Heterogeneous Asset Returns, Wealth Inequality and Monetary Policy

Rajarshi Datta

A dissertation submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington

2024

Reading Committee:

Yu-chin Chen, Chair

Brian Greaney, Chair

Fabio Ghironi

Program Authorized to Offer Degree:

Economics

University of Washington

Abstract

Heterogeneous Asset Returns, Wealth Inequality and Monetary Policy

Rajarshi Datta

Co-Chairs of the Supervisory Committee:

Yu-chin Chen

Department of Economics

Brian Greaney

Department of Economics

This dissertation aims to study the interactions between heterogeneity in asset returns and wealth inequality in the US from both an empirical and theoretical perspective with implications for monetary policy. Specifically, the first chapter explores the short term distributional consequences for US consumption from changes in the federal funds rate through the wealth inequality channel. In the second chapter, three major sources behind the dramatic increase in wealth inequality over the past half-century in the US are investigated. In the third chapter, I examine the impact of U.S. household wealth on their mortgage refinancing and consumption decisions, revealing the interlinkage between wealth inequality and housing markets.

In the first chapter, I study how different returns and prices of housing and equity interact with heterogeneous marginal propensities to consume across households in the wealth distribution to cause uneven consumption effects from changes in the federal funds rate. The analysis unveils varying group susceptibilities to monetary policy, underscoring the diversified effects based on housing tenure, age, and borrowing constraints. Chiefly, a 1% federal funds rate drop increases consumption of outright homeowners by more than double relative to mortgage holders (3.02% vs

1.43%), yields a 1.72% rise for older individuals with a 1.29% boost for younger ones. The middle 50-90% net wealth distribution gain nearly twice as much as the bottom 50% (1.51% vs 0.8%). Besides identifying winners and losers, I also study how the distribution affects aggregate US consumption. A 1% reduction in the federal funds rate increases overall consumption by 1.63%. There also exists significant asymmetries at all levels with 1% increase curtailing aggregate consumption by merely 1.02%, signifying hurdles in achieving a 'soft landing.'

In the second chapter, co-authored with my Co-Chairs Professor Chen and Professor Greaney, we undertake a comprehensive empirical analysis using the Survey of Consumer Finances (SCF) data to quantify how differences in asset returns, inheritances, and investment opportunities such as costs of homeownership and equity-market participation explain observed inequality trends, including generational and racial wealth gaps for different birth cohorts in the US. In the 1960s, the average household of age 20-39 had one third the wealth of a 60+ household; in 2019, this share was less than one-sixth. At age 30, the average Black Millennial household has less than 5% of average wealth; in earlier generations, this ratio was more than twice as high. We use a dynamic heterogeneous-agent model that captures household's lifetime decisions regarding how much to save, whether to rent or own, and how to adjust portfolios in response to changing market conditions. We calibrate the model to the US economy to investigate possible broadly motivating factors behind the dramatic increase in wealth inequality over the past half-century. We can evaluate the role of mitigating measures like tax policies and reducing barriers to asset market participation.

In the third chapter, empirical analysis from the SCF data corroborates the interlinkage between household debt & their hand-to-mouth status. Further evidence from refinance approvals indicate strong demand for home equity extraction in periods of high unemployment often aided by higher house prices. I rationalize the measurement by setting up a 3 period partial equilibrium model with heterogeneous preferences to investigate the importance of considering mortgages distinctly from other illiquid assets in the determination of hand-to-mouth status. Simple counterfactuals in a calibrated model strongly matched the trends in house prices, unemployment and mortgage refinancing during the pandemic. Better estimates of the share of hand-to-mouth households is imperative for understanding the transmission and redistributive effects of monetary policy & fiscal transfers through household consumption.

Table of Contents

Page

List of Figures

Figure Number Page

List of Tables

Acknowledgments

I could not have completed this thesis without the support of many people, to whom I wish to express my sincere gratitude.

I sincerely thank my advisors Professor Yu-chin Chen & Professor Brian Greaney for their extensive time, guidance and effort throughout my academic journey. Their dedication and passion for research serve as a constant source of inspiration and learning for me. Their timely advice played a crucial role in shaping this dissertation, and their constructive feedback consistently pushed me to strive for excellence. I am also extremely thankful to them for the coauthored project. The knowledge and experience gained from this collaboration have been truly enriching, and I am excited for the outcomes of this and potential future projects.

I would also like to thank my committee members Professor Fabio Ghironi and Professor Stephen Turnovsky for their invaluable advice in improving my ability to present my academic research to diverse audiences while honing in on the policy deliberations. Their critical insights and feedback have been instrumental in revising and improving my dissertation.

Aside from my committee advisors, I am indebted to my fellow macro graduate students for their genuine kindness and interest in my work, which have been a constant source of support throughout the ups and downs of the Ph.D. program. My heartfelt appreciation also goes to all of my family, including my parents and friends, for believing in me and providing unwavering support throughout my Ph.D. journey. Their encouragements has been instrumental in helping me stay focused during challenging times.

DEDICATION

To Mom, Dad and my best friend Shreya.

Chapter 1

Heterogeneous Asset Returns and Distributional Effects of Monetary Policy

1.1 Introduction

Central banks have recently focused on understanding how wealth inequality influences the transmission of monetary policy, particularly its effects on short-run aggregate consumption. A shift in the federal funds rate triggers endogenous wealth transfers across the net wealth distribution. This redistribution leads to a net non-zero response on aggregate consumption since marginal propensities to consume ($MPCs$) are heterogeneous across different groups, contrary to our traditional understanding of monetary policy transmission. Auclert (2019) reveals that redistribution contributes to about one-third of the aggregate consumption response. He shows that the total consumption response can be divided into five channels resulting from changes in real interest, nominal prices, and idiosyncratic earnings. It is quantifiable with seven sufficient statistics all estimable from survey data. His work rightly adjusts for asset maturities in quantifying household balance sheets, moving the conversation beyond the usual focus on asset prices. He however postulates a uniform response across returns and prices for all assets, notably housing and equity, to changes in the federal funds rate.

I empirically show that an unexpected one-time monetary policy shock leads to heterogeneous responses in prices and returns for housing, equity, and liquid assets. Housing, characterized by illiquidity and significant transaction costs, responds more slowly and with lesser persistence compared to equity. Given the wide variation in portfolio shares for these assets across the net wealth distribution, different wealth deciles experience varying unrealized capital gains/losses from both nominal price (inflation or Fisher) and real interest rate channels. The contributions from housing and equity towards the overall wealth change is also myriad across the distribution.[1] The scale of redistributive wealth transfers depend on post-shock returns heterogeneity and existing household portfolio holdings. The specific gains and losses from monetary policy changes for various groups thereby requires a more precise calculation of exposures across the real interest rate and Fisher channels. Subsequently, I find a quantitatively sizable impact on short-run general equilibrium aggregate consumption for the US.

I create a model inspired by Auclert (2019) to analyze the impact of a one-time monetary policy shock on housing and equity relative to liquid assets on household consumption by employing the sufficient statistics approach. My model's three main contributions are: First, by conditioning my sufficient statistics on exogenous monetary policy, I can isolate and analyze the impact from housing or equity separately. Second, my model's framework can extend to estimate new redistribution measures from sustained changes to the federal funds rate. Third, the setup endogenizes an asymmetric consumption response to monetary policy. Additionally, using liquid assets as a benchmark enhances the comparison with existing findings. Since my framework rests on sufficient statistics, it avoids potential misspecification problems that could be latent in structural models.

I demonstrate the model's theoretical robustness to the inclusion durable goods and elastic labor supply, and its extension to incomplete markets, though these can be more challenging to estimate empirically. The significance of the differential asset returns channel is evident in both the aggregate general equilibrium consumption response besides the individual redistributative effects from a policy rate change. These are unit-free elasticity measures which can be compared across models while allowing conduct of limited policy counterfactuals. Given the substantial debate in empirically measuring the conditional impact of a one-time monetary policy shock on asset premia and prices, my model's flexibility in incorporating alternate estimates obtained using the

[1] See Kuhn and Rıos-Rull (2020) for a related discussion. They explore how SCF data can assess the joint distribution of earnings, income, and wealth in the United States and decompose contributions by income sources and asset classes.

econometric method of choice stands out.

I compute the sufficient statistics summarizing household exposures to real interest and Fisher channels from the consumer expenditure (CE) survey which richly captures consumption alongside reasonably extensive data on household balance sheets. This allows me to empirically identify the household level *MPC* from an unexpected fiscal transfer. Monetary policy influences households' heterogeneous consumption responses based on borrowing constraints and wealth levels. A decrease in the federal funds rate by 1% will increase consumption by 1.44% for the middle 50-90% of the net wealth distribution while increasing consumption by only 0.8% for the bottom 50% . Collateral-constrained households struggle to realize wealth changes and smooth consumption when interest rates decrease. My findings show homeowners with ample liquid assets and minimal housing debt have an elasticity of 3.02 since they face fewer constraints in taking on additional debt. In contrast, high-debt homeowners exhibit lower elasticity at 1.43, showing restrained consumption when rates decrease. Similarly, the young have an elasticity of 1.29 while the old have an elasticity of 1.72. These distributional consequences allow me to quantify more precisely the winners and losers from monetary policy. Monetary policy shocks lead to households with long-term liabilities like mortgages to have higher *MPCs*, while those with a positive net nominal position (*NNP*), holding housing as both asset and debt, have lower *MPCs*.[2]

The distribution also affects the aggregate. Key findings include: First, a 1% federal funds rate cut by the Fed would boost aggregate consumption by 1.63%, a 27% higher elasticity compared to reducing the same with identical returns for housing, equity, and liquid assets, as in Auclert (2019). This results in a two-third share of redistribution effects, an overall increase of 33% relative to the mentioned source. My elasticity is three-fourths larger than an analogous representative agent model. Conversely, a 1% rate increase would decrease aggregate consumption by only 1.02% , showing significant asymmetric effects. The reason is that *MPCs* are higher for households near borrowing constraints and a larger fraction of households move closer to their borrowing constraints during contractionary monetary policy. Separately by asset class, since the conditional impact on equity returns and prices is larger, household exposures are amplified more for equity relative to housing, raising quarterly consumption response by 30% above the benchmark during expansionary monetary policy. In a contractionary shock, the smaller impact on housing wealth reduces the

[2]Details of various elasticity values and responses are analyzed in the main text, showcasing the diverse impacts of monetary policy on different demographic and economic groups.

decline by nearly 19% (compared to 15% for equity). Strong asymmetric effects persist across the distribution and for housing tenure and demographics for aforementioned reasons.

Households, being forward-looking, correctly anticipate the unrealized capital gains/losses arising from transitory monetary surprises on asset prices and returns. Channeled through real interest and Fisher channels, it boosts asset prices and potentially reduces debt payments, making households feel wealthier and increasing their consumption when interest rates decline. Despite being unrealized, these gains are expected to be realized into liquid assets in the future. This leads to higher *MPCs* out of current income across much of the the net wealth distribution. My larger estimates reflect the two pronged heterogeneity in unrealized wealth and *MPCs*, differing from the literature focusing on realized wealth gains, particularly in housing. [3] The incorporation of returns heterogeneity indicates a significant rise in aggregate consumption, underscoring its essential role in effective estimation. The absence of such heterogeneity in *MPCs* makes a representative agent counterpart with multiple asset returns largely ineffective for quantifying aggregate consumption accurately.

From a policy standpoint, my exploration involves examining model predictions for expansionary and contractionary policies during specific economic times - the beginning of the pandemic and before the Global Financial Crisis (GFC), respectively. The robustness of the results for expansionary policy across years is noteworthy. When limiting asset maturities to a quarterly basis, the significance of returns heterogeneity is amplified, evidencing a 24% increase in 2019 (with a 67% share of redistribution). This evidence bolsters the Federal Reserve's aggressive quantitative easing strategies implemented at the onset of the pandemic. If we assumed all mortgages to rate-adjustable, this would translate to an even larger increase. This observation advocates for reducing refinancing costs for a substantial segment of the population, particularly in challenging times, to expedite consumption recovery. On the contrary, the model also foresees substantial consumption declines from rising rates pre-GFC. The reason for the reduced asymmetric effect is that housing wealth gains surpassed equity pre-GFC leading to lower wealth inequality. My paper underscores the interaction between three heterogeneous elements - asset returns heterogeneity, *MPCs* out of income and household portfolio shares - to demonstrate a larger short-run influence of wealth in-

[3] Paiella and Pistaferri (2017) report values in the range of 3-7.5% from home-equity channel, consistent with Mian and Sufi (2014). Di Maggio et al. (2020) reports *MPC* out of unrealized equity gains is in the range of 23% for bottom 50% and only 3% for the top 30%. *MPC* out of dividends is nearly 10 times higher than out of capital gains as estimated by Hartzmark and Solomon (2019). For more details and other comparisons see appendix A.4.

equality on the transmission of monetary policy to aggregate consumption than previously assessed.

I acknowledge some limitations of my results. They are heavily reliant on detailed household balance sheet information. I suggest my findings to be conservatively downward-biased, and more in-depth future research is necessary to support the claims. One alternative could be to utilize the PSID data for improved sampling of richer households, despite the trade-off in having limited consumption data. Additionally, while sufficient statistics have benefits, their utility in model-free environments is limited. A coordinated approach involving fiscal and monetary policy requires dependence on structural models. I aspire that my results will lead to the development of a HANK model with two illiquid assets bearing separate returns, despite anticipated complications. This path, although challenging, presents a valuable future extension.[4]

Related Literature - The paper contributes primarily to four main strands in the literature. An extensive empirical literature underscores the significant and diverse marginal propensities to consume (*MPC*) from unexpected fiscal transfers (Jappelli and Pistaferri (2010); Johnson et al. (2006)) and their implications for household finance (Colarieti et al. (2024)). I find aggregate *MPC* out of income is notably biased downwards without considering returns heterogeneity through unrealized wealth changes, emphasizing household balance sheets' critical role in determining aggregate consumption response.[5] I highlight the significance of these altered estimates in analyzing aggregate consumption response, comparing them with self-reported *MPCs* from the SHIW 2010 Jappelli and Pistaferri (2014).[6]

The debate on the impact of unexpected monetary policy shocks on real interest rates and asset prices involves mainly two approaches: structural VAR or local projections. Gertler and Karadi (2015) employs structural VAR with external instruments for assessing impact on credit costs, extending Mertens and Ravn (2013) and aligning with theoretical exercises by Auclert (2019). Conversely, Luetticke (2021) uses local projections for a 16-quarter impulse horizon, facing forecasting limitations.[7] I adopt the former for estimates of present discounted values of requisite

[4] Adding both returns and price heterogeneity would be even more difficult. I find that barring one or two cases, the interest rate channel is responsible for the majority of the variation. A suitable setup is Kaplan et al. (2018). Moreover, larger the returns gap, higher is the aggregate *MPC* as found by Kaplan and Violante (2020).

[5] A positive correlation between *MPCs* and return heterogeneity in household consumption, employment, and income responses during Covid-19 is documented Baker et al. (2020); Chetty et al. (2020).

[6] Maintaining the assumption of a uniform *MPC* out of income across asset classes, literature highlights *MPC* dependence on household balance sheet positions, especially housing Mian et al. (2013); Mian and Sufi (2014); Cloyne et al. (2020). For further details, see section 1.5.

[7] Plagborg-Møller and Wolf (2021) highlights local projections' superiority for small time horizons, with issues and

variables since they are proved reliable and robust. [8]

The advantage of sufficient statistics lies in minimizing dependence on potentially error-prone structural models, while allowing simple policy counterfactuals application in a largely model-free environment. Auclert and Rognlie (2020) employs them to estimate income inequality's impact on aggregate demand, Auclert et al. (2018) for intertemporal *MPCs* and obtaining empirically consistent *IRFs*. Utilizing PSID data, Berger et al. (2018) assesses house prices' effect on consumption movements. I obtain precise aggregate-level estimates and by asset class, addressing issues like housing's significance in HANK Hedlund et al. (2017). Unlike the U.S., Holm et al. (2021) leverages rich Norwegian data for overall consumption response estimation. My reduced form approach proves superior, avoiding the large noise observed in studies like Coibion et al. (2017). [9]

Fourthly, I compare alternative approaches in the literature for targeting aggregate consumption, which often overlook returns heterogeneity. Whereas studies like Gornemann et al. (2021) employ structural models with reduced form idiosyncratic discount factors, I focus on estimating consumption response changes through the impact of monetary policy on household portfolios, as directly observed in data. My approach proves ample for conducting simple policy experiments that expand the aggregate influence of household wealth holdings' heterogeneity. Contrary to Kekre and Lenel (2021), which notes a subdued consumption rise and significant investment increase, my method more effectively handles the impact of monetary policy, showcasing a larger consumption response from differential asset returns.[10]

Layout - The rest of the paper is structured as follows. Section 1.2 outlines the key economic intuition using a one period setup. Section 1.3 lays down the procedures used to infer the impact of monetary policy shocks on requisite variables and subsequent motivating evidence. The model and theoretical results are contained in Section 1.4. Section 1.5 details the measurement of the sufficient statistics from survey data while section 1.6 discusses the key findings. A final section 1.7 concludes. Robustness checks, proofs for model extensions and additional results are contained

related empirical puzzles mitigated by Bayesian techniques in Miranda-Agrippino and Ricco (2021).

[8] Despite improvements by Paul (2020), issues with impulse response function persistence emerge. Gertler and Karadi (2015) offers robust, non-persistent results, compared in appendix A.1.2.

[9] Ampudia et al. (2018) and Leombroni and Rogers (2021) emphasize heterogeneous asset returns' substantial general equilibrium effects from consumption changes, observing portfolio rebalancing and life-cycle effects impacting labor supply and output through consumption.

[10] Monacelli and Colarieti (2022) presents a heteroskedastic NK model, and my results stand robust even in varied conditions, consistent with Kaplan and Violante (2020)'s findings on the relationship between the asset returns gap and *MPC*. Further details are discussed in section 1.6.2 and appendix A.3.

respectively in appendices A.1 - A.6.

1.2 A simple one period setup

To highlight the main economic channels, consider a simple one period economy where there is a representative agent who has a net wealth of 100$. There is no wealth inequality in this economy At the beginning of the period, the central bank unexpectedly reduces the interest rate by 1% . Consumption goes up by more than 1% due to multiplier effect. Now compare with another economy where there are two agents and the net wealth is distributed as 60$ with one agent and 40$ with the other. The same 1% interest rate decline will lead to greater consumption response as compared to the representative agent setup owing to heterogeneous *MPCs* out of income. This is the central result of heterogeneous agent models as also succinctly summarized in Auclert (2019). Auclert (2019) stresses on a more accurate way to identify the unequal impacts of monetary policy which relies on measuring net wealth and not the kind of assets (eg - equity, housing, cash) that a household owns. With the same unequal 60:40 distribution of wealth, an economy with 60$ in equity and 40$ in housing has the same consumption response as one with 40$ equity and 60$ equity since the 1% decrease in interest rates leads to the same wealth change across all asset classes.

Empirically, the returns and prices of equity increase more than that of housing than that of cash from the 1% unexpected one time decrease in interest rates. Now on top of existing channels, the type of wealth that households hold matters. Now the economy with 60$ in equity and 40$ housing has a bigger response than one with 60$ housing and 40$ in equity. The unrealized increases in net wealth leads to higher current consumption from the permanent income hypothesis. Both economies show higher consumption increase as compared to the benchmark case where prices and returns of all assets respond identically to 1% decrease in the interest rates. Additionally, in Auclert (2019), the response was symmetric. In this case, heterogeneous *MPCs* out of income[11] and returns heterogeneity interacts to cause an asymmetric response where aggregate consumption decreases by a different amount when there is an unexpected increase of interest rates by 1% .

[11] Section 1.4 shows how I convert the *MPCs* out of wealth for the different assets like housing and equity to an equivalent *MPC* out of income.

