show results of probit regressions.

Circumstantial factors connected to income, such as % change in incomes between 2007-09 and changes to normal income expectations are not significant predictors of households’ HTM status in 2009. However, the level of normal income in 2007 is strongly and negatively correlated to the probability of switching into WHTM status. Older and higher educated households are also much less likely to lose their liquidity buffers in 2009. The only circumstantial variable significant in the regressions is the % change in housing values. These results suggest the households who switched to WHTM status were different already in 2007 to the group which did not, and they lost more in housing value as well.

I further explore whether there were some inherent differences between the two groups (NHTM households that stayed as NHTM vs. those that changed to WHTM status by 2009). I analyze their distributions for various important variables in 2007, including income, age, education, illiquid wealth size, house values, mortgage balance, leverage ratio for the house, liquid account wealth, credit card debt, net liquid wealth and net liquid wealth to income ratio. Table 7 shows the difference between the median levels for the two groups.
The group that stays NHTM is richer, and has a higher normal income. It also has higher illiquid wealth in 2007 and higher values for its housing assets and liabilities. The starkest difference between the two groups however comes from the median liquid wealth in 2007, 23 thousand for the group that stays in NHTM status against 1,200 for the group that changes its status. Below, I compare the liquid wealth to income ratio. Figure 3.5 shows the distribution of the two groups’ liquid wealth to income ratios. Group 1 is distributed around a much lower liquidity to income ratio in 2007. In 2009, these are the same households that become WHTM. In essence, I find that the group that changes to

<table>
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<th>(2 - LPM )</th>
<th>(3 - Probit)</th>
<th>(4 - Probit)</th>
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<td>0.006</td>
<td>0.039</td>
<td>0.036</td>
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<td></td>
<td>(0.011)</td>
<td>(0.012)</td>
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<td>(0.072)</td>
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<td>% Δ Normal Income</td>
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<td>0.009</td>
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<td>(0.107)</td>
</tr>
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<td>log Normal Income</td>
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<td>−0.046***</td>
<td>−0.356***</td>
<td>−0.350***</td>
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<tr>
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<td>(0.007)</td>
<td>(0.009)</td>
<td>(0.050)</td>
<td>(0.067)</td>
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<tr>
<td>% Δ Housing Value</td>
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<td>−0.048***</td>
<td>−0.424***</td>
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<td>(0.013)</td>
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<td>(0.036)</td>
<td>(0.252)</td>
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<td>Age in 2007</td>
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<td>(0.001)</td>
<td>(0.004)</td>
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<td>−0.047***</td>
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<td>(0.003)</td>
<td>(0.018)</td>
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<tr>
<td>Constant</td>
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<td>0.825***</td>
<td>2.546***</td>
<td>3.789***</td>
</tr>
<tr>
<td></td>
<td>(0.087)</td>
<td>(0.117)</td>
<td>(0.553)</td>
<td>(0.837)</td>
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</table>

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
Table 3.8: Differences between Group that stayed as NHTM and changed to WHTM

<table>
<thead>
<tr>
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<th>NHTMtoWHTM</th>
<th>NHTMtoNHTM</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image.png" alt="Table 3.8: Differences between Group that stayed as NHTM and changed to WHTM" /></td>
<td></td>
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</tr>
</tbody>
</table>

WHTM has (i) more negative changes in house prices, (ii) was poorer and held low total wealth, but (ii) was already holding low liquid wealth compared to its wealth.

Figure 3.5: Liquid Wealth to Income Ratio

These results put an emphasis on characteristics based factors as determinants of future liquidity status. The largest predictors of a switch in liquidity status are character-
istics from 2007 (such as income, education and age), rather than income circumstances that changed between 2007-09. The only change in circumstance which predicts switching is loss to housing wealth.\textsuperscript{23} Again, the importance of including valuation effects on the illiquid asset is highlighted.

### 3.4 Conclusion

Hand to mouth status has been espoused as an important variable in understanding the overall impact of fiscal and monetary policies during recessions. In this chapter, I have analyzed the trends in liquidity (and hand to mouth) status for households in the Great Recession period using the panel Survey of Consumer Finances (SCF). In doing so, I document three findings. First, the overall proportion of wealthy hand to mouth households stayed constant in the United States between 2007-09. Second, the wealthy hand to mouth status was very transitory, as half of the group transitioned into non hand to mouth during this period. For households building liquidity buffers, losses to permanent income and housing wealth were important variables which predicted liquidity management behavior. Third, such movement was primarily achieved through methods other than the extraction of illiquid assets. This implies households who build liquidity buffers during recessions do so through cutting consumption sharply. Finally, for households who lost liquidity buffers, characteristics in 2009 such as income, age, education are stronger predictors of behavior than changes to income circumstances, with one exception being change in housing values.