1.3 Empirical Methodology

I aim to discern the immediate effects of an unexpected monetary policy surprise on household balance sheets, especially its distinct effects on housing and equity. This helps me condition the sufficient statistics based on monetary policy. The effects of a real interest rate cut on the wealth distribution primarily manifests through the excess premia of these two asset classes and the associated price changes.[12] Another channel, albeit harder to pin down from data, is the immediate effect on idiosyncratic earnings. I emphasize the former two channels when gauging the immediate effect of monetary policy on household wealth distribution.

In section 1.5, I argue that capturing these changes is crucial for accurate household *MPC* measurements. Employing the SVAR method, I align with the specifications of Gertler and Karadi (2015). Given that my theoretical insights largely rely on a perfect foresight model, detailed in section 1.4, I look to present discounted values from Auclert (2015) for the most fitting empirical analogs. It's crucial to ensure stable and consistent *IRFs* over extended periods, a challenging endeavor with the local projections technique. While Luetticke (2021) uses a local projection exercise for similar variables, I juxtapose my findings against theirs in section A.1.3. My results, spanning 16 quarters and detailed in appendix A.1.3, exhibit qualitative similarities.

1.3.1 A structural VAR with external instruments approach

I require monthly data on excess premia and nominal asset prices for both housing and equity, alongside changes in the real interest rate and aggregate price level, which signify impacts for the benchmark liquid asset. I also incorporate industrial production to capture overall economic activity. This results in a 7-variable structural VAR, estimated with external instruments to identify monetary surprises. In the main text, I adopt a lag length of 7 to ensure stable *IRFs* over extended horizons. Lag and horizon length tests are in appendix A.1.1. Variable definitions and data sources mainly align with Luetticke (2021). However, I measure the housing premium differently, using

[12] I focus on excess returns and not real returns. Theoretically, I would normalize with the change in the real interest rate which is the change in the real return for the liquid asset. In reality, the return on the liquid asset varies nominally from the transitory monetary policy surprise. It is persistent because of which we need a measure of excess returns for the two assets before normalization of the PDVs.

monthly excess return data from Robert Shiller's house price index.[13] For a detailed estimation methodology, refer to section II of Gertler and Karadi (2015), using only their baseline specification approach.

The external instruments I utilize encompass surprises in the current and three-month-ahead monthly fed funds futures, as well as six-month, nine-month, and one-year-ahead futures on three-month Eurodollar deposits. My analysis spans from 1979:7 to 2012:6. Given that this study doesn't tackle forward guidance, the current fed funds futures surprise serves as the primary policy metric. A distinct advantage of this approach is the lack of necessity to incorporate the real interest rate separately. As indicated by Gertler and Karadi (2015) section C, the disparity between nominal and real rate shifts post a monetary policy surprise is minimal. Their Figure 4 reinforces the negligible influence of inflation on extended-term government bond rates.[14] I produce the *IRFs* for a one-standard deviation dip in the monetary policy surprise, focusing on expansionary effects. Figure 1.1 projects *IRFs* up to 4 years, while Figure A.1 extends this to a 1000-month horizon. Results align with expectations: stock price and excess return *IRFs* are both swifter and more pronounced compared to housing. The normalized PDV assessments are tabled in Table 1.1.

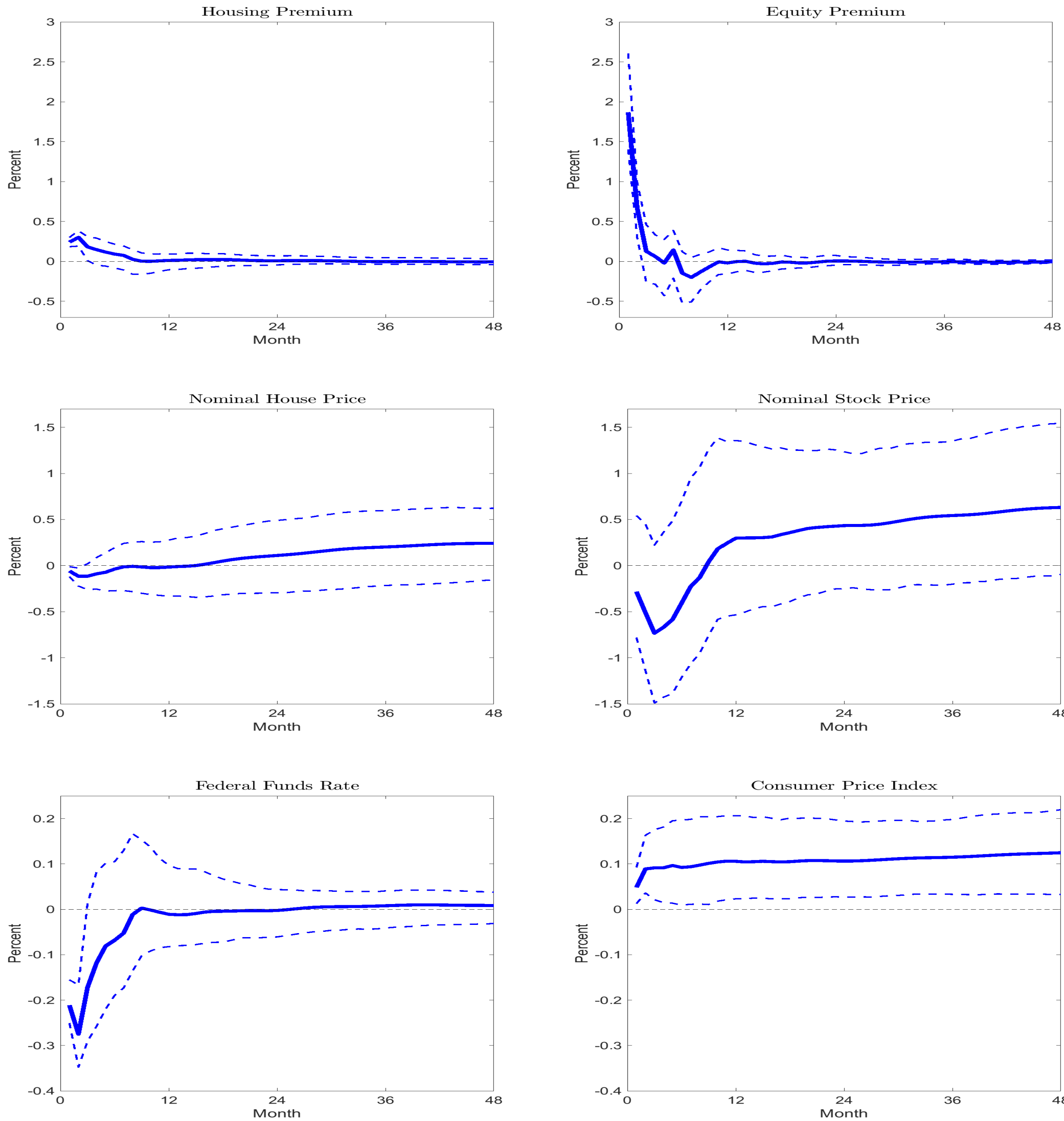
1.3.2 Unrealized Wealth Changes from Monetary Policy Shocks

Using the estimates in Table 1.1, I calculate the unrealized wealth changes from the SCF data to demonstrate that household wealth changes, as a percentage of gross wealth, are substantially different across gross wealth quantiles. I need to summarize the changes from the two channels - the real interest rate and the Fisher. Taking the SCF data for the interested year, I first calculate the gross (net) wealth and divide the sample into associated quantiles. Using the present discounted value estimates and the gross (net) wealth shares for housing, stocks and liquid assets, I can calculate the unrealized wealth change for each wealth decile for both excess premia and nominal price changes. Here, I present the results for 2001 (the year for which *MPC* will be estimated from the consumer expenditure survey). I follow it up with the results by wealth

[13] Excess returns on quarterly housing are computed in Luetticke (2021) following Gomme et al. (2011). Monthly data sources for the same are unavailable. Alternate monthly estimates can be calculated using rent changes, but full CPI rent data isn't available for the entire sample period, making substitutions unreliable. Appendix A.1.3 provides variable definitions.

[14] I've verified this minimal difference by introducing the real interest rate into our specification. This inclusion reduces the required lag length for stable outcomes. I value the *IRF's* stability over minor changes in PDV calculations when employing the real interest rate explicitly.

Figure 1.1: *IRFs* for an expansionary one time monetary policy for the requisite variables



Note - Derived for a one standard deviation decrease in the monetary policy surprise considered in Gertler and Karadi (2015) for VAR specification in section 1.3.1 which has seven variables and seven lags. *IRFs* generated for 1000 months ahead. 95 percent confidence bands computed using bootstrapping methods identical to Gertler and Karadi (2015).

Table 1.1: Present discounted value estimates from VAR based in section 1.3.1 using $\beta = 0.95$

Present Discounted Value at $t = 0$	Nominal House Price	Housing Premium	Nominal Stock Price	Equity Premium	Nominal House Price	Nominal Equity Price
Empirical	0.84	1.28	2.43	2.51	0.41	1.18
Normalized (Y/N)	**N (in%)**	Y	**N (in%)**	Y	Y	Y

Note - Specification used is detailed in 1.3.1. Results with $\beta = 0.95$ and one standard deviation positive monetary policy surprise for 1000 months ahead. Required for conditional impact of monetary policy. Most estimates normalized with respect to the liquid asset to make them comparable to the benchmark. See section 1.4.2 for more details and also section 1.5 for their use in measuring the sufficient statistics.

Figure 1.2: Estimated unrealized wealth gains as a percentage of gross wealth

Note - For a one unit decline in the real interest rate. The left panel summarizes the exposures to the real interest rate channel while the right summarizes the exposures to the Fisher channel.
Derived using portfolio wealth shares in the SCF data along with the PDV estimates in 1.1 for three separate returns. The mean of the change in wealth across quantiles is plotted on the y-axis.
The benchmark results in Auclert (2019) would lead to a mean growth of 1 uniformly across quantiles for both the real interest rate and Fisher channel.

Figure 1.3: Component wise unrealized wealth gains as a percentage of gross wealth

Note - Exact same exercise as in Figure 1.2 subdivided for housing and stocks. See corresponding notes for more details. Additionally, the benchmark results would lead to the same mean growth for both housing and stocks.

component, specifically housing and stocks. To demonstrate that the trend continues with latest available data, I present Figure A.3 using SCF 2019.

Figure 1.2 shows that the mean wealth growth is not homogeneous across quantiles for both the real interest rate and Fisher channels. This is true for the year for which *MPC* will be estimated (suggesting more precise estimates are possible) and it is not a one-off event as evidenced by the latest data available. The total gains hides substantial heterogeneity as in Figure 1.3 for both housing and equity holdings. The former plays a prominent role for the Fisher channel, for particularly the agents at the bottom of the wealth distribution. Similarly, for those towards the top, especially for the top 10% , almost all the gains are from equity for both the channels. The findings are along expected lines, exacerbated by the existing household portfolio heterogeneity along the wealth distribution. For comparison, I present additional evidence to support my main exercise in section 1.4.2 in appendix A.1.4 for reported unrealized & realized wealth changes, both as percentage of net and gross wealth, as well as a comparison with having a common illiquid return for both housing and equity.

1.4 Model

The theoretical framework is identical to Auclert (2019) with the exception of the inclusion of ex-post return heterogeneity across asset classes. Specifically, I consider separate returns & prices for housing, equity and the liquid asset. The liquid asset serves as the benchmark to the original results. For more details, see section I and related mathematical appendices A.2 - A.8 of Auclert (2019).

1.4.1 Household Balance Sheets and wealth effects

The consumer has separable preferences over nondurable consumption $\{c_t\}$ and hours of work $\{n_t\}$. For simplicity, there is no uncertainty with the exception of a one time unexpected monetary policy shock that results in the equivalent change of the real interest rate by one unit. It is a perfect-foresight setup with the consumer rationally forecasting the entire time path of nominal wages $\{W_t\}$, overall price level $\{P_t\}$ as well as the individual prices & returns for each of the three separate assets. The household has a lifetime real earnings stream given by $\{y_t\}$. The consumer solves the following discrete time utility maximization problem. The time horizon may be finite or infinite and need not to be specified.

$$
\begin{aligned}
&\max \ \sum_t \beta^t \{u(c_t) - (n_t)\} \ \text{ subject to} \\
P_t C_t &= P_t y_t + W_t n_t + \left({}_{t-1}B_t\right) + \sum_{s\geq 1} \left({}_t Q_{t+s}\right) \left({}_{t-1}B_{t+s} - {}_t B_{t+s}\right) \\
&+ P_t \left({}_{t-1}b_t\right) + \sum_{s\geq 1} \left({}_t q_{t+s}\right) P_{t+s} \left({}_{t-1}b_{t+s} - {}_t b_{t+s}\right) \qquad (1.1)
\end{aligned}
$$

The flow budget constraint (1.1) depicts the consumer household portfolio of assets in period t consisting of a portfolio of zero coupon bonds inherited from period $t-1$ as well as the ones carried over to the next period. ${}_tQ_{t+s}$ is the price at time t of nominal zero-coupon bond payable at time $t+s$. Analogously, ${}_tq_{t+s}$ denotes the price of a real zero-coupon bond with ${}_tB_{t+s}$ & ${}_tb_{t+s}$ denoting the respective quantities purchased. There is no arbitrage which is ensured by the Fisher equation for the nominal term structure, holding separately and across asset classes, broadly of the following form.

$$ {}_{t}Q_{t+s} = ({}_{t}q_{t+s}) \frac{P_t}{P_{t+s}}, \quad \forall t, s $$

The flow budget constraints consolidate into an intertemporal budget constraint by either use of terminal condition or transversatility condition depending on whether the setup is under finite or infinite horizon.

$$ \sum_{t \geq 0} q_t c_t = \underbrace{\sum_{t \geq 0} q_t (y_t + w_t n_t)}_{w^H} + \underbrace{\sum_{t \geq 0} q_t \left(({}_{-1}b_t) + \left(\frac{{}_{-1}B_t}{P_t} \right) \right)}_{w^F} \equiv \quad w \tag{1.2} $$

Keeping the notation consistent, (1.2) depicts the present value of consumption equals the present value of wealth denoted by w which is the sum of present value of all future income w^H and the total present value of all financial wealth w^F. Ex-ante before the shock, the distinct portfolio shares of balance sheet components for the three separate asset with associated prices can be represented equivalently by the composite portfolio using arbitrage.[15] Since it matters post shock, I expand explicitly as housing h_t, equity s_t & liquid assets ℓ_t for real (analogously nominal) terms at time $t-1$.

$$ ({}_{-1}b_t) \equiv ({}_{-1}\ell_t) + ({}_{-1}h_t) + ({}_{-1}s_t) $$

$$ \left(\frac{{}_{-1}B_t}{P_t} \right) \equiv \left(\frac{{}_{-1}L_t}{P_t} \right) + \left(\frac{{}_{-1}H_t}{P_t} \right) + \left(\frac{{}_{-1}S_t}{P_t} \right) $$

These general consolidated nominal & real claims due in each period allows pursuit of the problem using sufficient statistics. Each component denotes the net stocks of assets viz. bank deposits, directly and indirectly held real estate and corporate equities over corresponding liabilities like credit card debt, mortgages (FRM or ARM), etc.

[15] To support the explicit addition of housing services inside the utility function, composition of balance sheets need to matter ex-ante by the incorporation of modeling instruments that support multiple assets viz. portfolio adjustment costs. This complicates the derivation of sufficient statistics at both the household & aggregate level. A compromise is to consider how the relative price of durables changes with that of nondurables. I show in appendix A.2.2, this only modifies the measurement of the redistribution from the real interest rate channel. The other two redistribution channels are unaffected despite ex-post returns heterogeneity.

1.4.2 Main Theoretical Exercise

Keeping the notation consistent, I denote real wage at time t as $w_t \equiv W_t/P_t$. For the benchmark, the initial real term structure is $q_t \equiv {}_0q_t$, the initial nominal term structure is $Q_t \equiv {}_0Q_t$ and I use the normalization $q_0 = Q_0 = 1$. Keeping balance sheet components fixed at $\left\{{}_{-1}B_t\right\}_{t\geq 0}$ and $\left\{{}_{-1}b_t\right\}_{t\geq 0}$, the one time unexpected unit decline in real interest rate causes the following changes relevant for the consumer's problem.

1. All nominal prices rise in proportion across asset classes - housing H, equities S and liquid assets L.
$$\frac{dP_{x,t}}{P_x} = \frac{dP_x}{P_x} \quad \text{with} \quad \frac{dP_H}{P_H} \neq \frac{dP_S}{P_S} \neq \frac{dP_\ell}{P_\ell} \quad \forall\, t \geq 0,\ x = \ell, S, H$$

2. All present-value real discount rates rise in proportion for each asset class.
$$\frac{dq_{x,t}}{q_x} = -\frac{dR_x}{R_x} \quad \text{with} \quad \frac{dR_H}{R_H} \neq \frac{dR_S}{R_S} \neq \frac{dR_\ell}{R_\ell} \quad \forall\, t \geq 0,\ x = \ell, S, H$$

3. More specifically, the above two points imply that the prices and returns of each wealth component differ in their magnitudes ex-post the shock. Normalizing the changes with respect to the liquid asset, I have the following relations.
$$\frac{dR_H}{R_H} = \theta_1\frac{dR}{R}, \quad \frac{dR_S}{R_S} = \theta_2\frac{dR}{R}, \quad \frac{dP_H}{P_H} = \theta_3\frac{dP}{P}, \quad \frac{dP_S}{P_S} = \theta_4\frac{dP}{P}$$
$$\text{where} \quad \frac{dR_\ell}{R_\ell} = \frac{dR}{R} \quad \& \quad \frac{dP_\ell}{P_\ell} = \frac{dP}{P}$$

4. The Fisher equation holds for the new sequence of prices both across time & asset class and the agent's unearned income & real wage at $t = 0$ rise by dy & dw respectively.

In addition to the above, at the time of the shock, I quantify the relation between the prices of real zero-coupon bonds for housing with respect to the benchmark $q_{H,0} = \Theta_1 q_{L,0}$ & $q_{S,0} = \Theta_2 q_{L,0}$. Along with $\{\theta_i\}_{i=1(1)4}$, it gives the conditional impact of monetary policy on prices & returns of housing & equity relative to the benchmark liquid asset assumed by Auclert (2019). This particular variation is captured in a stylized version in the three panels of Figure 1.4 where the

Figure 1.4: The time paths of interest rates, prices and unearned income for the perfect foresight model across asset classes.

Note - The conditional changes on asset excess premia and nominal prices are normalized with respect to the liquid asset which serves as the benchmark. The exact values are obtained from Table 1.1 which summarize the instantaneous per unit exposures to the real interest rate and inflation change.

estimates are the present discounted values reported in Table 1.1. There is substantial heterogeneity across asset classes. These estimates are the theoretical analogue for the precise instantaneous response.

1.4.3 Defining Household Exposures

The net of consumption wealth change depends on the household exposure to the price change, summarized by its *NNP* and to the real interest rate change, summarized by its *URE*. I present the definitions of these two measures along with their economic implications in the presence of ex-post price & returns heterogeneity. I start by stating the net of consumption wealth change $d\Omega$ at the household level for the transitory shock as

$$d\Omega = dy + ndw - NNP\frac{dP}{P} + URE\frac{dR}{R} \tag{1.3}$$

The first term in equation (1.3) is the earnings change following the transitory shock. The second term is the product of the change in the individual balance sheets from the aggregate change in the overall price level dP. This is the *NNP* of the household affected by the Fisher channel and is given by

$$NNP \equiv \sum_{t\geq 0} Q_t \left\{ \left(\frac{_{-1}L_t}{P_0} \right) + \theta_3 \left(\frac{_{-1}H_t}{P_0} \right) + \theta_4 \left(\frac{_{-1}S_t}{P_0} \right) \right\} \tag{1.4}$$

In general, since debtors have higher *MPCs* than creditors, we can expect *MPCs* to decline as *NNP* rises. The conditional effect on nominal prices ex-post across asset classes leads to a larger heterogeneous household exposure to inflation. The third and final term is the household's *URE* which is the effect on the individual household from the aggregate change in the real interest rate dR at time t.

$$\begin{aligned} URE_t \equiv \Bigg\{ & y_t + w_t n_t + \left(_{-1}\ell_t\right) + \left(\frac{_{-1}L_t}{P_t} \right) \\ & + \Theta_1 \theta_1 \left[\left(_{-1}h_t\right) + \left(\frac{_{-1}H_t}{P_t} \right) \right] + \Theta_2 \theta_2 \left[\left(_{-1}s_t\right) + \left(\frac{_{-1}S_t}{P_t} \right) \right] - c_t \Bigg\} \end{aligned} \tag{1.5}$$

The *URE* at any time t is viewed as the difference between all maturing assets (including income) and liabilities (including planned consumption). Following Auclert (2019), it remains the appropriate measure of exposure for the real interest rate channel. Households with negative net *URE* are net debtors with higher *MPCs*. they would benefit from expansionary monetary policy which raises price of future consumption relative to current consumption is equivalent to the decline in the price of the former to the latter. Similar to *NNP*, it marks the importance of considering separate asset classes for a more precise exposure of households to real interest rates. The altered definitions in (1.4) & (1.5) are theoretical counterparts to section 1.3.2. At any point of time, the flexibility of the expressions in (1.4) & (1.5) allows a clear comparison with the original results by substituting $\{\theta_i\}_{i=1(1)4} = \{\Theta_j\}_{j=1,2} = 1$.

Detailed mathematical derivations are included in appendix A.2.1. As in Auclert (2019), the updated theorem makes no assumption about the functional form of the utility (except that it is separable) or about the time horizon. It can be readily applied to general functional forms. Moreover, (1.4) & (1.5) are valid under persistent shocks. These results are stated in appendix A.2.1. The setup is also flexible to the additions of durable goods, a derivation for which is contained in appendix A.2.2. The current environment also encompasses market incompleteness where individual income is subject to idiosyncratic shocks as in appendix A.2.3.[16]

[16]Empirically, it would be very challenging to estimate the *MPC* accurately as a function of the these two specific balance sheet exposures at the individual level using survey data for the case of incomplete markets.

1.4.4 Evaluating Importance of Return Heterogeneity

The altered definitions of the household exposures preserves the structure of existing work allowing similar economy-wide aggregation as the benchmark for a large class of heterogeneous agent modeling setups. I restate the economy-wide consumption response to the first order idiosyncratic response from individual income dY_i along with aggregate variables dY, dP and dR in (1.6). γ_i is the elasticity of individual income to aggregate income & σ_i is the individual *IES*. In section 1.5, I describe how to emprically measure & quantify these relations between exposures & corresponding *MPCs*.

$$dC = \underbrace{\mathbb{E}_I\left[\frac{Y_i}{Y}\widehat{MPC}_i\right]dY}_{\text{Aggregate income channel}} + \underbrace{\gamma \text{cov}_I\left(\widehat{MPC}_i, Y_i\right)\frac{dY}{Y}}_{\text{Earnings heterogeneity channel}} - \underbrace{\text{cov}_I\left(\widehat{MPC}_i, NNP_i\right)\frac{dP}{P}}_{\text{Fisher channel}}$$
$$+ \left(\underbrace{\text{cov}_I\left(\widehat{MPC}_i, URE_i\right)}_{\text{Interest rate exposure channel}} - \underbrace{\mathbb{E}_I\left[\sigma_i\left(1-\widehat{MPC}_i\right)c_i\right]}_{\text{Substitution channel}}\right)\frac{dR}{R} \tag{1.6}$$
$$\text{where } \widehat{MPC} = \frac{MPC}{1+wMPN} \geq MPC \quad \& \quad \gamma_i \approx \gamma \equiv \frac{\partial\left(\frac{Y_i}{Y}-1\right)}{\left(\frac{Y_i}{Y}-1\right)}\frac{Y}{\partial Y}$$

The above result shows that a set of seven sufficient statistics, all of which can be estimated from survey data having information on household balance sheets and consumption expenditures, completely characterizes the aggregate consumption response to the unexpected transitory shock. One way to evaluate is by comparing the economy-wide consumption response in both partial and general equilibrium. This forms the basis of results in section 1.6.2. The Representative agent counterpart has a single *MPC* which leads to all the covariance terms being 0 and three separate returns. It serves to isolate the importance of heterogeneity of *MPCs* for HANK models. Additionally, there is only one common *IES* σ.

$$dC = \widehat{MPC}dY - \sigma\left(1-\widehat{MPC}\right)C\frac{dR}{R} \quad \text{or} \quad \frac{dC}{C} = -\sigma\frac{dR}{R} \tag{1.7}$$

The class of sufficient statistics can also be estimated separately for housing and equity (which is important in its own regard as mentioned in section 1.1) by adding respective ex-post return & price heterogeneity relative to the benchmark. In summary, I therefore compare the results for 5 different models for the same one percent decline in the real interest rate and an accompanying one percent increase in inflation and aggregate income. This is denoted in the first panel of Figure 1.4 for the benchmark which is the liquid asset.

Second, one might be interested in quantifying the direct effects of monetary policy which is the interest rate elasticity of aggregate demand to the real interest rate.[17] Greater the proportion of unconstrained agents in the economy, larger is the response. The central bank's influence on aggregate demand is larger at this stage relative to second order price and income changes over which it has less control. It is given by the instantaneous consumption response to only the change in the real interest rate in partial equilibrium.

$$\frac{\partial C}{C}\frac{1}{\partial r} = \left(\underbrace{\mathrm{Cov}_I\left(MPC_i, \frac{URE_i}{\mathbb{E}_I[c_i]}\right)}_{\varepsilon_R\ <0} - \sigma\, \underbrace{\mathbb{E}_I\left[(1-MPC_i)\,, \frac{c_i}{\mathbb{E}_I[c_i]}\right]}_{S\ >0} \right)$$

$$\sigma^* \equiv \frac{-\varepsilon_R}{S} = \frac{-\mathrm{Cov}_I\left(MPC_i, \frac{URE_i}{\mathbb{E}_I[c_i]}\right)}{\mathbb{E}_I\left[(1-MPC_i)\frac{c_i}{\mathbb{E}_I[c_i]}\right]}, \quad \because \sigma S\ \neq\ -\varepsilon_R \tag{1.8}$$

Focusing on the relevant term in (1.6), (1.8) shows the ratio of the *URE* & the corresponding substitution channel in a RANK. It is typically positive since the covariance between *URE* & *MPC* is negative (see section 1.4.3). Measuring σ^* does not depend on the value of *IES*, reported estimates for which can vary widely. One can simply redefine the *IES* parameter as the sum of σ^* & σ without amending the existing calibrated value of the latter. The model now gets more realistic partial consumption dynamics through its sole channel of transmission. The measure benefits applications where a RANK is preferred over the complexities of structural incomplete market models. The relevant results are in section 1.6.4 using analogous across model comparison as described in section 1.6.2.

[17] The first generation of HANK models pioneered by Kaplan et al. (2018) report that direct effects typically never exceed on-third of the total impact. Extensive work has since been conducted to analyze the quantitative contributions of the interest rate channel primarily in structural models. Notwithstanding its limitations as detailed in section 4 of Auclert (2015), I approach the problem instead from the sufficient statistics approach which incorporate the conditional impact of monetary policy. The advantage is having an environment free of misspecification errors while being backed up by extensive micro-data.

1.5 Measuring the sufficient statistics from survey data

Assuming a common *IES* σ & elasticity of relative income to aggregate income γ, the estimable moments are the counterparts of (1.6). For convenience, I summarize their definitions by referring to Figure 1.5 from Auclert (2019) corresponding to (1.9). I map the theoretical definitions given by equations (1.4) & (1.5) to household survey data and the estimates from Table 1.1 using the consumer expenditure survey (CE) data from 1999-2002.

$$dC = (\mathcal{M} + \gamma \varepsilon_Y) \frac{dY}{Y} - \varepsilon_P \frac{dP}{P} + (\varepsilon_R - \sigma \mathcal{S}) \frac{dR}{R} \tag{1.9}$$

For (1.10) - (1.11), C_i is all expenditure on consumption including rent & interest payments (non-durables) with robustness checks for durable expenditure, fraction $= 1 - \epsilon$. Assets A_i includes deposits & bonds while liabilities L_i is composed of primarily adjustable rate mortgages & credit cards. T_i is taxes net of transfers. Y_i is gross income from all sources - labor, dividend, and interest income, as well as realized capital gains.

$$NNP_i = (1 + NSP) \times S_i + LiqA_i - (1 + NHP) \times HL_i - NHL_i \tag{1.10}$$

$$\begin{aligned} URE_i = {} & Y_i - T_i - C_i + (1 + SPC) \times (1 + NEP) \times S_i + LiqA_i \\ & - (1 + HPC) \times (1 + NHP) \times HL_i - NHL_i \end{aligned} \tag{1.11}$$

I maintain the assumption of excluding reported unrealized capital gains from income. Equations (1.10) & (1.11) aim to incorporate ex-post returns & price heterogeneity from the Fisher and real interest rate channels. Accordingly, directly held net nominal positions of equity is weighed by the normalized stock price change (*NSP*). For housing, it is the normalized house price change (*NHP*). Analogously, the interest rate exposure is adjusted to include the normalized changes in equity premium & housing premium (*NEP* & *NHP*) with the corresponding changes in the nominal prices of these assets (*SPC* & *HPC*). The values are listed in Table 1.1 and expressed in appropriate units. The rest of the sufficient statistics are identically estimated. If one wishes, they can use their preferred estimates obtained using the method of their choice for Table 1.1 to measure (1.11) & (1.10).

The main estimating equation is of the form (1.12). I follow the exact same method as

Auclert (2019) to estimate the *MPC* from a windfall fiscal transfer based on stratification of the population depending on the measure of household exposure. I present here the specification for the real interest rate channel. $c_{i,m,t}$ is household $i's$ consumption expenditures in month m and at date t, α_m is month fixed effects while $X_{i,t}$ are controls. R_{t+1} is the dollar amount of the rebate at $t+1$ & $QURE_{i,j}$ is a dummy indicating that household $i's$ URE in group $j = 1...J$. In each URE bin, the average normalized URE, $NURE_j$ is the average over households in group j of $\frac{URE_j}{\bar{c}}$ where $\bar{c}$ is average consumption expenditure in the sample. The household panel is resampled around 100 times with replacement by a Monte-Carlo procedure to minimize sampling uncertainty before calculating the sufficient statistic. In line with the logic in section 1.4.3 for the *URE* channel, the ex-post returns heterogeneity amplifies the exposures leading to higher *MPC* estimates for the lower quantiles. Both of these amplify the covariance which is the corresponding sufficient statistic. Analogous equations and intuition exist for the inflation & earnings heterogeneity channels.

$$C_{i,m,t+1} - C_{i,m,t} = \alpha_m + \beta X_{i,t} + \sum_{j=1}^{J} MPC_j R_{i,t+1} QURE_{i,j} + u_{i,t+1}$$

$$\widehat{\varepsilon}_r = \frac{1}{J}\sum_{j=1}^{J} MPC_j NURE_j - \left(\frac{1}{J}\sum_{j=1}^{J} MPC_j\right)\left(\frac{1}{J}\sum_{j=1}^{J} NURE_j\right) \;\; \& \;\; \widehat{S} = 1 - \left(\frac{1}{J}\sum_{j=1}^{J} MPC_j\right) \tag{1.12}$$

Following the discussion in section 1.4.3, to get the impact of changing estimates of *MPC*, I use a second survey data which has self-reported *MPCs*. The Survey of Household Income and Wealth (SHIW) 2010 is one of the very few publicly available sources that serves the purpose. I carry out the identical exercise as with the CE. I concede that the household portfolio heterogeneity and subsequent quantitative implications of monetary policy in section 1.3.2 are very different for US and Italian data. The exercise nevertheless gives implications from holding the heterogeneous *MPCs* at the household level invariant to adjusted balance sheet exposures.

I maintain the same assumptions as the benchmark case for dealing with durables and asset maturities. Alternate fiscal policy where the external sector (viz. the Government) withholds lumpsum transfer from the household sector rather than an instantaneous rebate gives the second set of sufficient statistics, labelled as the no rebate numbers. Issues of concern with the survey data centers around the limited information on household asset holdings. This is true for both the CE and SHIW data, both of which chronically under represent the rich. These pose more acute

Figure 1.5: Seven cross-sectional moments that determine consumption in (1.9)

	Definition	Name	Channel
$\mathcal{E}_R$	$\operatorname{cov}_I\left(MPC_i, \frac{URE_i}{\mathbb{E}_I[c_i]}\right)$	Redistribution elasticity for R	Interest-rate exposure
$\mathcal{E}_R^{NR}$	$\mathbb{E}_I\left[MPC_i \frac{URE_i}{\mathbb{E}_I[c_i]}\right]$	—, no rebate	—
$\hat{S}$	$\mathbb{E}_I\left[(1 - MPC_i)\frac{c_i}{\mathbb{E}_I[c_i]}\right]$	Hicksian scaling factor	Substitution
$\mathcal{E}_P$	$\operatorname{cov}_I\left(MPC_i, \frac{NNP_i}{\mathbb{E}_I[c_i]}\right)$	Redistribution elasticity for P	Fisher
$\mathcal{E}_P^{NR}$	$\mathbb{E}_I\left[MPC_i \frac{NNP_i}{\mathbb{E}_I[c_i]}\right]$	—, no rebate	—
$\mathcal{E}_Y$	$\operatorname{cov}_I\left(MPC_i, \frac{Y_i}{\mathbb{E}_I[c_i]}\right)$	Redistribution elasticity for Y	Earnings heterogeneity
$\mathcal{M}$	$\mathbb{E}_I\left[MPC_i \frac{Y_i}{\mathbb{E}_I[c_i]}\right]$	Income-weighted MPC	Aggregate income

Note - Reproduced from Auclert (2019). Essentially there are five sufficient statistics for the three channels along with the traditional income and substitution channels. To minimize the measurement errors with the sufficient statistics for interest rate and inflation, there are two corresponding numbers given in rows 2 and 5 respectively.

problems for my exercise since I require extensive household wealth information to quantify the role played by wealth inequality in measuring redistributative effects. To get an estimate of the scale of the problem and for further details, I refer the interested reader to section III. B, particularly Tables 2 and 3 as well as appendix C.6 of Auclert (2019).

1.6 Results

Notwithstanding the limitations of the survey data, I intend to demonstrate using sufficient statistics that the conditional impact of transitory monetary policy is very different in the absence of returns heterogeneity. The overall magnitude of transmission to aggregate consumption depends extensively on the redistribuative channels, especially those arising from the real interest rate & nominal price changes.[18] Instead of relying on a structural model that could be prone to misspec-

[18] As mentioned in section 1.5, the unrealized capital gains reported in the survey data are excluded as the existing redistribution channels summarize the household exposures for the same. Instead, I focus on the best way to incorporate the conditional impact. One of the feasible channels of interest is returns heterogeneity that I focus exclusively on. To get an idea of how reported unrealized capital gains/losses affect wealth changes across wealth quantiles, see appendix A.1.4.

ification errors, the relatively restriction free theoretical framework of section 1.4 can be mapped to the empirics in section 1.5. Further, one can analyze the results by isolating the role of housing and equity taking into cognizance that returns heterogeneity interacts with portfolio heterogeneity, both within and across asset classes. The approach can also be used to conduct simple policy counterfactuals. As HANK models progress in their complexity they should remain consistent with the aggregate moments, derived specifically for the dimension of the wealth distribution that they seek to incorporate and explain. Of course, there could be alternate channels that I do not consider that have similar impacts (I briefly compare the results in section 1.1). I choose the one that is both intuitive as well as easily verified with publicly available micro-data using appropriate techniques.

The section is broadly divided into 5 parts. First, section 1.6.1 discusses the broad results across the net wealth distribution, along with other dimensions of heterogeneity such as housing tenure and demographics in line with the intuition in section 1.4.4. It also explains their interaction with heterogeneity in asset returns. Next, I measure aggregate consumption and compare it across models (section 1.6.2). I explain how intuitively the results are expected to be different from the additional dimension of heterogeneity. I stress on the importance of estimating *MPCs* out of unrealized wealth changes. I measure the asymmetric consumption response from a contractionary shock in 1.6.3. Next, I present the enhancements in direct effects (section 1.6.4). I conclude the section by a brief discussion of model predictions in 1.6.5. Analogous to Auclert (2019), I present the updated sufficient statistics in appendix A.3.1 along with associated figures depicting covariance between the measures of redistribution and estimated *MPCs* qualitatively.

1.6.1 Identifying Winners and Losers from Monetary Policy

Table 1.2 illustrates the consumption elasticities across different net wealth distribution groups in response to economic shocks. It's observed that the middle 50-90% wealth group exhibits higher consumption elasticities as compared to the bottom 50% group, particularly during expansionary shocks. This could be interpreted as a result of the middle wealth group having more liquid assets and lesser debt, which facilitates a higher propensity to increase consumption when positive economic shocks occur. Conversely, the lower consumption elasticity in the bottom 50% group during contractionary shocks may highlight their financial vulnerability and lower asset liquidity, causing a more subdued consumption response. Furthermore, the final column sheds light

Table 1.2: Consumption elasticities with $\sigma = 0.5$ & $\gamma = -0.5$ for CE data by net wealth distribution

Net Wealth Distribution	**Expansionary Shock**	**Contractionary Shock**	**Unconditional**
Middle 50-90%	1.51	1.32	1.28
Bottom 50%	0.78	0.44	0.8
Aggregate	1.63	1.06	1.28

Note - For details regarding the shock please see associated table notes in Table 1.5 & Table 1.8. Unconditional refers to the benchmark results without asset returns heterogeneity under Auclert (2019).

on the effects of returns heterogeneity on consumption elasticities. It suggests that the distinctions in consumption responses across wealth groups are more pronounced when there's asset returns heterogeneity. This analysis aligns with the referenced work by Auclert (2019), indicating that heterogeneity in asset returns could further widen the consumption response gap among different wealth distribution groups during economic shocks.

The substantial surge in aggregate consumption arises from the expectation that households will eventually convert their wealth changes into liquid assets. But if significant financial constraints impede these future realizations, the resultant rise in consumption might be more subdued. Two key constraints are housing tenure and demographics. Homeowners have lower leverage compared to mortgage holders, and renters often carry substantial non-housing debt. Younger individuals typically amass more debt, primarily for housing, whereas the middle-aged and elderly generally have less. This section delves into how specific wealth changes from ex-post return heterogeneity interact with these two household facets. The more unconstrained a household, the likelier they'll boost current consumption from unrealized wealth gains, leading to a more pronounced aggregate reaction. There are other relevant factors intersecting with balance sheet effects, but they're more challenging to scrutinize in this context.