Taken together, these findings imply that both circumstantial and characteristics views on household liquidity are important when analyzing deep recessions with housing crises. In the case of circumstantial models, separation between assets and liabilities

\textsuperscript{23} These results are supported by regression tables .18 and .19 in the appendix, where I regress the changes in various illiquid and liquid accounts on whether a household that is NHTM in 2007 changed its status to WHTM in 2009 or not. I control for log of labor income, age and education again.
is necessary, as valuation changes in home values and subsequent tightening of borrowing constraints are important factors driving consumer finance and liquidity status in a balance sheet recession.
Bibliography


Appendix A

A.1 Scaling

As the NCP dataset only includes spending on goods with barcodes, coverage is focused on grocery, drugstore, mass merchandise goods. Healthcare spending and apparel spending is not included. I am interested in MPC out of nondurable spending in general, but the dataset only covers around 35% of total nondurable spending as measured by the Consumption Expenditure Survey of 2008.

One simple way to scale from MPC out of NCP spending to MPC out of nondurables spending is to assume that the elasticity of spending across goods is the same. I do this by multiplying the MPC in the results by 2.8. There are reasons why the MPC out of NCP spending may be higher or lower than the MPC out of total nondurables. While some categories of goods and services not included in the NCP such as healthcare generally have lower MPC out of transitory income, the NCP dataset caters more to spending on necessary goods, which have lower MPC than the average consumption basket. I argue there is no systematic bias after netting these effects out.
A.2 Nonmonotonicity Results

As I highlighted in Chapter 1, the nonmonotonic correlation between MPC and % changes in local house price values comes primarily from households without liquid assets. Figure A.1 shows the results for illiquid households with 95% confidence bands. The nonmonotonic pattern is significant, as households in zipcodes that have housing price declines of over 30% have a large and significant MPC (over 30% MPC).

![Figure A.1: MPC for Illiquid Households](image)

In order to understand why only illiquid households have nonmonotonic MPC, I utilize a question in the dataset that asks households about their spending plans from the rebate. I separate the group that plans to deleverage in the regressions against other groups of illiquid households and liquid households. Figure A.2 shows the nonmonotonic result is driven by illiquid households who claim to use the rebate for deleveraging. For these households, the MPC in the areas with largest house price declines is

---

1 Households can answer they are using the rebates to pay down debt, spend, save or do not know. Respondents who plan to use the rebates to pay down debt are considered deleveragers.
very strongly positive (over four times as much as the sample average) and significant at 95% significance level. Such deleveragers first comprise around 65% of the illiquid households group, hence the nonmonotonicity for the full group.

Figure A.2: MPC for Illiquid Deleveragers

\[
\text{% Housing Price Change}
\]
On the other hand, Figure A.3 shows illiquid households who are not planning to deleverage (including saving, spending and those not sure) show pattern similar to liquid households.

Figure A.3: MPC for Illiquid Non-Deleveragers
A.3 Detailed Empirical Results

Figure A.4 shows the histogram of the housing price changes in zipcodes between 2005 and 2008.
Figure A.5 shows the second month MPC by tercile.

**Figure A.5: Month 2 MPC by Housing Price Change**

Terciles of % Housing Price Change
Figure A.6 shows the spending responses in the polynomial model for the second month.

**Figure A.6: Spending Response by Housing Price Change (Month 2)**
Figure A.7 shows the spending responses in the polynomial model for the first two months.

Figure A.7: Spending Response by Housing Price Change (Total)
Figure A.8 shows MPC along with confidence bands for liquid households in Month 1.

Figure A.8: MPC for Liquid Households
Figure A.9 shows MPC along with confidence bands for illiquid households in Month 1.

Figure A.9: MPC for Illiquid Households
Figure A.10 shows mean weighted MPC when proportion of liquid households is calculated in two different ways.

Figure A.10: *Average MPC using various Liquid Household Proportions*
Figure A.11 shows MPC for richer and poorer households.

Figure A.11: MPC by Income
Figure A.12 shows MPC for younger and older households.

Figure A.12: MPC by Age
Figure A.13 shows the results for the winsorized data.

Figure A.13: *Regressions with winsorized data*
Figure A.14 shows MPC for each decile.

Figure A.14: Spending Response by Housing Price Change (Month 1)
Figure A.15 shows the correlation between changes in unemployment rates and housing prices.

Figure A.15: Changes in Unemployment Rates and Housing Price Changes by Zipcode
Figure A.16 shows the correlation of housing price changes in 2002-05 with changes in 2005-08.

Figure A.16: Changes in Housing Price Changes by County (2002-05 vs. 2005-08)
Figure A.17 shows the geographical distribution of housing price changes.