Following Cloyne et al. (2020), I categorize households into three groups based on housing tenure: outright homeowners, mortgage holders, and renters. Demographic distinctions align with Wong (2019). I assess the change in general equilibrium instantaneous responses for these household groups with return heterogeneity compared to benchmark figures in Auclert (2019). Further results

Table 1.3: Consumption elasticities with $\sigma = 0.5$ & $\gamma = -0.5$ for CE data by housing tenure

Housing Tenure	**Outright Homeowner**	**Mortgage Holder**	**Renter**
Sample Size (in %)	26.27	40.65	33.08
Expansionary Shock	3.02	1.43	0.7
Contractionary Shock	1.55	0.66	0.72

Note - For details regarding the shock please see associated table notes in Table 1.5 & Table 1.8.

on implied *IRFs* concerning demographics and housing tenure can be found in appendix A.5. As indicated in Table 1.3, mortgage owners don't necessarily see an increased consumption response from amplified wealth changes due to return heterogeneity. Instead, outright homeowners, with lower debt by choice and fewer constraints, register a much more prominent response. Renters, typically less endowed to take on substantial debt, exhibit minor absolute elasticities in both models, even with a notable percentage increase. Table 1.4 illustrates age-based responses. Drawing a loose comparison to Table 4 in Wong (2019), though methodologies differ significantly, the elderly and middle-aged demonstrate a higher consumption response compared to the young in terms of aggregate elasticities. This aligns with the understanding that older individuals, facing fewer financial constraints and having shorter lifespans, are likely to liquidate gains faster. Conversely, the young, being potentially more financially constrained, might see muted effects from unrealized wealth gains after a positive shock.

1.6.2 Comparing aggregate consumption response across models

I present the expansionary policy results and rank the response of aggregate consumption in partial and general equilibrium across models using only sufficient statistics.[19] Using equation (1.9) and the data from Figure 1.4, I compute the total percent change in general equilibrium.[20] From

[19]This transitory shock results in a one-period response. Details on handling persistent real interest rate changes due to unexpected monetary policy surprises are in appendix A.2.1 and A.1.3.

[20]The use of the liquid asset benchmark evaluates the importance of returns heterogeneity compared to Auclert (2019). The updated household exposure definitions offer flexibility to consider or ignore additional sources like housing and stocks.

Table 1.4: Consumption elasticities with $\sigma = 0.5$ & $\gamma = -0.5$ for CE data by demographics

Demographics	**Young** (25-34 yrs)	**Middle** (35-64 yrs)	**Old** (64-75 yrs)
Sample Size (in %)	33.64	54.67	11.69
Expansionary Shock	1.29	1.57	1.72
Contractionary Shock	1.48	0.75	0.06

Note - For details regarding the shock please see associated table notes in Table 1.5 & Table 1.8.

this, I derive the partial equilibrium response, and the RANK response is given by (1.7). Results interpretation is expanded upon in sections 1.6.2 and 1.6.3. For each data source, I tabulate the responses; for instance, Table 1.5 details various model results. Analogous tables should be interpreted similarly. The parameters chosen are $\sigma = 0.5$ & $\gamma = -0.5$ with σ being consistent with the original model. Sensitivity tests for γ are in appendix A.3.

In Table 1.5, stock excess returns and price changes significantly outperform housing. Specifically, the high conditional impact of stocks results in the most substantial consumption increase from a one percent reduction in the real interest rate: approximately 30% and 50% higher in partial and general equilibrium compared to the initial findings. Examining the redistribution from the real interest rate, Fisher, and unearned income channels in general equilibrium, we find their combined share rises by 15% to 48% . The real interest rate and Fisher individually account for 3% and 12% increases. Including both these sources leads to an overall rise in consumption by 27% and 15% , with redistribution shares at 43% ; broken down, the two channels contribute 9% and 2% .

Emphasizing the redistribution channel boosts the overall monetary transmission, especially via the real interest rate and Fisher channels, due to heightened *MPCs* heterogeneity. The partial equilibrium response is also more substantial because the net income effect counters the impact. However, adding one or two returns to a RANK doesn't substantially assist in quantifying this transmission. Figure A.6 panel (b) reveals a hump-shaped response when utilizing self-reported MPCs, causing decreased *MPCs* across the *URE* distribution, hence smaller consumption changes. As shown in Table 1.6, this reduction in consumption response across models aligns with prior

Table 1.5: Percent change in aggregate consumption for expansionary shock with $\sigma = 0.5$ & $\gamma = -0.5$ in CE data for benchmark case

Model with estimated *MPCs*	Consumption Response		In corresponding RANK	
	PE	GE	PE	GE
Auclert + House + Stock	0.90	1.63	0.33	0.77
Auclert + House	0.84	1.28	0.32	0.77
Auclert + Stock	1.06	1.52	0.33	0.79
Auclert	0.71	1.17	0.32	0.78

Note - Expansionary shock refers to the transitory unexpected one percent decrease in the real interest rate accompanied by an increase in the overall price level & aggregate income by one percent. Row 4 represent the benchmark numbers using baseline calibration and additionally setting the value of γ. Rows 1-3 add(s) the additional conditional differential impact in asset excess premium/premia & price(s) on top of the benchmark. Numbers represent the elasticity of aggregate consumption. Columns 2 and 3 refer to partial equilibrium and general equilibrium elasticities. RANK is counterpart of model in each row with constant *MPC*.

Table 1.6: Percent change in aggregate consumption for expansionary shock with $\sigma = 0.5$ & $\gamma = -0.5$ in SHIW data for benchmark case

Model with fixed *MPCs*	Consumption Response		In corresponding RANK	
	PE	GE	PE	GE
Auclert + House + Stock	0.44	0.93	0.28	0.77
Auclert + House	0.43	0.92	0.28	0.77
Auclert + Stock	0.48	1.03	0.28	0.83
Auclert	0.51	0.97	0.28	0.74

Notes - For more details see notes in Table 1.5. Here identical exercise for SHIW data.

Table 1.7: σ^* across models for benchmark case with $\sigma = 0.5$ for contractionary policy

Measure	**Survey**	Auclert	Housing + Stock	Housing	Stocks
$\boldsymbol{\sigma^*}$	**CE**	0.36	0.39	0.26	0.16
% Change		—	9.48	-27.01	-55.12
	SHIW	0.18	0.25	0.27	0.16
		—	40.0	50.0	10.0

Note - Contractionary shock refers to the transitory unexpected one percent increase in the real interest rate. See notes in Table 1.10 for more details.

explanations about the distribution shift pushing individuals to report lower *MPCs*.[21]

In the context of understanding the significance of no-rebate numbers, which shed light on the mismeasurement issue, I detail the outcomes for the four models across two datasets with heterogeneous *MPCs* in Table A.14. These figures are empirically more trustworthy. Results indicate that incorporating returns heterogeneity, contingent on the shock, enhances redistribution to aggregate consumption, irrespective of if *MPCs* are static or variable based on the shock. The general equilibrium boost is 48% in CE and 73% in SHIW. Even solely integrating the relative heterogeneity in housing returns, which empirically results in fewer unrealized wealth shifts relative to equity, sees boosts of 53% and 48% . An exception exists for the impact exclusive to equities in CE data, where aggregate consumption notably drops for both equilibria. When leaning on conservative redistribution estimates, no scenarios result in a negative aggregate consumption elasticity, a marked improvement over initial findings.

1.6.3 Response to a contractionary shock

Including the conditional impact of the shock on sufficient statistics allows me to mechanically generate results for the contractionary monetary policy. Empirically, the estimates in Table 1.1 reverse their signs. The contractionary one time monetary policy surprise produces symmetric changes in the prices and excess premia for housing & equity. I present results analogously

[21] Acknowledging previous caveats, the data and household portfolio heterogeneity aren't directly comparable for the identical shock. However, it provides insight into changing *MPCs* impacts. Even on the conservative side, the response from unrealized wealth effects would be considerably lower.

Table 1.8: Percent change in aggregate consumption for contractionary shock with $\sigma = 0.5$ & $\gamma = -0.5$ in CE data for benchmark case

Model with estimated *MPCs*	Consumption Response		In corresponding RANK	
	PE	GE	PE	GE
Auclert + House + Stock	0.53	1.02	0.31	0.80
Auclert + House	0.46	0.95	0.31	0.80
Auclert + Stock	0.54	1.00	0.31	0.77
Auclert	0.71	1.17	0.32	0.78

Note - Contractionary shock refers to the transitory unexpected one percent increase in the real interest rate accompanied by a decrease in overall price level & aggregate income by one percent. See notes in Table 1.5 for more details.

for sections 1.6.4 and 1.6.2 for a transitory one percent increase in real interest rate. It highlights how heterogeneity in *MPCs* produces asymmetric responses in HANK models.[22] It also demonstrates the flexibility of the theoretical setup. Though all the signs are positive in Table 1.8 - Table A.15, the elasticities (where applicable) correspond to an increase, and not decrease, in the real interest rate. The benchmark results are identical since the original results are unconditioned on the shock. The fact that the other estimates are substantially different from their counterparts in sections 1.6.4 and 1.6.2 highlight the scale of asymmetricity by asset class. I present additional results in appendix 1.6.2.

In Table 1.7, direct effects on stocks appear minimal since they experience the most significant wealth reductions. Consequently, the final consumption response from this channel is subdued due to associated lower *MPCs*. This pattern is mirrored in housing, albeit with less pronounced declines. Incorporating both stocks and housing results in a more marked decrease in consumption. Yet, assessing only the real interest rate channel can be misleading, as the final consumption response diminishes considerably, as evidenced in Table 1.8. Here, the Fisher channel counteracts the decline.

In the three analyzed cases, wealth reduction heightens the redistribution measure at the lower distribution end and diminishes it for the upper half. Due to the negative covariance, wealth

[22] I refer to this growing literature briefly in section 1.1 in connection with my sufficient statistics approach.

Table 1.9: Percent change in aggregate consumption for contractionary shock with $\sigma = 0.5$ & $\gamma = -0.5$ in SHIW data for benchmark case

Model with fixed *MPCs*	Consumption Response		In corresponding RANK	
	PE	GE	PE	GE
Auclert + House + Stock	0.53	1.16	0.28	0.91
Auclert + House	0.53	1.16	0.28	0.91
Auclert + Stock	0.46	1.01	0.28	0.83
Auclert	0.51	0.97	0.28	0.74

Note - Contractionary shock refers to the transitory unexpected one percent increase in the real interest rate accompanied by a decrease in overall price level & aggregate income by one percent. See notes in Table 1.6 for more details.

declines result in smaller estimated *MPCs*. The product of these two factors results in a decrease smaller than that caused by the wealth change alone. The aggregate outcome is influenced by existing household portfolio heterogeneity. The response is not only asymmetric, but redistribution also moderates the final consumption impact. Given that estimated unrealized wealth reductions are negative, equity takes precedence over housing; the former experiences the steepest declines and the least change in associated *MPCs*, thus amplifying the asymmetric response. As per Table 1.9, the associated consumption reductions are minimal for both equilibria, outperforming the benchmark model's decline by 35% and 18% for partial and general equilibrium, respectively. Integrating both housing and equity leads to a more modest decrease, surpassing the benchmark model's decline by up to 25% and 12% in partial and general equilibrium respectively.

Crucially, we must re-estimate the associated *MPCs*. Table 1.9 indicates larger declines when solely considering wealth changes. Here, diminished wealth, as gauged by the redistribution measure, leads to heightened *MPCs*. The net consumption response results from the combination of a smaller *MPC* decrease and the related wealth reduction. For completeness, results accounting for sampling error are in Table A.15. With constant *MPCs*, some aggregate consumption elasticity values appear counter-intuitive. The absence of a pronounced negative correlation between redistribution and *MPC* in the SHIW, unlike in the CE, seems to be a factor. In the final model using CE data, consumption declines are 81% and 52% less than baseline estimates. Only with housing does the asymmetric response inverse, causing a greater consumption drop. A potential reason

Table 1.10: σ^* across models for benchmark case with $\sigma = 0.5$ for expansionary policy

Measure	Survey	Auclert	Housing + Stock	Housing	Stocks
$\boldsymbol{\sigma^*}$	**CE**	0.36	0.58	0.54	0.53
% Change		—	62.68	49.83	47.56
$\boldsymbol{\sigma^*}$	**SHIW**	0.18	0.13	0.11	0.20
% Change		—	-31.25	-41.07	10.00

Note - Expansionary shock refers to the transitory unexpected one percent decline in the real interest rate. Column 1 are benchmark numbers using baseline calibration. Percentage change is with respect to the benchmark. Columns 2-4 add the additional conditional differential impact in asset excess premium/premia & price(s) on top of the benchmark.

might be the minimal wealth declines for agents who predominantly have their wealth in housing, given that their usual *URE* is negative.

1.6.4 The interest rate elasticity of aggregate demand

To evaluate the efficiency of the refined sufficient statistics in capturing the conditional returns heterogeneity channel, I introduced two comprehensive measures in 1.4.4. The primary measure determines the aggregate demand's elasticity to the real interest rate, represented by the total of σ and σ^*. A sizable σ^* implies overlooking market incompleteness has led to significant underestimation of direct consumption impacts. The original model, which considered consistent asset class impacts, can be contrasted against three distinct cases. I can either include returns for both housing and equity or introduce them individually. Table 1.10 showcases both the magnitude and percentage change from the original in two scenarios - one with variable *MPCs* from CE data and another with stable *MPCs* from SHIW data. The combined returns yield the most substantial impact, highlighting the importance of factoring in unrealized wealth changes for complete redistribution. Even with housing's lower premia compared to equity, disregarding housing's unrealized wealth alterations prevents many from experiencing heightened *MPCs* from sudden wealth gains. These results accentuate the real interest rate's amplified role in redistribution within this framework, underlining the importance of both recognizing household portfolio variety and aligning it with asset return heterogeneity.[23]

[23] While some may argue against the reliability of survey data, this paper's goal is to create a robust framework tied to empirical data to substantiate these critical assertions. Future work includes additional tests using the PSID

As highlighted earlier, if policy nuances targeting specific asset classes aren't a concern, structural models should at least yield accurate aggregate responses. My metrics, designed for sharper estimations, are poised to be beneficial in this context. Aligning with previous outcomes, if *MPCs* aren't allowed to vary, the redistribution's utility (particularly from the real interest rate avenue) for overarching monetary transmission is essentially constrained, evident from the fourth row. Naturally, the comprehensive consumption response would integrate the indirect impacts, which I will address subsequently. Asset maturity related robustness checks are catalogued in appendix A.3.

1.6.5 Policy Experiments

To quantify the interaction of wealth inequality with/without ex-post returns heterogeneity, I calibrate the household balance sheets for different years and assume that consumption expenditures remain similar as 2001 CE. I analyze both expansionary and contractionary monetary policy. I use SCF data for 2007 and 2019 to target the GFC and the pandemic respectively. Of particular interest is a contractionary policy around 2007 to approximate the tightening of the interest rate that preceded the collapse of the housing bubble. Similarly, faced by the pandemic, the Fed undertook massive quantitative easing that is akin to an exogenous expansionary surprise in my setup. For mortgage design, I look at a widespread prevalence of adjustable rate mortgages (ARMs). In the US, most fixed rate mortgages carry an option for low cost refinancing (either cash-out or no cash-out). These can be approximated by assuming a greater share of mortgages being ARMs. The results vary significantly if I shorten asset maturity.

Using CE data and examining the *MPC* channel, I analyze aggregate consumption elasticity in general equilibrium. In 2019, a 1% decrease in real interest rate led to a 16% increase in aggregate consumption with a 51% redistribution rate. At quarterly maturity, these values rise to 24% and 67% . With all mortgages as ARMs, the figures are 30% and 58% , but jump to 53% and 79% for quarterly maturity. This data supports the Federal Reserve's early pandemic monetary expansion. More ARMs enhance wealth gains, particularly elevating *MPC* for constrained households. Similar policies had even stronger effects in 2007. The outcome is shaped by housing and equity market dynamics, where increased housing wealth results in higher consumption response, despite lower

data.

returns per unit.[24]

The model counterfactual improvements in the aggregate consumption response for contractionary policy, in line with section 1.6.3. In 2007, a contractionary shock would have lead to an improvement in aggregate consumption by 9%. Having only returns for housing would improve by 14%. Having ARMs and/or restricting to quarterly maturity does not improve upon the results. Full results are reported in Table A.18 - Table A.19, appendix A.6. These experiments are of course limited. The reduced form model free environment has limited appeal vs alternately estimating complex structural models with micro-data. Recently, there has been significant progress in bayesian estimation of HANK models. However, I have demonstrated the importance of treating ex-post return heterogeneity seriously when the primary purpose is analyzing aggregate moments of consumption from aggregate monetary policy surprises.

1.7 Conclusion

Overlooking the differential monetary policy effects on housing and equity leads to sizable underestimation of aggregate consumption through redistribution in the short run. Previous studies focusing on heterogeneity in discount factors or risk-taking propensities don't fully capture changing *MPCs* from unrealized wealth gains/losses, resulting in RANK-like consumption responses. My research stands out due to two distinctions: I evaluate a transmission mechanism based on publicly available asset data, and I find that larger disparities in asset returns bolster aggregate consumption. Using a robust sufficient statistics approach, I demonstrate a 28% increase in aggregate consumption, with redistribution contributing 43% from a 1% decrease in the federal funds rate. This is 74% higher than an equivalently calibrated RANK model, highlighting the importance of heterogeneity in MPCs, asset returns and household portfolio shares. The effect is also asymmetric with consumption declining by only 1.06% when the Fed raises rates by 1% instead. I also document how various groups can be classified as winners/losers depending on interactions between housing tenure, demographics and borrowing constraints and how they respond asymmetrically to monetary policy.

[24] From 2004-2007, housing outperformed equity. Post-GFC, equity rebounded faster, and by 2019, housing's relative share declined. See Kuhn and Rios-Rull (2020). Short-term wealth inequality can affect consumption due to limited redistribution.

However, limited data on household assets, especially equity in CE, is a challenge for better empirical estimates. Future research could leverage the more detailed PSID dataset on household wealth, albeit with some limitations in consumption data. My framework's primary advantage lies in its practical, data-driven approach. For example, my model posits that a proactive pandemic policy, treating all mortgages as ARMs, would have spurred a 30% rise in aggregate consumption. This effect was even more potent in 2007 when housing gains overshadowed equity. This suggests that wealth inequality exerts a more immediate influence on consumption than previously thought. My findings indicate that interaction between distinct asset returns and MPC out of income carry more weight than other sources of heterogeneity. Moving forward, constructing a HANK model incorporating both housing and equity as separate illiquid assets could offer a holistic policy exploration avenue.

Chapter 2

Asset Returns and Wealth Inequality

2.1 Introduction

Increasing wealth inequality in many countries during the past several decades has leapt to the fore as a central global concern. It has spawned a large-scale effort to uncover the underlying causes and reverse or at least curb the trend.[1] For the U.S. over the past half-century, a large decline in tax progressivity, together with persistent earnings differentials, have been identified as major contributing factors. Recent papers further highlight the significance of differential asset returns and household portfolio heterogeneity in driving U.S. wealth inequality. As composition and leverage of household portfolios differ systematically along the wealth distribution, Kuhn et al. (2020) show that differential returns in the equity and housing markets have led to a decoupling of the income and wealth distribution in postwar America. Extending the Survey of Consumer Finances, they report that middle-class portfolios are dominated by housing, while rich households predominantly own business equity. Housing booms lead to substantial wealth gains for leveraged middle-class households and tend to decrease wealth inequality, all else equal. Stock market booms primarily boost the wealth of households at the top of the wealth distribution, as their portfolios

[1] Piketty (2014), Hubmer et al. (2021), among others, provide comprehensive discussions of both the empirical trends and the major causes of the changing wealth distributions. In the U.S., for example, declines in tax progressivity, persistent earnings differentials, and household portfolio heterogeneity have all been identified as key contributors to the diverging wealth positions. See Curcuru et al. (2010), Jordà et al. (2019), Kartashova and Tomlin (2017), Alan (2006) for comprehensive surveys of household portfolio and asset return differentials.

are dominated by listed and unlisted business equity.[2]

Amid the focus in the literature on the diverging wealth accumulations within a population, wealth disparities are widening across other dimensions – age, generations, and race – as well.Figure 2.1 shows that in the 1960s, households aged 40-59 and 60+ were on average three times wealthier than households aged 20-39. By 2019 these ratios have grown to a factor of six to eight.[3] Looking across racial and ethnic lines over the past 30 years (Figure Figure 2.2), one sees large and growing racial wealth gaps. For instance, the average Black household wealth, measured as a fraction of the average White household wealth, has declined from over 30% to below 15% since the 1960s.