Figure A.17: US Zipcodes in Various Deciles
<table>
<thead>
<tr>
<th>Deciles</th>
<th>Income</th>
<th>HH Size</th>
<th>Age</th>
<th>Liquidity</th>
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<td>60</td>
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<td>13</td>
<td>151</td>
<td>24</td>
</tr>
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</table>

Notes: Income denotes mean household income in 2006. HH size denotes the mean size of the household. Age is the maximum of the age of the male and female heads of the households. Liquidity is the percentage of households answering Yes to the liquidity question in the survey. Black and Hispanic denote the percentage of those groups in the subsamples. Spending denotes the average weekly spending in the subsamples. Finally, Work denotes the proportion of households where the male head of the family is not working. There is no data in NCP to denote unemployment directly. Finally, all results are weighted by the NCP projection factor weights.
Table A.2: Sample Balance (Extended)

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<td>51</td>
<td>22.1</td>
<td>56.0</td>
<td>55.2</td>
</tr>
</tbody>
</table>

Notes: Mail denotes the percentage of households who received their rebates in mail. Reb. Receipt denotes the mean week of the year when households received the rebate. Male and Female Education denote the percentage of male and female heads of households who had finished college or had more education.
Table A.3: Baseline Regressions (Full Sample and Terciles 1-3)

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Notes: Dependent variable is spending. Time and Household Fixed Effects are included. The Reb variable is an indicator of rebate receipt. Standard errors clustered at household-level in parentheses. ***/**/* indicates significance at 99%/95%/90%-level respectively. All sample statistics are weighted by the NCP projection factor for 2008. Calculated based on data from The Nielsen Company (US) LLC and provided by the Marketing Data Center at the University of Chicago Booth School of Business.
Table A.4: Polynomial Regression

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<tr>
<th>Variable</th>
<th>Variable $\times \Delta H$</th>
<th>Variable $\times \Delta H^2$</th>
<th>Variable $\times \Delta H^3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Reb_t$</td>
<td>17.89***</td>
<td>-97.95</td>
<td>-444.6</td>
</tr>
<tr>
<td></td>
<td>(3.14)</td>
<td>(121.1)</td>
<td>(314.9)</td>
</tr>
<tr>
<td>$Reb_{t-1}$</td>
<td>14.56***</td>
<td>36.23</td>
<td>-87.8</td>
</tr>
<tr>
<td></td>
<td>(3.08)</td>
<td>(141.1)</td>
<td>(345.7)</td>
</tr>
<tr>
<td>$Reb_{t-2}$</td>
<td>3.54</td>
<td>65.3</td>
<td>-117.1</td>
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<tr>
<td></td>
<td>(2.89)</td>
<td>(120.9)</td>
<td>(305.7)</td>
</tr>
<tr>
<td>$Reb_{t-3}$</td>
<td>4.84</td>
<td>-1.54</td>
<td>-356.4</td>
</tr>
<tr>
<td></td>
<td>(3.16)</td>
<td>(153.42)</td>
<td>(366.7)</td>
</tr>
<tr>
<td>$Reb_{t-4}$</td>
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<td></td>
<td>(3.12)</td>
<td>(140.26)</td>
<td>(373.1)</td>
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<tr>
<td></td>
<td>(3.67)</td>
<td>(227.2)</td>
<td>(529.4)</td>
</tr>
<tr>
<td>$Reb_{t-6}$</td>
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<td>(157.3)</td>
<td>(379.4)</td>
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<td>$Reb_{t-7}$</td>
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<tr>
<td></td>
<td>(3.76)</td>
<td>(186.5)</td>
<td>(437.1)</td>
</tr>
</tbody>
</table>

Notes: Dependent variable is spending. Time and Household Fixed Effects are included. The $Reb$ variable is an indicator of rebate receipt. Standard errors clustered at zipcode-level in parentheses. ***/***/* indicates significance at 99%/95%/90%-level respectively. All sample statistics are weighted by the NCP projection factor for 2008. Calculated based on data from The Nielsen Company (US) LLC and provided by the Marketing Data Center at the University of Chicago Booth School of Business.
Appendix B

B.1 Policy Analysis

This appendix derives the formula characterizing optimal targeted transfer policy described in the main text.

Time is discrete, $t = 1, 2, \ldots$. The economy consists of $I$ equally sized local regions within a currency union.

**Households.** The representative household within region $i$ (henceforth, ‘individual $i$’) has preferences

$$V_i^1 = u(c_{i1}) - v(n_{i1}) + \beta_i V_i^2(x_{i2})$$

where $c_{i1}$ denotes date 1 consumption, $n_{i1}$ hours worked, and $x_{i2}$ real net worth at date 2. We do not make any particular assumption about the individual’s problem at date 2, except that it can be summarized by some continuous, increasing, concave expected value function $V_i^2(x)$, which is independent of the policies discussed in this section.