Figure 2.1: Average Wealth / Average Wealth for 20-39

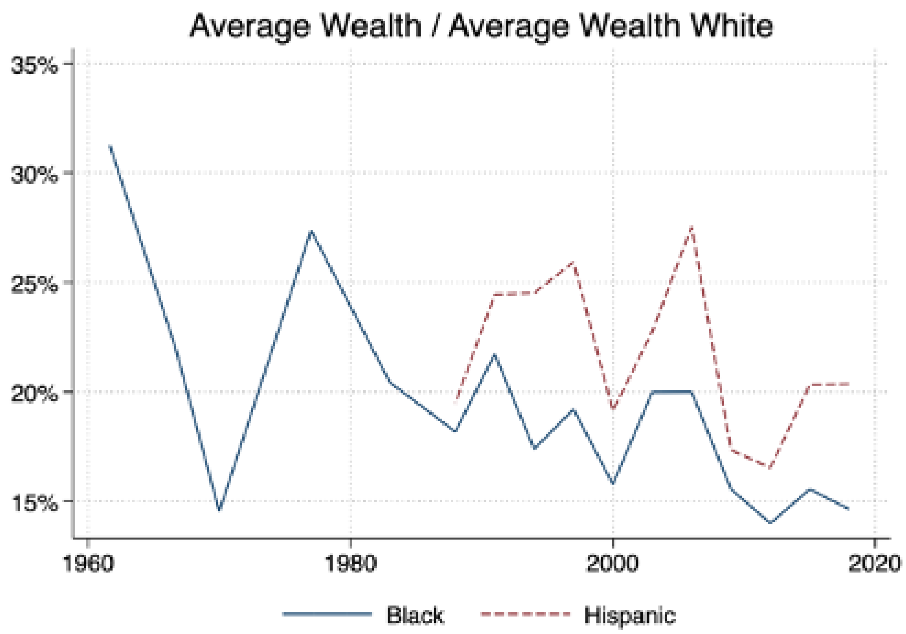
Notes - For each SCF and SCF+ wave, divide net wealth by average net wealth for that year. Take the average by year. The resulting variable for 40-59 and 60+ age groups is divided by the value for 20-39 age group.

Figure 2.3 shows the life cycle wealth profiles of various birth cohorts, grouped by decades.

[2]See Kuhn et al. (2016) for both complimentary evidence and for a richer set of empirical stylized facts for the US economy. The results have been updated to include the 2019 wave of the SCF.

[3]Wealth refers to net wealth from the Survey of Consumer Finances. The divergence is more pronounced if one looks at the relative median household wealth of the age groups rather than the averages.

Figure 2.2: Average Wealth / Average Wealth White



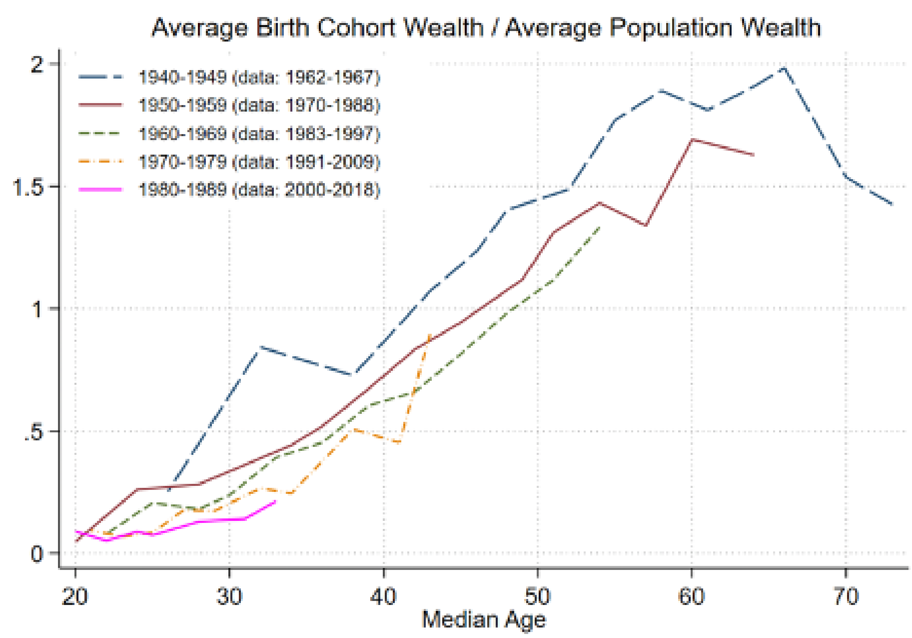
Notes - Similar to above graph. After normalizing net wealth with average net wealth, instead of age groups we have racial groups. Plot resulting time series data.

As a given cohort ages (the x-axis), it accumulates more wealth relative to the average wealth of the entire population in the same year. Yet starting from the older Boomers to the younger Millennials, each successive generation held a smaller fraction of the overall per-capita wealth. Since all generations start with similar levels of wealth, later cohorts have accumulated wealth at slower rates. Analogous data for non-Hispanic White and Black households, considered separately, show similar generational declines in relative wealth and rates of wealth accumulation, especially for the Millennials.[4] What shapes the differing levels and rates of wealth accumulation over a lifetime? In terms of differential asset returns channel, Figure 2.4 shows the house price changes faced by a median person aged 30 in each of the three selected generations. The age could correspond roughly to the time when agents would start investing in housing in their life cycle. A boomer faced the highest increases in house prices while the millennial had to experience a major crash from the Global Financial Crisis of 2008 (GFC). For the analogous trend in stock prices, Figure 2.5 shows that the median Gen Y aged 30 years would benefit the most. On either end, both boomers and

[4]Consistent cohort data by race and ethnicity are available only for non-Hispanic White and Black households for data prior to 1989 (SCF+). Note also that these figures do not yet control for household size, which likely differ by cohorts.

millennials faced about similar decline in prices with the former seeing rapid recovery post the GFC. Bauluz and Meyer (2021) investigate life cycle wealth accumulation of different US birth cohorts in the last six decades and links this to the aggregate evolution of household wealth and private saving. They find that the the life cycle wealth profile has steepened over time and his steepening is driven by the top half of the distribution, so that wealth inequality within cohorts rises. The sources of wealth accumulation have changed over time, where older cohorts relied more on saving and more recent generations on an increase in housing and equity prices, which accounts for the steeper wealth profile. [5]

Figure 2.3: Average Birth Cohort Wealth / Average Population Wealth



Notes - Generate 10 year cohorts born from 1940 based on birth year = SCF/SCF+ year - age of household head. Agents start from age 20. Divide net wealth by average net wealth for each sample unit. Take averages by year and birth cohort. Plot resulting time series data.

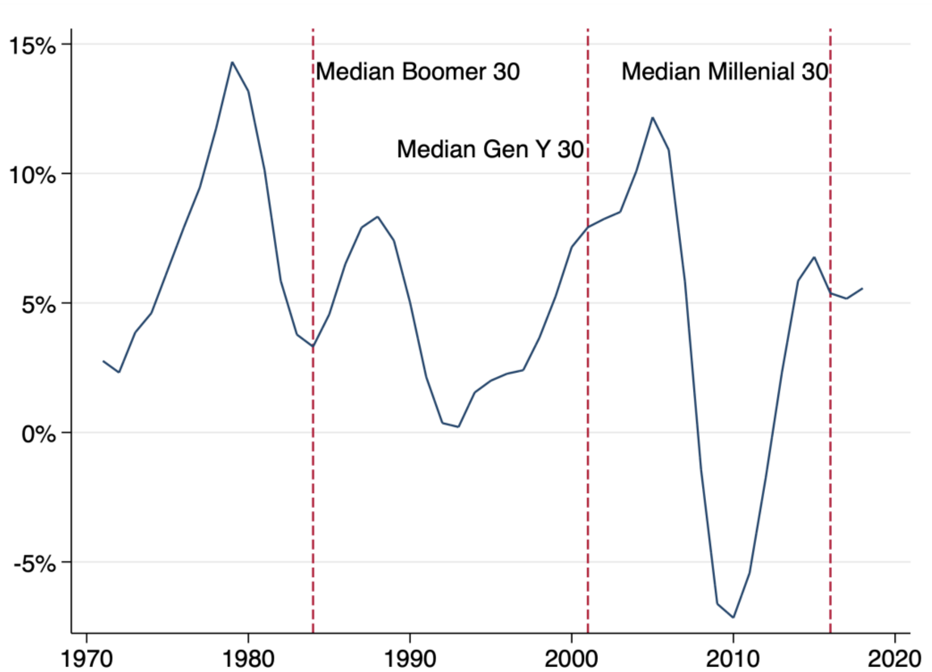
What are the welfare consequences of the observed widening wealth gaps across generational and racial lines? Complementing the emphases of the previous literature, we identify distributional impacts from three broad motivating factors; namely asset and housing market price dynamics over each generation's lifecycle, wealth portfolio at the start of a household's lifecycle: inheritances and debts and barriers to entry & costs of market participation. These three factors are likely

[5]Also see Jäger and Schacht (2023) for additional details about the descriptions of the underlying SCF+ data and evidence in favor of the trends and inter-cohort differences.

mutually-reinforcing. Much of the generational variations in household wealth profiles can be attributed to the different asset-market conditions they faced at various stages of their life cycle. For example, the GFC is likely to have had a very different impact on Millennials than households near retirement. Homeownership rates differ significantly by age - Figure 2.6. As is expected, a small fraction of young households are outright homeowners. The trend has been declining over time with larger fraction of people in their middle or even old ages owning their own homes indicating and feeding into the rising life cycle wealth inequality. This is even more pronounced for equity participation rate as indicated by Figure 2.7. Pre mid 1970s, there was no major variation by age groups. Post this period, the young have clearly fallen behind with the gap steadily widening over time. People born in this period have been unable to realize capital gains from the rise in stock prices early on the life cycle, a consequence as well as cause of rising life cycle wealth inequality. Moreover, as homeownership rates and equity market participation rates differ significantly across racial groups, our model captures the life cycle wealth impact of these household differences in asset-holdings. Homeownership rates are about twice as high for non-Hispanic White households as for Black households (Figure 2.8), and equity-market participation rates are about three times as high (Figure 2.9). For more details, see for example Bennett and Chien (2022).

Literature Review: Cioffi (2021) and Catherine (2022) take similar approaches but focus on very different research questions. Cioffi (2021) develops a partial equilibrium model optimal portfolio choice with aggregate risk featuring a rich menu of assets which is meant to capture the main properties of households' portfolio shares as a function of wealth in a parsimonious yet realistic characterization. He feeds in the observed returns to particularly capture the dual role of housing as a risky investment and a necessary good is crucial to generate the right schedule of portfolio shares. He finds that from the data on expenditure shares on housing, housing is a necessary good and, consequently, consumer preferences are non-homothetic. However, his model is not a life-cycle model. Catherine (2022) develops a life cycle model for portfolio choices that incorporates the relationship between market returns and the skewness of idiosyncratic income shocks. The cyclicality of skewness can explain low stock market participation among young households, why the equity share of participants slightly increases until retirement and why renters invest less in stocks than homeowners, housing and equity shares are not positively correlated and equity shares are not negatively correlated with the wealth-to-earnings ratio. Her paper does not look at the aspect of rising inter-generational wealth inequality both on the aggregate and disaggregated by

Figure 2.4: House Price Growth (3-year MA) - Shiller (2023)



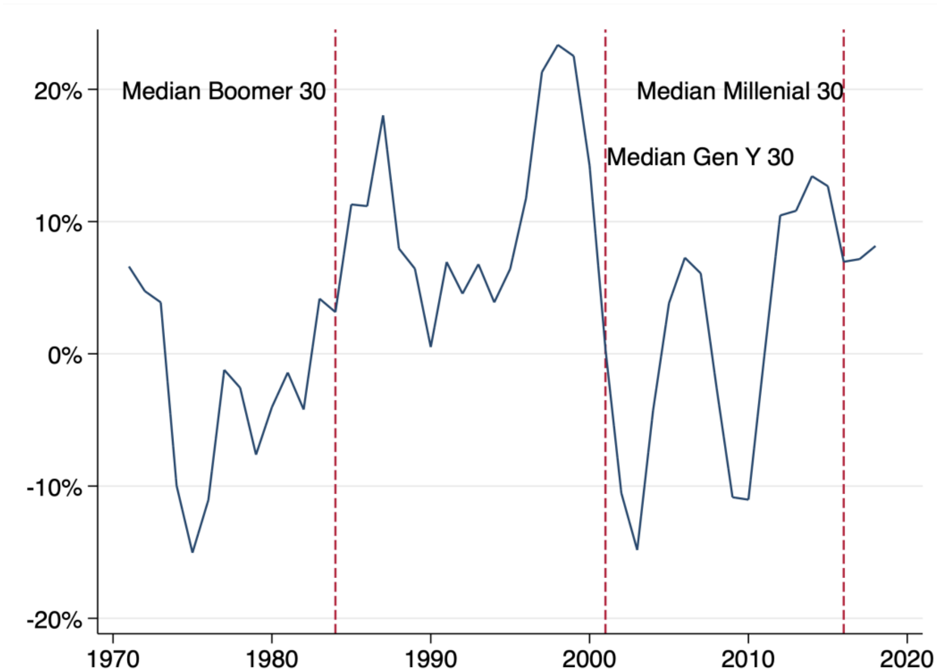
Notes - Boomers are the generation between 1946 – 1964. The median boomer is aged 30 years in 1984. Gen Y are the generation between 1965 – 1980. Median Gen Y is aged 30 years in 2002. Millenials are the generation from 1981 – 1996. Median Millenial aged 30 years is 2018. Monthly house price data is from 1890.

age and race.

Different asset market dynamics or investment portfolios may explain divergent wealth gaps across generations, but the wealth positions of a household at the start of its working lifecycle may play a role as well, especially for explaining within-cohort differences (see e.g. Black et al. (2020) & Black et al. (2022), Bauluz and Meyer (2021), Elinder et al. (2018)). A young household receiving large inheritances will be able to participate in the equity market or establish homeownership much earlier than a household burdened with debt, and the life cycle profiles of their wealth-accumulation patterns are likely to diverge significantly. We can calibrate the PCWD model to match the data of household asset or debt positions at the start of working life, and assess their impact in explaining the observed differences in lifetime wealth profiles. Incorporating bequest motives and inheritance is an added element to our model that was absent in our previous proposal. This additional mechanism allows us to incorporate observed end-of-life wealth transfers in the data.

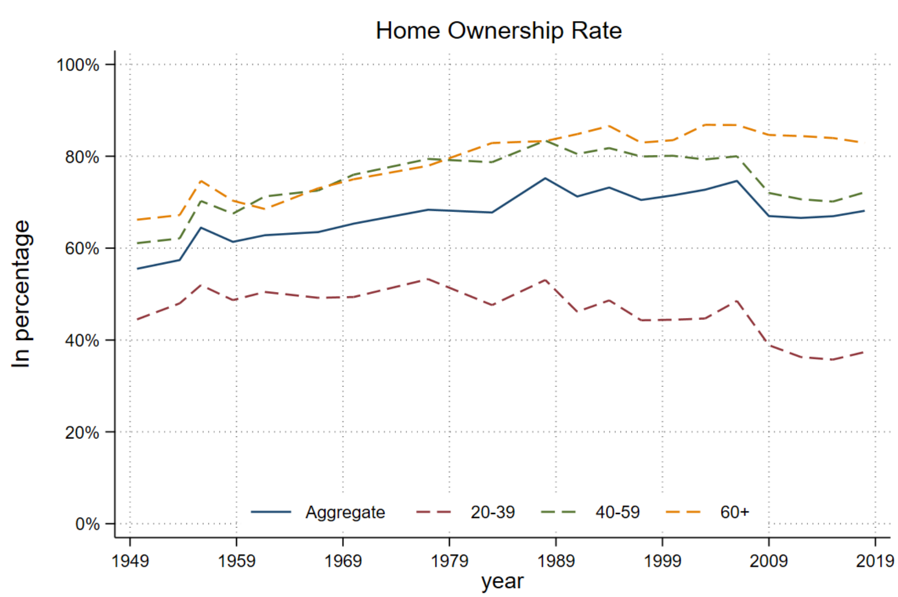
Households face collateral constraints and costs for borrowing, proportional transaction fees for home purchases and sales, and equity-market participation costs (see, for example, Alan

Figure 2.5: Stock Price Growth (3-year MA) - Shiller (2023)



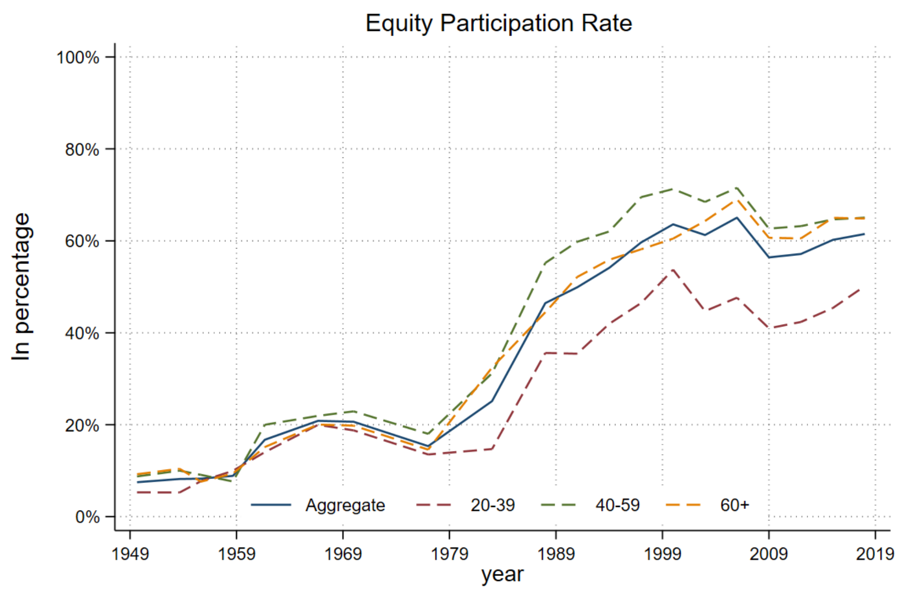
Notes - Boomers are the generation between 1946 – 1964. The median boomer is aged 30 years in 1984. Gen Y are the generation between 1965 – 1980. Median Gen Y is aged 30 years in 2002. Millenials are the generation from 1981 – 1996. Median Millenial aged 30 years is 2018. Monthly stock price data is from 1871.

Figure 2.6: Home ownership rate on the aggregate and across age groups over time



Notes - Homeownership rate is defined for sample units with positive housing wealth. Average homeownership rate is derived for aggregate and each age group.

Figure 2.7: Equity participation rate on the aggregate and across age groups over time



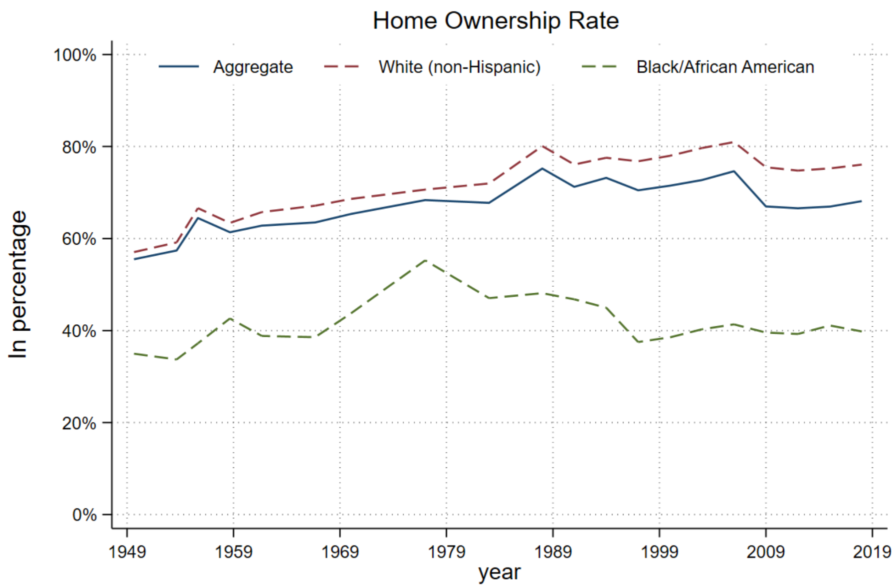
Notes - Equity participation rate is defined for sample units with positive housing wealth. Average homeownership rate is derived for aggregate and each age group.

(2006) and Favilukis (2013). While we discipline these values via the data as much as we can (such as by using mortgage premiums), these costs are in many cases not as readily observable, or as conceptually clean, as the two mechanisms described above. Realistically, on the other hand, households across generational and racial lines likely face substantially different participation barriers, either for actual access or for information. These barriers or frictions surely affect a household's ability to manage its asset portfolio optimally to take advantage of market-return dynamics and initial wealth. An advantage of our structural modeling approach is that we can estimate these frictions and perform counter-factual analyses to assess the dependencies of wealth profiles on them.

The literature emphasizes additional mechanisms, such as spatial or geographical differences, demographics, inter-vivo gifts, tax policies, late-life medical care considerations and so forth.[6] Regarding geographic locations, housing decisions are region-specific, unlike equity investment. Greaney (2020) quantifies the distributional and welfare implications of geographically-specific economic changes, and homeownership is a key transmission mechanism in the dynamic

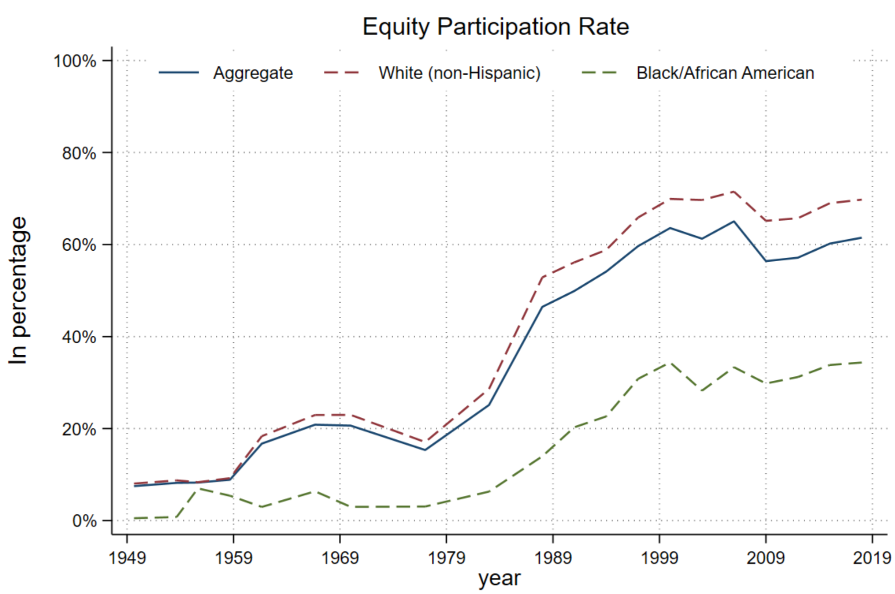
[6] We note that our model ignores inter-vivos transfers or gifts, as well as other more nuanced wealth transfers discussed in the references above.

Figure 2.8: Home ownership rate on the aggregate and across race over time



Note - similar to Figure 2.6 except averages over time are taken by race.

Figure 2.9: Equity participation rate on the aggregate and across race over time



Note - similar to Figure 2.7 except averages over time are taken by race.

spatial modeling there. The households in our model are geographically-averaged U.S. households, and the distributional data patterns we aim to explain are also geographical averages (but disaggregated by age, birth-cohorts, and race). We therefore view the current project as complementary to the spatial literature, though we hope to examine the interactions between the two in future projects. Nuanced wealth transfers may also arise endogenously, termed redistribution as explored in ongoing work in Fagereng et al. (2022). They use a sufficient statistics approach to empirically compute welfare gains and losses which can be now expressed in pecuniary terms due to observed asset price changes for the time period 1994 to 2015, relative to a baseline scenario with constant price-dividend ratios for the Norwegian economy. Asset price changes are purely redistributive causing welfare changes for buyers and sellers. they however do not consider any structural model that is calibrated to match observed household portfolio heterogeneity. Consequently, policy experiments are difficult to conduct in their setup especially across the life cycle. [7]

Since all the motivational graphs have been utilizing the SCF data which is unfortunately not available in the panel format, the targets for our model are cross-sectional moments from the data – whether grouped by age, race, birth-cohort, or wealth positions. This is a common assumption in the literature, and is motivated by the fact that the SCF is the only dataset in the U.S. that provides comprehensive information about wealth and portfolios (wealth panel data is only available for some Nordic countries). In our calibrations, we disciplined the model to match observed portfolios in the data across age and wealth groups. We do not aim to match the portfolio changes of individual households, and indeed, are unable to control for many household-specific characteristics that are likely important. One option is to experiment with, for example, varying risk aversion coefficient within our model to assess its likely quantitative impact. For details about introducing transformations to convert the SCF into a pseudo panel structure, see Feiveson and Sabelhaus (2019) and the literature contained therein.

[7]Similar results pertaining solely to the Great Recession have been put forth in Glover et al. (2020). The model the model predicts that the young experience smaller welfare losses than older cohorts. The overall allocation of welfare losses from a recession depends crucially on the quantitative importance of asset price risk, the age differences in the exposure to this risk, and the age differences in the direct effect of recessions on labor income.

2.2 Empirical Exercise

2.2.1 Data and Methodology

We use the Survey of Consumer Finances (SCF) data from 1989 to 2019 and the SCF+ dataset available from 1949 from Kuhn et al. (2020). Stock and house prices are obtained from Robert Shiller's website. Mortgage premium is obtained from FRED. For characterizing the intergenerational inequality, we also looked at data from the Distributional Financial Accounts (DFA).

Asset Prices Across Generations: We conducted an analysis of asset price trends from 1990 to 2020, focusing on the stock price index (SPI) and housing price index (HPI). To ensure a clean and focused dataset, we filtered the data to include only the relevant years and normalized both indices by their values in the starting year for each particular generation as required. This normalization allowed us to compare the relative growth of stock and housing prices over time, rather than their absolute levels, making the trends more intuitive and directly comparable. Additionally, we smoothed the indices using moving averages to highlight long-term patterns and reduce the influence of short-term fluctuations, ensuring a clearer representation of underlying trends.

To visualize the results, we created a time-series graph displaying the indexed trends for stock and housing prices side by side. The graph includes a clear title, labeled axes, and a legend that distinguishes between the two indices with distinct colors. By customizing the layout and design, we ensured the visualization was easy to interpret while maintaining a professional appearance. This graph provides a compelling depiction of how the stock and housing markets have evolved over three decades, offering valuable insights into their relative performance and behavior during the specified period.

Wealth Relative to Median: We conducted an analysis of wealth distribution trends relative to the median across various demographic groups using data from the Survey of Consumer Finances (SCF) spanning the years 1989 to 2019. Our objective was to combine data from multiple survey years into a unified dataset for comparative analysis. To ensure meaningful comparisons, we focused on key variables such as net worth, gross wealth, and total income, while filtering the data to include individuals aged between 25 and 75 and excluding observations with negative wealth values. We also grouped individuals into broader age categories to streamline demographic comparisons and reduce noise.

Once the dataset was prepared, we analyzed wealth metrics relative to the median within and across demographic (age categories) and racial groups. The visualization highlights trends in wealth accumulation and distribution over three decades, showcasing disparities in net worth and income growth. This analysis provides insights into inter-generational wealth inequality, capturing how wealth relative to the median has shifted over time and across demographic and racial groups.

Data Alignment between SCF+ before 1989 and SCF post 1989: We prepared the SCF+ dataset for an inter-generational wealth analysis by implementing a detailed cleaning procedure. The dataset spans multiple survey years, and we focused on aligning it for cross-year comparability. The cleaning process involved filtering records to include only individuals aged 20 and older and recoding survey years into standardized waves, as defined by Bauluz and Meyer (2021). Key variables, such as net worth, income, and weights, were selected for analysis while ensuring consistency in definitions across years. We also constructed a new variable, hsizegroup, to classify households by family structure (e.g., single with no children, single with children, families with or without children).

In addition to processing the SCF+ dataset, we harmonized it with raw SCF data from 1989 to 2019. For each wave, we ensured uniformity in age ranges and key wealth variables. Household-level adjustments were made to account for family structure differences in wealth distribution. For example, variables representing wealth-to-income ratios were standardized by dividing net worth by average wealth, enabling a comparative analysis across demographic groups. Data were then reshaped and collapsed to focus on age cohorts and family structure, creating a consistent format for subsequent analysis.

This process ensured a robust dataset for generating figures and visualizations, such as average wealth comparisons by age group and wealth distributions adjusted for household size in line with the recent literature on inter-generational wealth inequality viz Bauluz and Meyer (2021). The cleaned and processed data provide a foundation for understanding wealth dynamics across generations and evaluating how family structures impact wealth accumulation and distribution over time to which we turn next.

Wealth by Race and Cohorts in SCF/SCF+ Data: Post the above analysis, we use the prepared SCF/SCF+ dataset to examine wealth distribution across racial groups and generational cohorts. Our cleaning process involved filtering data to include individuals aged 20 and older while retaining critical variables such as net worth, income, and demographic details. For cohort analysis, we generated variables to classify individuals by their birth years and adjusted wealth measures relative to population averages. This pre-processing step facilitated the comparison of wealth dynamics across groups over time.

To analyze wealth by race, we standardized racial classifications and ensured consistency in the definitions across SCF waves. Data for each year was aggregated to provide median wealth metrics for racial groups, normalized against average population wealth. This approach highlighted disparities in wealth accumulation among White (non-Hispanic), Black/African American, Hispanic, and other racial groups. A similar process was employed for SCF+ data before 1989, aligning it with SCF data to extend the historical analysis.

For generational analysis, we grouped individuals into cohorts based on birth years and tracked their wealth trajectories over time. Wealth and income variables were collapsed by cohorts to calculate their median levels and wealth-to-income ratios. These metrics were normalized relative to the average wealth, enabling an inter-generational comparison of financial trends. Data visualization included age-adjusted wealth for each cohort, illustrating changes in wealth accumulation at various life stages.

Inter-generational wealth trends for Baby Boomers, Gen X and Millennials: We conducted an analysis to study the inter-generational distribution of wealth shares across cohorts defined by their birth years, focusing on generations born between 1946 and 2016. The SCF does not follow individuals longitudinally, so we constructed synthetic cohorts by grouping individuals based on their birth years and observing their wealth trajectories at various ages over time. This approach allowed us to approximate generational wealth dynamics and assess how wealth shares evolved across different cohorts despite the cross-sectional nature of the SCF data.

To create these synthetic cohorts, we categorized individuals into three main birth-year groups: 1946–1964 (Baby Boomers), 1965–1980 (Generation X), and 1981–2016 (Millennials and Generation Z). Within each cohort, we analyzed key metrics such as net worth, gross wealth, and household debt, excluding negative or invalid entries to ensure data accuracy. By aligning individuals' wealth levels with their respective ages over time, we were able to track changes in wealth accumulation patterns and compare how different generations have fared economically during various life stages. This analysis highlights significant trends in wealth distribution across cohorts, revealing disparities in asset ownership, debt burdens, and inter-generational wealth shifts. The aim of the exercises is to generate results that offer a deeper understanding of the inter-generational dynamics shaping wealth accumulation and distribution in the United States.

Constructing Synthetic Cohorts from SCF data: Based on the motivation for 33 year spaced cohorts, we analyzed wealth dynamics relative to median wealth across synthetic cohorts 10 years apart spanning the years 1989 to 2018. The SCF is not a panel dataset, meaning it does not follow the same households over time. To overcome this limitation, we constructed synthetic cohorts by aligning individuals of similar ages across different survey years. This approach allowed us to approximate longitudinal analysis and track generational wealth patterns, even without observing the same households repeatedly. By grouping individuals into cohorts based on their age at the start of three key periods—1989–1998, 1999–2008, and 2009–2018—we could better understand inter-generational wealth trajectories.

In creating the synthetic cohorts, we emphasized the relationship between wealth and income, generating metrics such as net wealth-to-income ratios to evaluate financial well-being across the cohorts. This required calculating age-adjusted wealth levels for individuals within the defined periods and aligning them to their respective starting ages. By grouping the data this way, we captured how wealth levels for each cohort evolved relative to their peers and how they compared to the median wealth levels over time.

Our findings provide insights into the structural evolution of wealth inequality, highlighting generational differences in wealth accumulation and the impact of economic cycles. The analysis like before intends to reveal distinct trends in financial stability and wealth-to-income ratios for each cohort, shedding light on the challenges and advantages faced by different age groups during these three decades. This work contributes to a deeper understanding of how generational wealth disparities emerge and persist over time.

Constructing Data Moments used for proposed PWCD Model Calibration: We processed data from SCF+ (pre-1989) and SCF (post-1989) to construct calibration targets for a structural model analyzing wealth dynamics across generations - the PWCD model in section 2.3. Our analysis focused on individuals aged 20 to 79, standardizing key variables such as net worth, income, homeownership, and equity participation. We removed outliers and normalized wealth measures relative to average per-capita income, ensuring consistency and comparability across different data waves.

We summarized wealth and equity metrics by financial deciles to understand portfolio allocation and calculated lifecycle profiles of wealth accumulation and equity participation for different age groups. Additionally, we produced national-level statistics that highlight trends in wealth and debt, as well as distributional metrics to capture disparities in wealth accumulation across income levels. These steps allowed us to create a comprehensive dataset for evaluating inter-generational wealth trends.

The cleaned and aggregated datasets were used to generate visualizations and flexible calibration targets, such as trends in net and financial wealth over time and equity shares as a proportion of financial wealth at different points in time. These outputs provide insights into inter-generational wealth dynamics and serve as a foundation for calibrating the structural model, enabling us to explore the hypothesized mechanisms driving wealth inequality over time.

2.2.2 Widening Inter-generational and Racial Inequality

Similar to motivating graphs Figure 2.1 and Figure 2.3, Figure 2.10 shows the disparities in wealth accumulation across different generations, with older generations (especially Baby Boomers) holding a disproportionately larger share of wealth compared to younger ones. baby Boomers consist consists of individuals born from 1946 to 1964, Generation X are individuals born from 1965 to 1980 and Millennial refer to individuals born from 1981 to 1996.

Figure 2.11 indicates Millennials have a much flatter curve, starting with almost no share and only beginning to grow more noticeably as they approach their 30s, suggesting a slower rate of financial asset accumulation compared to the previous generations. Baby Boomers, beginning their accumulation in early adulthood and experiencing a significant growth in financial assets, reaching over 50% of the total share by their 60s. This steep rise reflects their sustained investment and savings habits during periods of economic growth. Generation X, following a similar but less pronounced trajectory, starts accumulating later but shows a steady increase, reaching around 30% by their late 40s.

Figure 2.10: inter-generational Median Wealth Shares over time for Millennial, Gen X and Baby Boomer

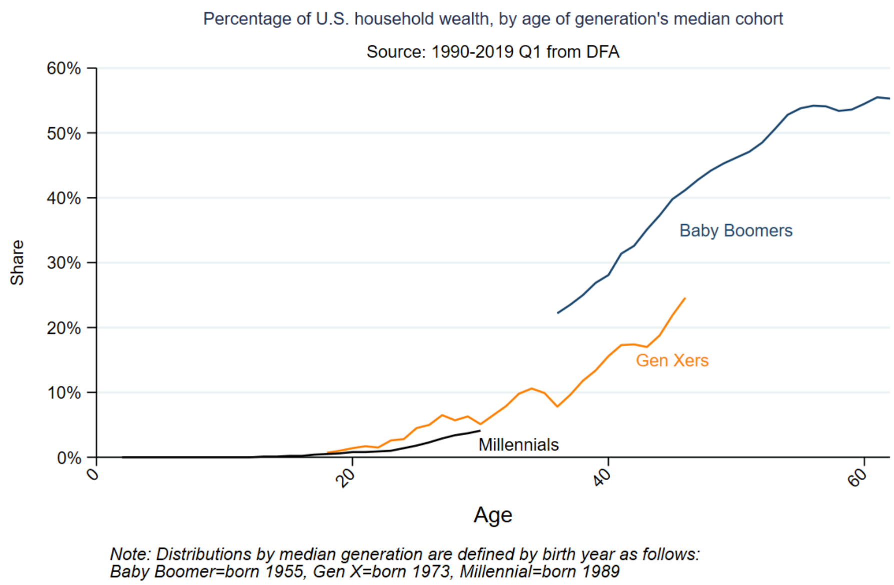
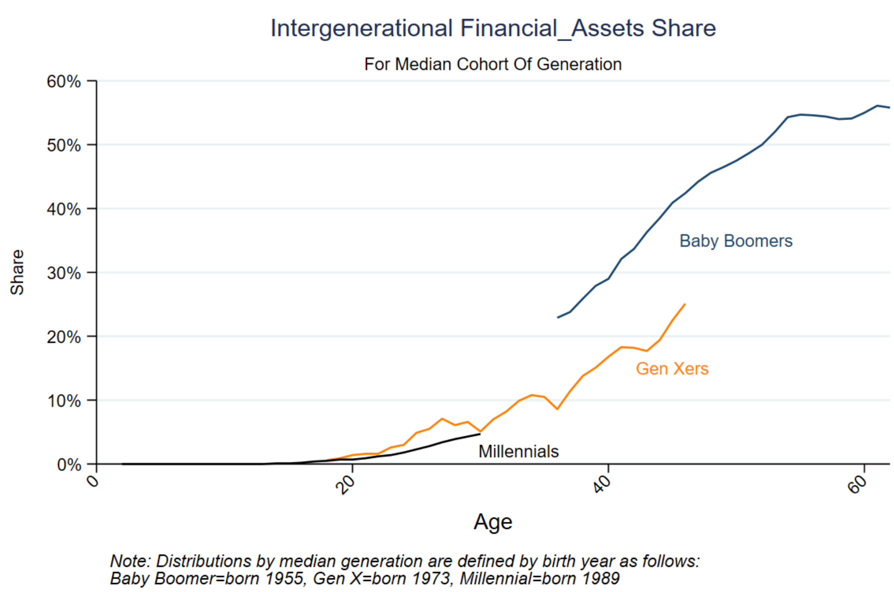


Figure 2.11: Financial Wealth from DFA 1990-2019 for Millennial, Gen X and Baby Boomers