Consumption is an aggregate of locally produced and imported goods:

$$c_{i1} = (c_{H,1}^i)^{\alpha} (c_{F,1}^i)^{1-\alpha}$$

$$c_{F,1}^i = \exp \left( \sum_{j=1}^I \frac{1}{I} \ln c_{j,1}^i \right)$$

where $c_{H,1}^i$ denotes $i$’s consumption of the locally produced good, and $c_{j,1}^i$ denotes $i$’s consumption of the good produced in region $j$. The parameter $\alpha$ indexes the degree of home bias. The price index for total nondurable consumption is therefore

$$p_1 = \frac{\bar{p}_{H,1}^{\alpha} \prod_{j=1}^I p_{j,1}^{\frac{1-\alpha}{1-\alpha}}}{\alpha^{\alpha \left( \frac{1-\alpha}{1-\alpha} \right)}}$$
Households in each region seek to maximize utility subject to the budget constraint

\[ P_{i,1}c_{H,1}^i + \sum_j P_{j,1}c_{j,1}^i + \frac{P_2x_2^i}{1+i_1} \leq W_1^i n_1^i + P_1x_1^i + P_2T^i \]

and the borrowing constraint

\[ x_2^i \geq -\phi^i \]

where \( P_{j,1} \) denotes the date 1 price of the good produced in region \( j \), \( 1+i_1 \) denotes the gross nominal rate of return on the risk free bond traded by households, \( W_1^i \) denotes the nominal wage in region \( i \), and \( T^i \) denotes the net real transfer from the federal government to households in region \( i \).

Nominal wages are sticky at date 1 with \( W_1^i = W \) for all \( i \). As a result, agents are not necessarily on their labor supply curves: \( \frac{W_0}{P_0} \neq \frac{v'(n_0^i)}{u'(c_0^i)} \). We assume that hours are equally rationed, \( n_0^i = n_0^j := n_0, \forall i, j. \)

**Firms.** Good \( i \) is produced by competitive firms according to the production function

\[ y_1^i = An_1^i \]

Given a nominal wage \( W \), perfect competition implies that \( P_1^i = \frac{W}{A} \), for all \( i \).

**Government.** We consider a scenario in which monetary policy is constrained by the zero lower bound at date 1 \( (i_1 = 0) \), and the monetary authority targets zero inflation at date 2 \( (P_2 = P_1) \). The fiscal authority collects a uniform lump sum tax \( \bar{T} > 0 \) from each region at date 1, and distributes these resources in the form of nonnegative, targeted lump sum transfers to households in different regions, \( T^i \geq 0 \). The government runs a balanced budget:

\[ \sum_i T^i = I\bar{T} \]

**Equilibrium.** Given a fiscal policy \( \{T^i\}_{i=1}^I \), an equilibrium is a collection \( \{c_{H,1}^i, \{c_{j,1}^i\}_{j=1}^I, n_1^i, x_2^i, y_1^i, P_1^i\}_{i=1}^I \) such that households and firms maximize, there is equal...
rationing \( n_i^i = n_j^i = n_1, \forall i, j \), and markets clear,

\[
c^i_{H,1} + \sum_j c^j_{i,1} = y_{i,1}
\]

**Optimal policy.** We consider the problem of a fiscal policymaker who assigns Pareto weight \( \lambda^i > 0 \) to individuals in region \( i \), and chooses transfers \( \{T^i\} \) in order to maximize social welfare

\[
\sum_i \lambda^i V_i^1
\]

In order to describe the solution to this problem, it is first useful to characterize equilibrium. It is straightforward to see that individual \( i \)'s optimization problem yields a value function \( V_i^1(n_1, T^i) \) which depends on hours worked and public transfers, and a consumption function \( c^i_1 = C^i(w_1n_1^i + T^i - \bar{T}) \) which depends on total income \( w_1n_1^i + T^i - \bar{T} \), where \( w_1 = \frac{W}{P_1} \) denotes the real wage (which, under our assumption, is independent of fiscal policy). Since perfect competition yields constant prices across regions, spending on local and foreign goods is given by \( P_i^i c^i_{H,1} = \alpha P_1 c^i_{1}, P_j^i c^i_{j,1} = \frac{1-\alpha}{I} P_1 c^i_{1} \). Substituting into the market clearing condition and using the fact that \( \frac{P_i}{P_1} = \frac{w_1}{\bar{A}} \), we have

\[
\alpha c^i_1 + \sum_j \frac{1-\alpha}{I} c^j_1 = w_1n_1^i
\]

The policymaker’s problem can therefore be written as

\[
\max_{\{n_i^i, T^i\}_{i=1}^I} \sum_i \lambda^i V_i^1(n_1, T^i) \tag{B.1}
\]

s.t. \( \alpha C^i(w_1n_1^i + T^i - \bar{T}) + \sum_j \frac{1-\alpha}{I} C^j(w_1n_1^j + T^j - \bar{T}) = w_1n_1^i, i = 1, ..., I \tag{B.2} \)

\[
\sum_i T^i = IT \tag{B.3}
\]

\[
T^i \geq 0, i = 1, ..., I \tag{B.4}
\]
yielding first order conditions

\[ \lambda^i \frac{\partial V^i}{\partial n_i^1} + \psi_i w_1 - \left( \alpha \psi_i + \frac{1 - \alpha}{I} \sum_j \psi_j \right) w_1 \frac{\partial C^i}{\partial T^i} = 0 \quad (B.5) \]

\[ \lambda^i \frac{\partial V^i}{\partial T^i} - \left( \alpha \psi_i + \frac{1 - \alpha}{I} \sum_j \psi_j \right) \frac{\partial C^i}{\partial T^i} - \mu \leq 0 \quad (B.6) \]

where \( \psi_j \) and \( \mu \) denote the Lagrange multipliers associated with constraints (B.2) and (B.3), respectively. If \( T^i > 0 \) at an optimum, (B.6) holds with strict equality. We can rearrange (B.5) as

\[ \psi_i = -\frac{\lambda^i}{w_1 - \alpha w_1 \frac{\partial C^i}{\partial T^i}} \frac{\partial V^i}{\partial n_i^1} + \frac{1 - \alpha}{I} \frac{1}{w_1 - \alpha w_1 \frac{\partial C^i}{\partial T^i}} \sum_j \psi_j w_1 \]

\[ \sum_i \psi_i = -\sum_i \frac{\lambda^i}{w_1 - \alpha w_1 \frac{\partial C^i}{\partial T^i}} \frac{\partial V^i}{\partial n_i^1} + \sum_i \frac{1 - \alpha}{I} \frac{1}{w_1 - \alpha w_1 \frac{\partial C^i}{\partial T^i}} \sum_j \psi_j w_1 \]

\[ \sum_i \psi_i = \frac{\sum_i \frac{\lambda^i}{w_1 - \alpha w_1 \frac{\partial C^i}{\partial T^i}} \frac{\partial V^i}{\partial n_i^1}}{\sum_i \frac{1 - \alpha}{I} \frac{1}{w_1 - \alpha w_1 \frac{\partial C^i}{\partial T^i}} \sum_j \psi_j w_1} \]

This in turn allows us to solve for \( \psi_i \):

\[ \psi_i = -\frac{\lambda^i}{w_1 - \alpha w_1 \frac{\partial C^i}{\partial T^i}} \frac{\partial V^i}{\partial n_i^1} + \frac{1 - \alpha}{I} \frac{1}{w_1 - \alpha w_1 \frac{\partial C^i}{\partial T^i}} \sum_k \frac{\lambda^k}{w_1 - \alpha w_1 \frac{\partial C^k}{\partial T^k}} \frac{\partial V^k}{\partial n_i^1} w_1 - 1 \]

\[ \alpha \psi_i + \frac{1 - \alpha}{I} \sum_j \psi_j = -\frac{\lambda^i}{w_1 - \alpha w_1 \frac{\partial C^i}{\partial T^i}} \frac{\partial V^i}{\partial n_i^1} + \frac{1 - \alpha}{I} \frac{1}{w_1 - \alpha w_1 \frac{\partial C^i}{\partial T^i}} \sum_k \frac{\lambda^k}{w_1 - \alpha w_1 \frac{\partial C^k}{\partial T^k}} \frac{\partial V^k}{\partial n_i^1} w_1 - 1 \]
Substituting into (B.6), we have

$$\lambda_i \frac{\partial V_i}{\partial T^i} + \alpha \left[ \frac{\partial V_i}{\partial n^i} \right] + \lambda_i \frac{\partial C^i}{\partial T^i} - \frac{1 - \alpha}{\sum_k \lambda_k \left( \frac{\partial V_k}{\partial T^k} \right)} = \mu$$

Finally, using the Envelope Theorem, we have

$$\frac{\partial V_i}{\partial T^i} = u'(c^i_1)$$
$$\frac{\partial V_i}{\partial n^i_1} = w_1 u'(c^i_1) - v'(n^i_1)$$

Define the MPC $m^i := \frac{\partial C^i}{\partial T^i}$; the social marginal utility of individual $i$, relative to the shadow cost of funds for the government $g^i := \frac{\lambda_i u'(c^i_1)}{\mu}$; and the labor wedge $\tau^i := 1 - \frac{v'(n^i_1)}{w_1 u'(c^i_1)}$. Using these results and definitions, we obtain the formula in the main text:

$$g^i \left( 1 + \tau^i \frac{am^i}{1 - am^i} \right) + \frac{m^i}{\sum_k \frac{g^k \tau^k}{1 - am^k}} \leq 1$$

which holds with strict equality for all regions receiving positive transfers.
B.2 Buffer Stock Model Details

A 2-period version of the canonical buffer stock model is

$$\max \ln c_1 + \mathbb{E} \ln c_2$$

s.t. $c_2 = Ra + y$

$$c_1 + a = x$$

where $y$ is stochastic. Here $x$ should be interpreted as date 1 income plus liquid wealth. We can interpret a fall in house prices in two ways - as a decrease in $x$ (if houses are perfectly liquid) or as a decrease in the mean of $y$ (if houses cannot be sold today but will be sold tomorrow).