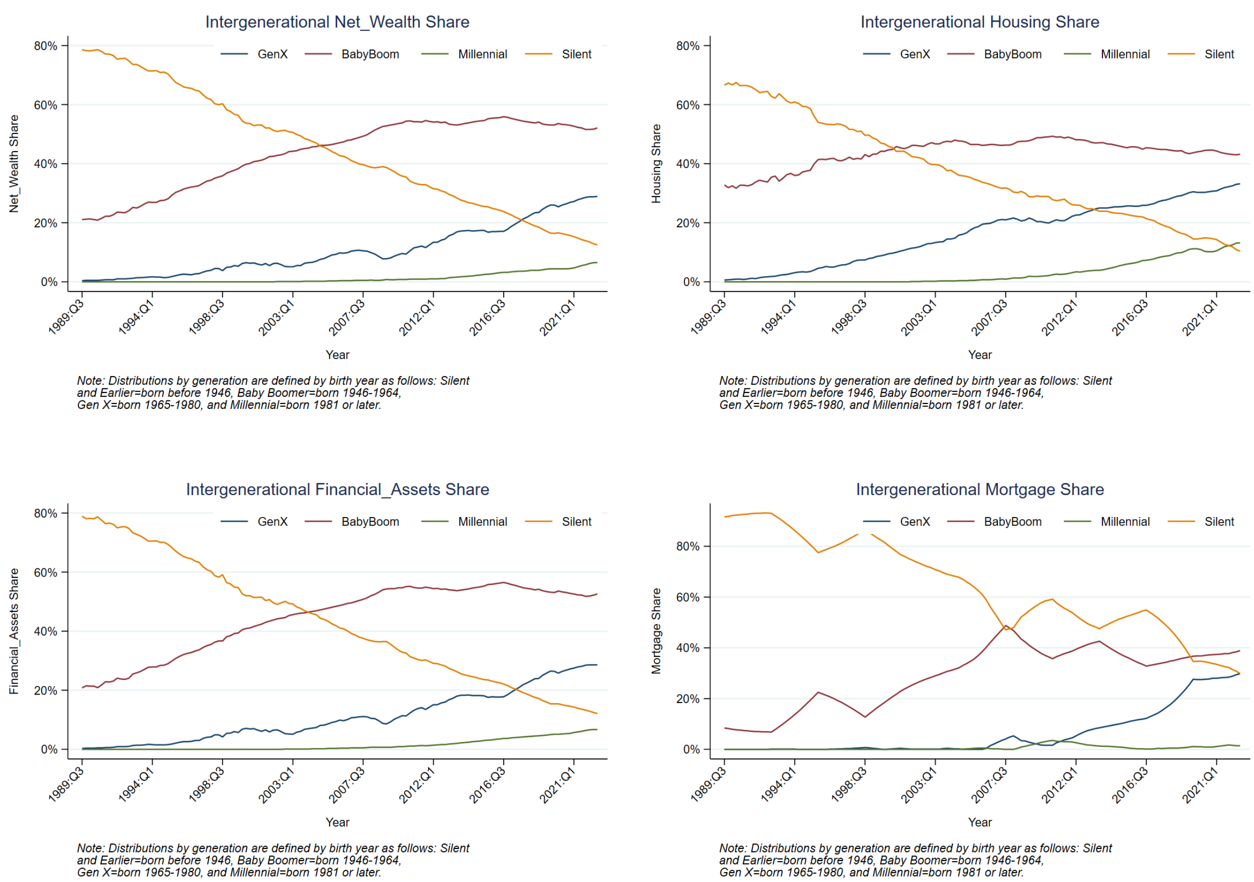
The left panel of Figure 2.12, illustrating the inter-generational Housing Share, shows that Baby Boomers consistently hold the highest proportion of housing wealth, indicating a stable and increasing investment in housing from early adulthood into their 60s. Generation X follows a gradual upward trend in housing share beginning in their late 20s, while Millennials start with a very small share, slowly increasing as they approach their 30s, highlighting a slower and later entry into the housing market. The right panel of Figure 2.12 depicting the inter-generational mortgage

Figure 2.12: Housing Wealth and Mortgage Shares from DFA 1990-2019 for Millennial, Gen X and Baby Boomers

share, reveals fluctuating mortgage shares for Baby Boomers, peaking as they approach retirement, likely due to property acquisitions and refinancing. Generation X experiences a sharp rise in mortgage share during their prime home-buying years, maintaining a steady level thereafter. In contrast, Millennials show a gradual increase, entering the market later but consistently increasing their mortgage share, suggesting growing involvement in home financing and purchases.

Inline with Figure 2.10, the four-panel graph in Figure 2.13 provides a detailed breakdown of inter-generational wealth components—net wealth, housing, financial assets, and mortgages—over time, offering deeper insights into the economic dynamics among different generations. Baby Boomers have maintained dominance across all wealth categories, reflecting their significant economic accumulation since the late 20th century. Their share of net wealth and financial assets

Figure 2.13: Inter-generational Wealth and Asset Shares Over Time from DFA

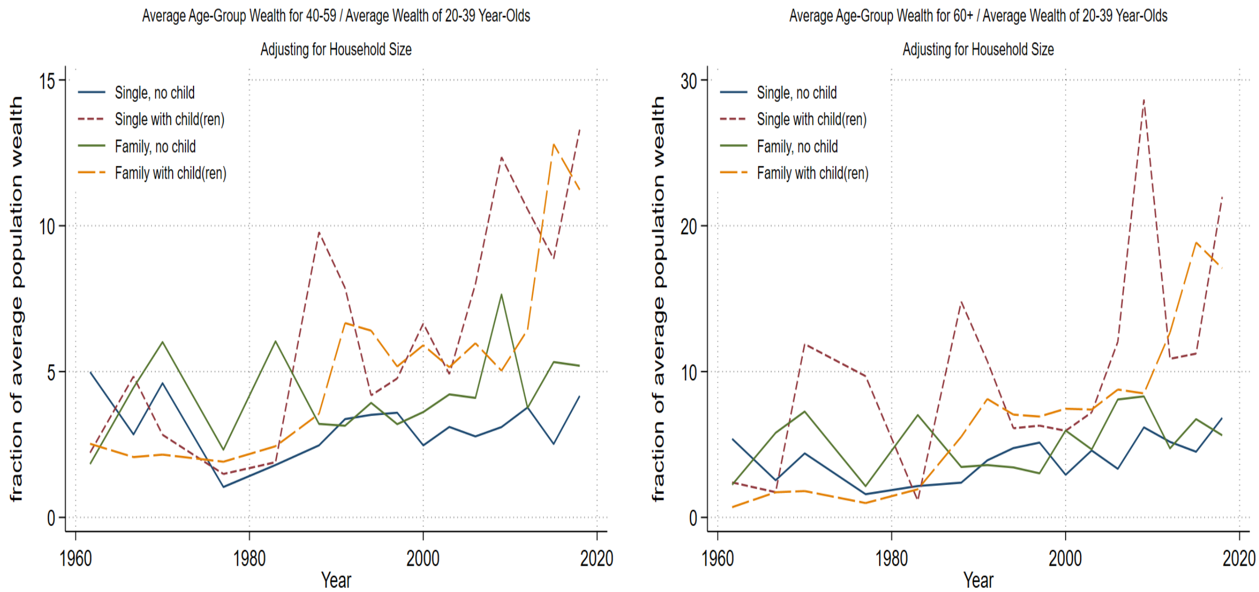


peaked as they entered their peak earning and asset accumulation years during favorable economic conditions, including robust stock market growth, affordable housing markets in earlier decades, and greater access to high-paying jobs compared to subsequent generations. This dominance is especially pronounced in financial asset ownership, where Baby Boomers have outpaced both Gen Xers and Millennials, highlighting the generational advantages in accessing wealth-generating opportunities.

Gen Xers, while steadily increasing their share of net wealth and assets, have done so at a slower pace than Baby Boomers, reflecting delayed economic entry and financial pressures, including higher housing costs and stagnant wages during their early career stages. Their housing share has grown over time, but their financial asset accumulation lags behind Baby Boomers, partly due to economic crises like the 2008 financial crash, which disproportionately affected middle-aged households. Millennials, on the other hand, exhibit minimal gains across all wealth components, especially in housing and financial assets. Their share of net wealth remains alarmingly low relative to their population size and age, signifying significant barriers to wealth accumulation. Rising student debt, higher housing costs, and limited access to high-quality jobs have impeded their financial progress.

The mortgage share graph reveals another critical trend: a generational shift in housing debt burdens. As Baby Boomers have paid down their mortgages, Gen Xers and Millennials have increasingly taken on housing debt to enter the market, often at less favorable terms due to higher property prices and stricter credit requirements. This trend suggests that homeownership—a key driver of generational wealth—has become increasingly difficult for younger generations to achieve without significant debt. The persistent economic dominance of Baby Boomers, combined with the slow progress of Gen Xers and Millennials, underscores the structural economic challenges and inequalities that shape wealth distribution across generations. These trends suggest a growing concentration of wealth in older generations, raising questions about long-term economic equity and inter-generational financial mobility. Figure 2.14 provides a more nuanced view of wealth distribution by adjusting for household size, offering critical insights that were missing in the earlier cohort-based analysis than Figure 2.1. This adjustment highlights significant disparities in wealth accumulation across both age groups and family compositions, which are obscured when household size is not considered. Notably, older households (60+) with children and single individuals without children have increasingly captured a larger fraction of average population wealth, with their

Figure 2.14: Adjusting for Household Size for Inter-generational Wealth Gap



dominance accelerating after 2000. This pattern underscores an inter-generational wealth shift, where older generations maintain economic dominance regardless of their household composition. Such households may benefit from reduced financial obligations (e.g., paid-off mortgages or grown children) or a longer period of asset accumulation, particularly in favorable economic conditions.

In contrast, middle-aged households (40–59) and younger households (20–39) show relatively modest wealth shares, especially among families with children. This finding reflects the financial pressures faced by these groups, such as the rising costs of childcare, housing affordability issues, and stagnating income growth. Families with children in younger and middle-aged cohorts are disproportionately burdened, as their wealth growth is constrained by higher expenses and limited opportunities for asset accumulation. Compared to Figure 2.1, which only analyzes wealth relative to population averages, Figure 2.14 emphasizes the importance of accounting for household size to understand wealth dynamics fully. Without this adjustment, the role of financial obligations tied to family structure—such as the challenges faced by younger families—is understated, painting an incomplete picture of wealth inequality across generations. By incorporating household size, Figure 2.14 reveals how demographic and structural economic factors exacerbate wealth disparities within and across age groups.

Figure 2.15: Life-cycle wealth profiles of various birth cohorts, grouped by decades and race

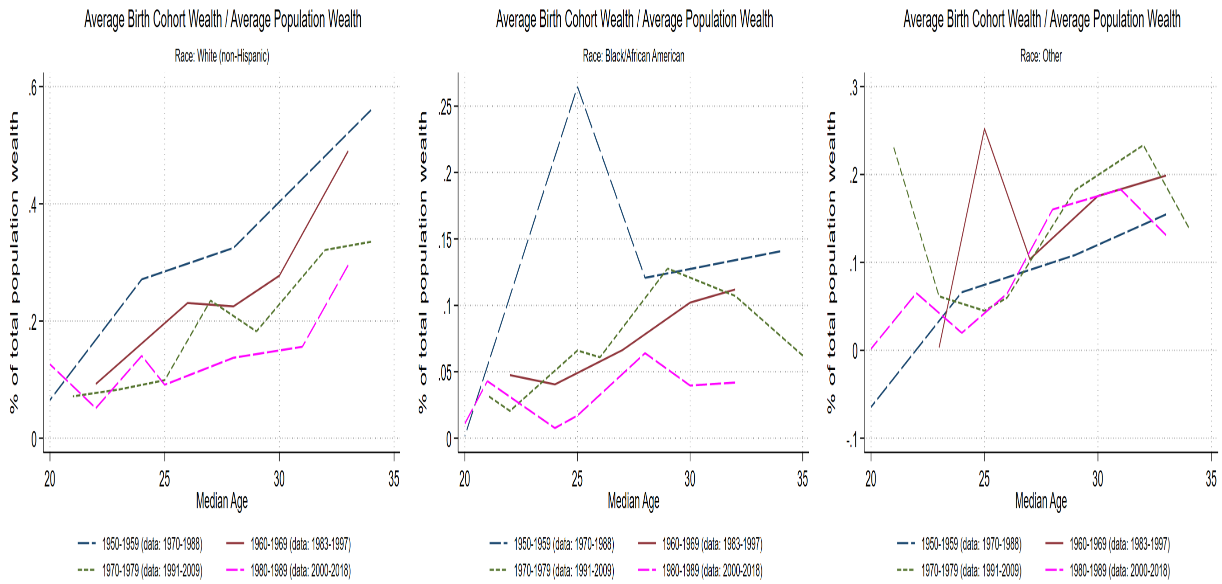
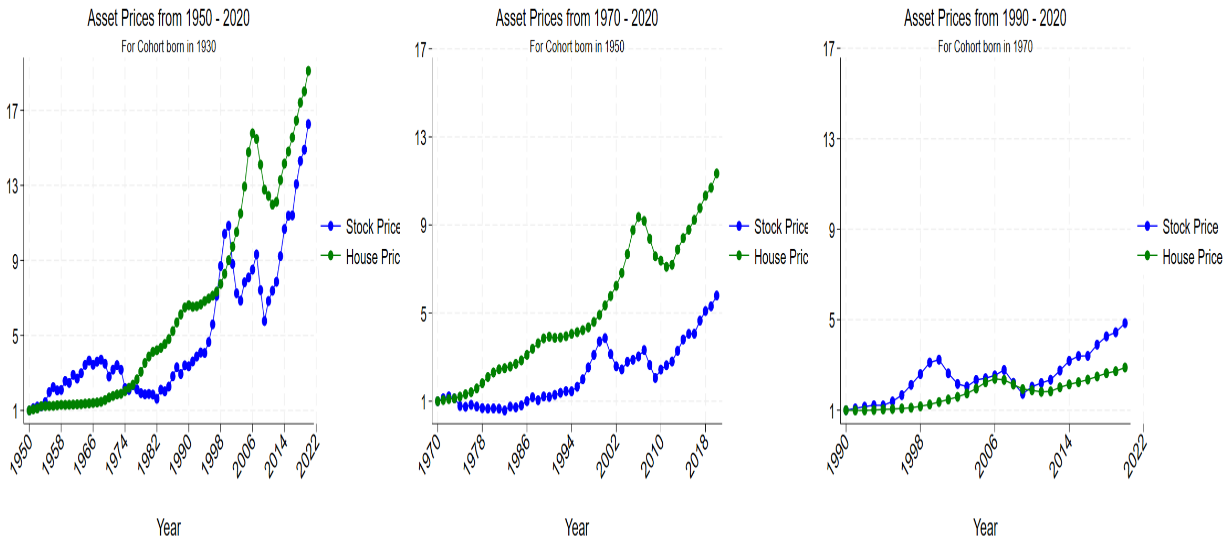


Figure 2.15 decomposes Figure 2.3 by race. It examines life-cycle wealth profiles across birth cohorts, segmented by race (White non-Hispanic, Black/African American, and Other), and reveals stark inter-generational and racial disparities in wealth accumulation. For White non-Hispanic cohorts, wealth accumulation follows a consistent upward trajectory, with newer cohorts (e.g., 1980–1989) reaching comparable or higher levels of relative wealth compared to earlier cohorts by their mid-30s. In contrast, Black/African American cohorts show significantly flatter wealth trajectories, with each successive cohort lagging further behind earlier generations in wealth accumulation. This gap highlights systemic barriers, such as racial discrimination in housing, employment, and financial markets, that persist across generations.

The "Other" racial category exhibits more variability, with certain cohorts (e.g., 1970–1979) achieving relative wealth parity with White non-Hispanic cohorts in their 30s, while others (e.g., 1980–1989) lag. These findings underscore how inter-generational wealth accumulation is deeply intertwined with racial disparities, where systemic advantages allow White non-Hispanic cohorts to consistently build wealth across generations, while Black/African American cohorts face structural impediments that limit upward mobility. Addressing these disparities requires policies aimed at reducing inter-generational racial wealth inequality, particularly through equitable access to housing, education, and financial resources.

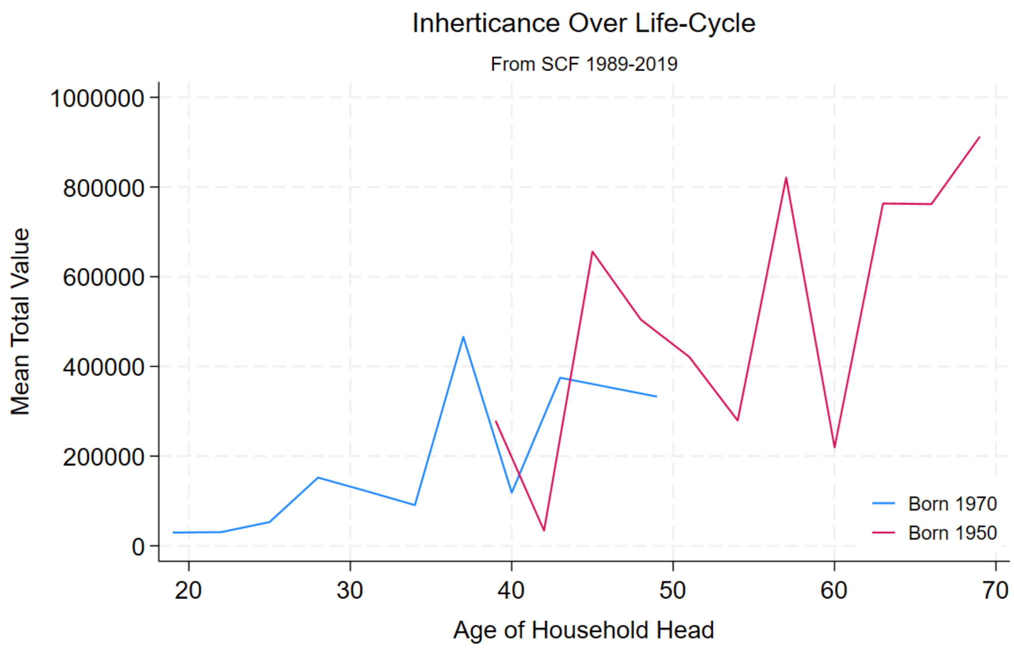
Figure 2.16: Stock And House Prices Relative to Age 20 for the median cohort



We present the relevant graphs for the three possible sources of the rising inter-generational inequality: 1) asset market booms and busts that occur at different stages of each cohort's life cycle; 2) differing levels of inheritance and debt obligation at the start of working life; and 3) barriers to investment, such as costs of homeownership and equity-market participation.