It is a standard result that $c_1$ is an increasing, concave function of $x$. The proof here is a special case of the one given in Carroll and Kimball. We have the Euler equation

$$u'(c_1) = R \mathbb{E} u'(Ra + y) = \phi'(x - c_1)$$

where we define $u(c) = \ln c$, $\phi(s) = \mathbb{E} \ln(Rs + y)$. Since $u'' < 0, u''' > 0$, we likewise have $\phi'' < 0, \phi''' > 0$. First we show that $\frac{\phi''' \phi'}{(\phi'')^2} \geq \frac{u'''}{(u'')^2} = 2$. We need to show that $\phi''' \phi' - 2(\phi'')^2 \geq 0$. This expression is the determinant of the matrix

$$A = \begin{bmatrix} \phi'''(s) & \sqrt{2}\phi''(s) \\ \sqrt{2}\phi''(s) & \phi'(s) \end{bmatrix} = \mathbb{E} \begin{bmatrix} R^3u'''(Rs + y) & \sqrt{2}\phi''(Rs + y) \\ \sqrt{2}\phi''(Rs + y) & \phi'(Rs + y) \end{bmatrix} := \mathbb{E} B$$

so we need to show that $A$ is positive semidefinite. For all realizations of $y_2$, the matrix $B$ has determinant $R^4(u'''u' - 2(u'')^2) = 0$ and thus is positive semidefinite. Because the weighted sum of positive semidefinite matrices is positive semidefinite, $A$ is positive semidefinite.

We now differentiate the Euler equation with respect to $x$.

$$u''c_x = \phi''(1 - c_x)$$

$$c_x = \frac{\phi''}{u'' + \phi''}$$
Thus the MPC lies in \((0,1)\). Also note that we can write

\[
\frac{(1-c_x)^2}{c_x^2} = \frac{(u'')^2}{(\phi'')^2/\phi'}
\]

Differentiating a second time:

\[
u '''c_x^2 + u''c_{xx} = \phi'''(1-c_x)^2 - \phi''c_{xx}
\]

\[
c_{xx} = \frac{1}{u'' + \phi''} \left[ \phi'''(1-c_x)^2 - u'''c_x^2 \right]
\]

\[
= \frac{u'''c_x^2}{u'' + \phi''} \left[ \frac{\phi'''(1-c_x)^2}{u'''c_x^2} - 1 \right]
\]

\[
= \frac{u'''c_x^2}{u'' + \phi''} \left[ \frac{(u'')^2/(u'u''')} {((\phi'')^2/(\phi'\phi'''))} - 1 \right]
\]

Since the term in square brackets is nonnegative and the term multiplying it is negative, overall we have \(c_{xx} \leq 0\). The consumption function is concave, and the MPC is positive and (weakly) decreasing in initial wealth.
B.3 Toy Model with Default

Households initially have a mortgage which implies certain mortgage payments, and a house which they plan to sell in the second period. They can default in the first period, in which case they are forced to rent, are excluded from credit markets, and don’t get to sell their house in the second period. The size of a house is normalized to $h > 1$ for owners and 1 for renters. To simplify, let’s first consider the case in which there is no liquid asset. The value of not defaulting is

$$V^r(x, p) = \ln c_1 + \ln h + \ln(c_2)$$

s.t. $c_1 = x - m$

$$1 + p$$

where $x$ denotes first period income, second period income is normalized to 1, $m$ is the date 1 mortgage payment, and $p$ is the house price at date 2 net of any remaining mortgage. The value of defaulting is

$$V^d(x, p) = \ln c_1 + \ln 1 + \ln(c_2)$$

s.t. $c_1 = x$

$$c_2 = 1$$

Here we normalize rental payments to zero. So $x$ should really be interpreted as wealth net of today’s rental payment, and $m$ should be interpreted as the difference between the mortgage payment and rent (assumed to be positive).

Thus a household will default if

$$V^d(x, p) > V^r(x, p)$$

$$\ln x + \ln 1 > \ln(x - m) + \ln h + \ln(1 + p)$$

$$p < \frac{x}{h(x - m)} - 1 := p^*$$
This defines a decreasing relationship between $p^*$ and $x$. Alternatively, the highest level of cash on hand at which households default, given price $p$, is

$$x_d(p) = \frac{mh(1 + p)}{h(1 + p) - 1},$$

a decreasing function. In other words, households default either when they have a low house price or a low income.

Consumption is given by

$$c_1 = c(x, p) = \begin{cases} 
x & \text{if } x < x_d(p) \\
x - m & \text{if } x \geq x_d(p) \end{cases}$$

For an individual with given cash on hand $y_1$ and expected house price $p$, we can ask how that individual would change consumption given a rebate check of size $z$. Abusing terminology, we can define $MPC(p) := \frac{c_1(x + z, p) - c_1(x, p)}{z}$. We have the following result.

$$MPC(p) = \begin{cases} 
1 & \text{if } p < \frac{1}{z(1 - m/(x + z))} - 1 \\
1 - \frac{m}{x} & \text{if } p \in \left[\frac{1}{h(1 - m/(x + z))} - 1, \frac{1}{h(1 - m/x)} - 1 \right] \\
1 & \text{if } p > \frac{1}{h(1 - m/x)} - 1 
\end{cases}$$

In words, the MPC is 1 if house prices are so low that the consumer is going to default with or without the rebate, or so high that the consumer never defaults with or without the rebate. It is $1 - \frac{m}{z}$ - which is negative whenever the mortgage payment is larger than the rebate - if house prices are in an intermediate range, where the household would default without the stimulus check, but would repay with the check.
B.4 Model Figures and Tables

Figure B.1: Example of a Life Cycle
Figure B.2: HTM Proportions by Age (Data vs. Model)

Figure B.3: LTV by Age (Data vs. Model)
Figure B.4: Default Rates in Model vs. Data by Tercile

Notes: Default rates in the model are the percentage of all households who default in the period. We use percentage of mortgages that are more than three months delinquent at the 4th quarter of 2008 as the data analog.

Figure B.5: Median Income through Recession
Table B.1: Asset Holdings of US Households based on 2007 SCF

<table>
<thead>
<tr>
<th></th>
<th>Bottom 80%</th>
<th>Top 20%</th>
<th>All Households</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median Labor Income</td>
<td>35,000</td>
<td>122,000</td>
<td>43,000</td>
</tr>
<tr>
<td>Median Liquid Assets</td>
<td>1,161</td>
<td>27,386</td>
<td>2,121</td>
</tr>
<tr>
<td>Median Illiquid Assets</td>
<td>50,000</td>
<td>349,000</td>
<td>84,000</td>
</tr>
<tr>
<td>Housing Value</td>
<td>170,000</td>
<td>400,000</td>
<td>210,000</td>
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<td>Mortgage Size</td>
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<td>Housing Equity</td>
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<td>52,000</td>
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</table>

**Liquid Wealth**

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<th>All Households</th>
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</thead>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10th Percentile</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>25th Percentile</td>
<td>0</td>
<td>5,718</td>
<td>0</td>
</tr>
<tr>
<td>Median</td>
<td>1,161</td>
<td>27,386</td>
<td>2,121</td>
</tr>
</tbody>
</table>

**LTV for Homeowners**

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<th>Bottom 80%</th>
<th>Top 20%</th>
<th>All Households</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median</td>
<td>0.31</td>
<td>0.42</td>
<td>0.35</td>
</tr>
<tr>
<td>75th Percentile</td>
<td>0.65</td>
<td>0.66</td>
<td>0.65</td>
</tr>
<tr>
<td>90th Percentile</td>
<td>0.86</td>
<td>0.81</td>
<td>0.84</td>
</tr>
<tr>
<td>95th Percentile</td>
<td>0.94</td>
<td>0.90</td>
<td>0.93</td>
</tr>
</tbody>
</table>

Notes: Data is from the 2007 Survey of Consumer Finances (SCF). All liquid asset values are set to zero if they are negative.

Table B.2: Moments Not Used in Calibration

<table>
<thead>
<tr>
<th></th>
<th>Homeowners</th>
<th>Renters</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A. Liquid Wealth</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10th percentile</td>
<td>0</td>
<td>350</td>
</tr>
<tr>
<td>25th percentile</td>
<td>265</td>
<td>700</td>
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<tr>
<td>50th percentile</td>
<td>5,050</td>
<td>3,280</td>
</tr>
<tr>
<td>75th percentile</td>
<td>32,940</td>
<td>16,860</td>
</tr>
<tr>
<td><strong>B. LTV for Homeowners</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median</td>
<td>0.31</td>
<td>0.51</td>
</tr>
<tr>
<td>75th Percentile</td>
<td>0.65</td>
<td>0.72</td>
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<tr>
<td>90th Percentile</td>
<td>0.86</td>
<td>0.86</td>
</tr>
<tr>
<td>95th Percentile</td>
<td>0.94</td>
<td>0.95</td>
</tr>
</tbody>
</table>

Notes: Data is from the 2007 Survey of Consumer Finances (SCF). All liquid asset values are set to zero if they are negative. Model values are only for non-retirees.
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Appendix C

Figure C.1: Changes in Checking and Savings Accounts Balances for WHTM switchers
Figure C.2: Non-Housing Illiquid Assets for WHTM Switchers

Illiquid Accounts for Switchers in 2007
Figure C.3: *Comparisons between Groups that stay as WHTM vs. change status to NHTM*

Mean Changes in Illiquid Asset Accounts between 2007 and 2009
For group that changed its status from WHTM to NHTM

Source: SCF
Table C.1: Differences between Group that stayed as WHTM and changed to NHTM

<table>
<thead>
<tr>
<th></th>
<th>WHTMtoNHTM</th>
<th>WHTMtoWHTM</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta ) Labor Income</td>
<td>2,000</td>
<td>500</td>
</tr>
<tr>
<td>Labor Income 2007</td>
<td>46,000</td>
<td>32,000</td>
</tr>
<tr>
<td>Normal Income 2007</td>
<td>53,249</td>
<td>34,079</td>
</tr>
<tr>
<td>Liquid Wealth 2007</td>
<td>195</td>
<td>49</td>
</tr>
<tr>
<td>Illiquid Wealth 2007</td>
<td>55,340</td>
<td>29,515</td>
</tr>
<tr>
<td>Housing Value 2007</td>
<td>105,147</td>
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<tr>
<td>Housing Liability 2007</td>
<td>31,360</td>
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<td>Housing Leverage 2007</td>
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<td>33</td>
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<td>Liquidity to Income 2007</td>
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<tr>
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<tr>
<td>Education 2007</td>
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Figure C.4: *Net Illiquid Wealth in 2007 NHTM Households*
Figure C.5: Changes in Checking and Savings Accounts Balances for NHTM switchers
Table C.2: Regressions for 2007 WHTM Households

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
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<tbody>
<tr>
<td></td>
<td>∆ Net Liquid</td>
<td>∆ Net Illiquid</td>
<td>∆ Illiquid Assets</td>
</tr>
<tr>
<td>WHTM Status 09</td>
<td>-4557.5***</td>
<td>21687.7***</td>
<td>18628.5***</td>
</tr>
<tr>
<td></td>
<td>(-392.81)</td>
<td>(374.50)</td>
<td>(306.67)</td>
</tr>
<tr>
<td>Age in 2007</td>
<td>2.532</td>
<td>-617.6***</td>
<td>-880.1***</td>
</tr>
<tr>
<td></td>
<td>(0.98)</td>
<td>(-340.68)</td>
<td>(-484.47)</td>
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<tr>
<td>Education in 2007</td>
<td>36.05***</td>
<td>827.0***</td>
<td>562.9***</td>
</tr>
<tr>
<td></td>
<td>(10.82)</td>
<td>(68.47)</td>
<td>(45.06)</td>
</tr>
<tr>
<td>Log of Labor Income</td>
<td>1425.1***</td>
<td>-13486.9***</td>
<td>-12865.6***</td>
</tr>
<tr>
<td></td>
<td>(17.20)</td>
<td>(-315.94)</td>
<td>(-304.15)</td>
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<td>133184.5***</td>
<td>143723.9***</td>
</tr>
<tr>
<td></td>
<td>(-10.60)</td>
<td>(245.98)</td>
<td>(271.41)</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.002</td>
<td>0.035</td>
<td>0.036</td>
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</table>

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Table C.3: Regressions for 2007 WHTM Households

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<tr>
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<td>Δ Housing Asset</td>
<td>Δ Housing Liability</td>
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<td>12916.6***</td>
<td>-3059.2***</td>
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<tr>
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<td>(274.14)</td>
<td>(-120.06)</td>
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<tr>
<td>Age in 2007</td>
<td>-597.1***</td>
<td>-262.4***</td>
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<tr>
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<td>(-414.11)</td>
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<td>942.5***</td>
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<td>(88.75)</td>
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<tr>
<td>Log of Labor Income</td>
<td>-10380.4***</td>
<td>621.3***</td>
</tr>
<tr>
<td></td>
<td>(-315.49)</td>
<td>(40.07)</td>
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<td>Constant</td>
<td>106540.6***</td>
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<tr>
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<td>(270.84)</td>
<td>(57.84)</td>
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<tr>
<td>Adjusted $R^2$</td>
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<td>0.009</td>
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$t$ statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.4: Regressions for 2007 NHTM Households

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<td>-34685.9***</td>
<td>-37002.2***</td>
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<td>(-21.41)</td>
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<td>(-289.97)</td>
</tr>
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<td>Age in 2007</td>
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<td>-1779.0***</td>
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<td></td>
<td>(-137.69)</td>
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<td></td>
<td>(40.64)</td>
<td>(360.25)</td>
<td>(342.21)</td>
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$t$ statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
### Table C.5: Regressions for 2007 NHTM Households

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<td>Δ Housing Liability</td>
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<td>7775.9***</td>
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<td></td>
<td>(133.57)</td>
<td>(224.12)</td>
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<td>Log of Labor Income</td>
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<td>(293.54)</td>
<td>(-59.19)</td>
</tr>
</tbody>
</table>

Adjusted $R^2$ 0.005 0.006

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$