Using the SCF+ and SCF data, we target the median of three generations in Figure 2.16. It charts the asset price trends for cohorts born in 1930 (median, 1950, and 1970, tracking the evolution of stock and house prices from each cohort's early adulthood through to 2020. The first panel shows significant growth and volatility in stock prices starting from the late 1980s and a steep rise in house prices beginning in the early 1970s for the 1930 cohort. The second panel, for the 1950 cohort, illustrates gradual increases in stock prices with peaks around 2000 and sharp fluctuations in house prices, particularly pronounced during the financial crisis of the late 2000s. The third panel, representing the 1970 cohort, displays more subdued fluctuations with a modest rise in both stock and house prices after the mid-2000s, reflecting the different economic conditions each cohort faced during their financial maturation. Figure 2.17 visualizes the mean total value of inheritance received by two different cohorts, born in 1950 and 1970, as tracked from 1989 to 2019. The cohort born in 1950 shows significant fluctuations in inheritance amounts, peaking in their early 50s and again in their mid-60s, suggesting large inheritances are received around these ages, possibly linked to the passing of their parents. The trajectory for the 1970 cohort indicates a

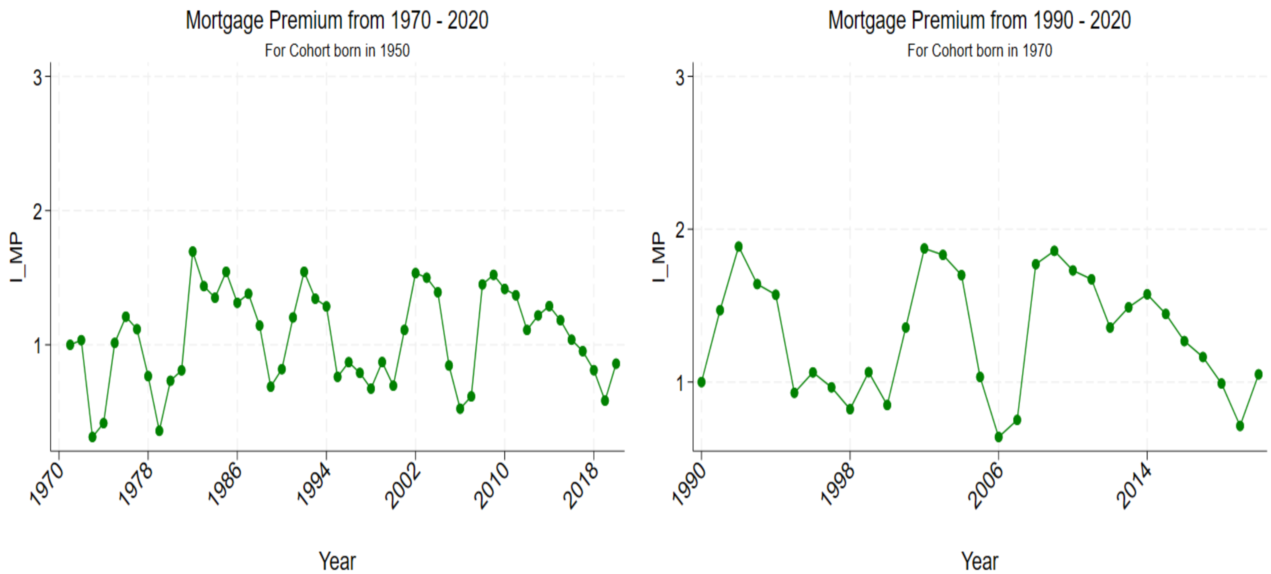
Figure 2.17: Inheritances from SCF data 1989-2019 for median cohort



Notes - Generate age of household head = Year of SCF - Median cohort (1970 or 1950). Generate mean total inheritance by age in the combined data for the two cohorts.

steadier climb in inheritance values starting in their 30s, with fewer fluctuations but generally lower amounts compared to the earlier cohort, indicating possible changes in generational wealth transfer patterns over time. The data reflects variations in inheritance timing and amounts, influenced by demographic shifts and possibly differing economic conditions faced by each generation. Since inheritances are difficult to parse from the SCF+ data, the figure shows only two generations by relying on the SCF data. For the asset market participation costs, Figure 2.18 illustrate the trends in mortgage premiums for cohorts born in 1950 and 1970, spanning the years 1970-2020 and 1990-2020, respectively. The cohort born in 1950 experiences significant fluctuations in mortgage premiums throughout their mortgage lifecycle, with notable peaks and valleys that suggest varying mortgage cost burdens over time, particularly high during the early 1980s, mid-1990s, and early 2010s. Similarly, the cohort born in 1970 shows variability in their mortgage premiums, with a pronounced peak around 1998 and another in 2006, followed by a general decline towards 2020, indicating a decrease in the relative cost of mortgages for this group as they age. These graphs highlight the dynamic nature of mortgage costs that each cohort faced during different economic cycles, impacting their home financing decisions and overall financial planning.

Figure 2.18: Mortgage Premium faced by different Median Cohorts



2.3 Model

We propose setting up a quantitative heterogeneous-agent Portfolio Choice-Wealth Distribution (PCWD) model that endogenously matches key features of lifecycle wealth distributions and portfolio heterogeneity in the U.S. data. Our PCWD model extends the standard life cycle consumption-savings decision to incorporate explicitly the home-ownership and equity market participation decisions of households across the wealth distributions and facing different income risks. In addition to properly quantifying the distributional effects of asset price movements, we augment the model to incorporate household debts, inheritances, and barriers to market participations. They correspond to the three possible sources that we analyze as part of the broad empirical motivation. Our goal is to analyze how these factors shape the observed generational and racial wealth disparities described below and assess policy options aimed at reducing wealth inequality. Model specification details, calibration and preliminary results are presented in Appendix sections B.1 - B.5.

2.4 Conclusion

Increasing wealth inequality in many countries during the past several decades has leapt to the fore as a central global concern. For the U.S. over the past half-century, a large decline in tax progressivity, together with persistent earnings differentials, have been identified as major contributing factors. Amid the focus on increasing wealth inequality within a population, we conduct exhaustive empirical analysis to show that wealth disparities have widened not only between the rich and the poor, but also across generational and racial lines. In the 1960s, the average household of age 20-39 had one third the wealth of a 60+ household; in 2019, this share was less than one-sixth. At age 30, the average Black Millennial household has less than 5% of average wealth; in earlier generations, this ratio was more than twice as high.

Complementing this literature, which focuses on aggregate inequality, we identify three possible broad motivational sources that contribute to wealth inequality across birth cohorts and race: 1) asset market booms and busts that occur at different stages of each cohort's life cycle; 2) differing levels of inheritance and debt obligation at the start of working life; and 3) barriers to investment, such as costs of homeownership and equity-market participation. Existing structural models are unable to capture portfolio-adjustment and savings-rate responses of households to changing asset prices generating biases in estimating the relative contribution to wealth inequality from the asset-portfolio channel. Our proposed heterogeneous agent PWCD endogenously matches key features of lifecycle wealth distributions and portfolio heterogeneity in the U.S. data while incorporating household debts, inheritances, and barriers to asset market participations. The goal is to consider counterfactuals and evaluate policy prescriptions for reducing wealth inequality in the future.

Chapter 3

Choice of Refinancing and Hand-to-mouth Status

3.1 Introduction

Kaplan et al. (2014) (hereafter KVW) initiated the discourse on a detailed classification and determination of households' hand-to-mouth (hereafter HtM) status based on wealth. Briefly, HtM refers to households living paycheck to paycheck due to zero savings. The simplistic categorization of households based on negative net worth has proven inadequate for understanding monetary policy transmission. In standard Representative Agent New Keynesian models, monetary policy efficacy diminishes with lower-than-empirical marginal propensity to consume (MPC) values, a phenomenon also seen with transitory fiscal transfers in fiscal policy. The existing one-asset spender-saver models in both complete and incomplete market setups fall short in portraying agents' consumption dynamics, particularly in response to lump-sum tax rebates and government transfers. KVW introduced a new household category termed wealthy HtM, characterized by significant holdings in illiquid assets like housing and retirement accounts, but minimal liquid asset holdings. This classification reveals unique consumption dynamics, substantiated by the Panel study of income dynamics (PSID) and is affirmed to be substantial after analysis using the Survey of Consumer Finances (SCF). In this paper, I propose a further subdivision of wealthy HtM agents based on their home equity extraction choices. This delineation would not only provide a clearer estimation of households at their borrowing limits but also unveil diverse MPCs compared to those determined by KVW. This variation, when extrapolated, offers intriguing insights into aggregate MPC, significantly impacting monetary policy transmission and redistribution.

Upon refinancing approval, households are faced with three options: cash-out, no cash-out, or cash-in refinance.[1] The prevalent no cash-out refinance, accounting for approximately 97.7% of US mortgages[2], typically reduced Fixed Rate Mortgage (FRM) payments, while cash-out refinancing or an additional Home Equity Line of Credit (HELOC) provided emergency liquidity, albeit likely at a higher new FRM rate or increased unpaid balance.[3] Figure 3.1 shows trends in refinancing (cash-out and no cash-out) and home purchases in the U.S. from 1999 to 2020, with refinancing spikes during economic downturns (e.g., 2008 financial crisis and COVID-19). Figure 3.2 highlights the volume of home equity cashed out, peaking before the 2008 crisis and showing a resurgence in 2020, with both cash-out refinancing and total equity volumes (including HELOCs) contributing significantly during these periods. Together, the figures underscore the cyclical nature of refinancing activity and equity extraction during economic fluctuations.

Table 3.1: MPCs from IV reg, Kaplan et al. (2014)

	P-HtM	**W-HtM**	**N-HtM**	**HtM-NW**	**N-HtM-NW**
Baseline	0.243***	0.301***	0.127***	0.229***	0.201***

A deeper exploration into the portfolio composition of home equity-extracting households, especially under KVW's wealthy HtM classification, is important for getting a more accurate measure of aggregate consumption. Traditional classifications, such as those dividing HtM households into wealthy HtM and Poor HtM based on liquid and illiquid asset holdings, provide a foundational framework but fail to capture the heterogeneity in MPC within these groups. wealthy HtM households, characterized by positive illiquid wealth (e.g., housing) but zero liquid wealth, differ substantially from Poor HtM households, who possess near-zero wealth of any kind. This distinction becomes particularly relevant when analyzing the role of home equity extraction, a behavior with significant consumption effects, as evidenced by Zhu et al. (2019), who show that the MPC of

[1] Black Knight estimates $ 6.2 trillion of liquidatable home equity as of Q1 2020. Source: `https://www.blackknightinc.com/black-knights-january-2020-mortgage-monitor/`

[2] Source: Origination Report Ellie Mae (2021) `https://static.elliemae.com/pdf/origination-insight-reports/ICE_OIR_JAN2021.pdf`

[3] For more details, see Chen et al. (2020). Rising house prices can ease borrowing constraints and cash-out refinancing decisions can be largely driven by precautionary savings and household liquidity needs amid income uncertainties. For a recent discussion & observed empirical trends using bank account data see Farrell et al. (2020)

home equity is nearly double that of general housing wealth. Moreover, consumption effect from home equity extraction is 2.5 times higher for wealthy HtM than non HtM. These findings underscore the need to refine measurements of HtM households, especially to better understand how their refinance choices influence consumption patterns and financial vulnerability. Table 3.1 report the MPC estimates for Poor HtM (p-HtM), wealthy HtM (W-HtM) and non HtM (N-HtM) based on the new definition based on illiquid assets from KVW. KVW also compares the MPCs with the original definition of HtM agents which miss the heterogeneity. Using the MPC estimates and the share of HtM agents from SCF 2019 (first row in Table 3.3), I calculate the aggregate weighted consumption to be 16.55% .

Table 3.2: *MPC* based on Home Equity Extraction from Zhu et al. (2019) Table 5

	Housing Wealth				**Other Illiquid Wealth**	
	Extract HE		**Did Not Extract HE**			
	W-HtM	**N-HtM**	**W-HtM**	**N-HtM**	**W-HtM**	**N-HtM**
MPC	0.307	0.079	0.089	0.037	0.078	0.004

Building on this, I aim to extend the work of KVW by incorporating refinance choice as a critical dimension of HtM classification. Households that extract home equity not only exhibit higher MPCs but also demonstrate a significant divergence in consumption behavior based on their wealth classification. By using SCF data, I aim to quantify the share of HtM households based on their refinance choices and to examine how this approach refines the aggregate picture of HtM households. While the overall HtM share remains unchanged, this decomposition reveals critical differences in how these households respond to liquidity shocks and engage with their housing wealth. Table 3.2 gives the estimates for MPC from Table 5 in Zhu et al. (2019). Agents with housing wealth can be either wealthy HtM or non HtM. Similarly for agents with other illiquid wealth, agents can be either wealthy or non HtM. The MPC for poor HtM remains as in KVW. Using the same process, the corresponding aggregate consumption in the economy is instead estimated to be around 9.98% . The number is dependent on the particular estimates of MPC used. For instance, Zhu et al. (2019) have multiple estimates of MPC for different individuals depending on different portfolio compositions. The 9.98% is instead aimed to motivate the importance of measuring HtM agents based on their refinance choice which is the subject of this paper. These insights not only provide a more nuanced understanding of household financial behavior but also have significant implications for monetary policy, particularly in assessing the aggregate consumption effects of refinancing in the U.S. housing market.[4]

Figure 3.1: Frequency of Refinancing vs Purchases in the US

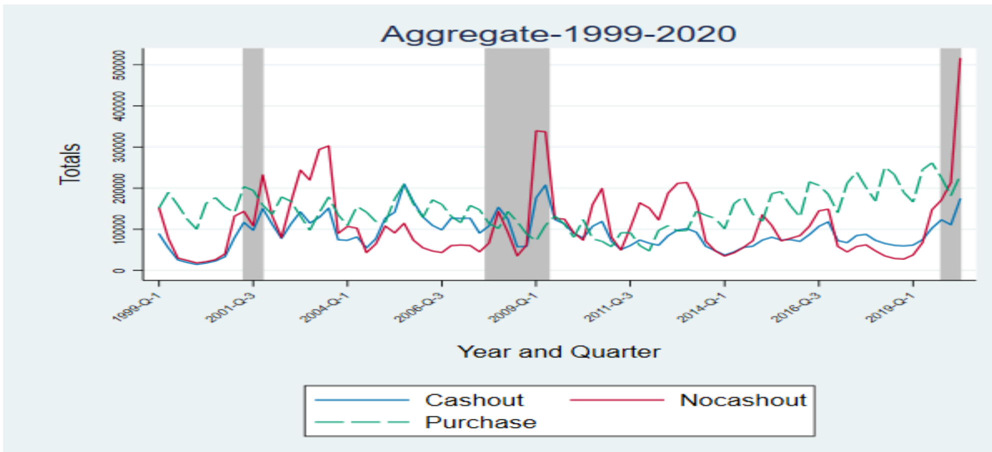
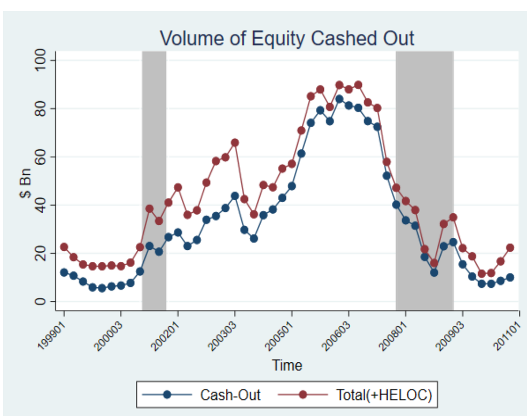
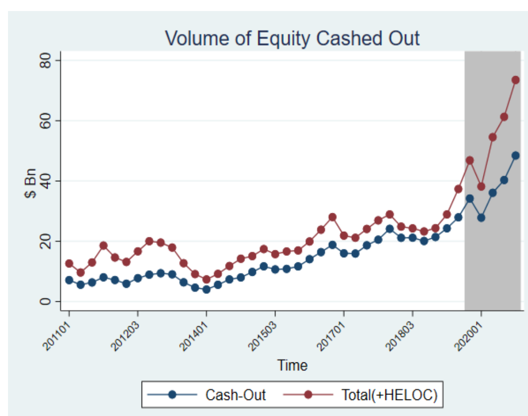


Figure 3.2: Volume of Home Equity Cashed Out over the years

(a)



(b)



To empirically substantiate my arguments, I undertake two exercises using public data. Initially, I emulate KVW's method with the latest SCF data to determine the wealthy HtM's share and analyze their portfolio composition, presenting a tailored subset of results for clarity; detailed insights are in Section 3.3.1. Notably, since KVW's data ended around the GFC in 2010, and the latest data is from 2019, the wealthy HtM share has predictably dwindled as shown in Table 3.3.

[4]For more details about calculation of aggregate weighted consumption please see Appendix section C.1.

Table 3.3: Share of W-HtM for all 3 relevant subsets of data in 2010 vs 2019

	2010		**2019**	
	Total HtM	**% of Wealthy HtM**	**Total HtM**	**% of Wealthy HtM**
Kaplan et al. (2014)	0.3404	59.60	0.2507	65.13
Extracted HE	0.2913	85.41	0.1871	99.86
Did not extract HE	0.2150	100	0.2418	100

Yet, the housing wealth share among illiquid assets for this group significantly rose, indicating a preference for home equity extraction for emergency funding, as evidenced by Table 3.4. [5]

Next, subdividing data based on home equity extraction decisions reveals a higher wealthy HtM share among those not opting for extraction or refinance, as seen in Table 3.3. However, those extracting home equity held more housing wealth in 2019 than in 2010, implying a potential shift among agents towards extracting home equity to mitigate reduced labor earnings amidst the Covid-19 crisis, though recession-induced refinance barriers could hinder this transition as inferred from Table 3.4. The leverage ratio analysis in Figure 3.9 shows most wealthy HtM are considerably leveraged, with a notable portion facing negative home equity, suggesting rising house prices not only ease collateral constraints but also facilitate home equity extraction. In conclusion, this exploration sheds light on the heightened importance of housing within wealthy HtM's illiquid asset portfolio, underlining the quantitative significance for my hypothesis and potential policy implications.

Secondly, I utilize publicly available Freddie Mac approvals data to proxy household liquidity demand via refinance choice. The analysis, focusing on cash-out refinance frequency against various regressors in my logit model, provides reassuring results devoid of counterfactuals. Predictably, households with higher Debt to Income (DTI) ratios, higher Loan to Value (LTV), and lower credit scores lean towards cash-out over no cash-out refinance, with opposite inclinations for higher outstanding loan balances and lower original interest rates. The significance of house prices

[5] For a recent exploration regarding loan-to-income (LTI) & payment-to-income (PTI) constraints, see Greenwald (2018)

Table 3.4: Portfolio Shares of Wealthy HtM by their holdings of illiquid assets in 2010 vs 2019

	2010			2019		
Total Wealthy HtM (in %)	**Only Housing**	**Housing + other illiquid assets**	**Other Illiquid Assets**	**Only Housing**	**Housing + other illiquid assets**	**Other Illiquid Assets**
Overall	21.99	57.43	20.59	34.86	44.72	20.42
Extracted HE	14.16	83.86	1.98	29.72	70.28	0.00
Did not extract HE	20.26	79.74	0.00	55.11	44.89	0.00

and unemployment emerges during crises. [6] The analysis denotes a stronger home equity extraction channel amid recessions with soaring unemployment, showcasing notable interactions across unemployment quantiles.

Inspired by the empirical findings, I propose a 3-period partial equilibrium model, extending KVW's setup with minimal deviations, to delve into HtM dynamics based on home equity extraction. [7] In this model, housing-owning agents weigh refinance options against their heterogeneous discount rates, now exogenously set. Impatient agents, favoring immediate consumption, opt for cash-out refinance, undeterred by future higher debt burdens. Conversely, agents valuing future utility more, dictated by a calibrated threshold, choose no cash-out refinance. A higher likelihood of HtM status is observed among cash-out choosers, confirmed via baseline calibration and preliminary shock experiments.

Related Literature - This paper primarily expands upon the wealthy HtM estimation pioneered by KVW, and further delves into the refinance choice revealing HtM status from the SCF data. It contributes a three-period partial equilibrium model, inspired by empirical findings, endogenizing refinance choice and aligning with current economic conditions. Additionally, it explores home equity extraction, as discussed in Bhutta and Keys (2016), revealing a nuanced relationship between wealthy HtM and home equity extraction, consequently impacting MPCs, a

[6] Contrasting proprietary data usage in literature, as seen in Bhutta and Keys (2016), Beraja et al. (2019), and Chen et al. (2020), my findings align with these studies.

[7] For a deeper dive into the model, refer to section 3.4.

critical aspect for policy implications. The empirical channels evaluated underscore the dominance of unemployment rate changes over interest rate channels in crisis times, aligning with wealthy HtM's insensitivity to interest rate shifts, as elucidated in Farrell et al. (2020) and Beraja et al. (2019). This work, while correlating with studies like Kaplan and Violante (2014a) and Kaplan and Violante (2014b), distinctively emphasizes housing within the broader discourse on liquidity, refinance choices, and their implications on economic policy and HtM characterization.

This paper explores the "Houses as ATM" channel, aligning with Chen et al. (2020), and highlights the role of household liquidity demand in mortgage refinancing and home equity extraction. It corroborates the diminished sensitivity of refinancing behavior to interest rate changes under liquidity constraints, as discussed in Beraja et al. (2019) and Maggio et al. (2020). The paper also touches on the decreased effectiveness of monetary policy when initial debt is high, as noted by Alpanda and Zubairy (2019), and how negative income shocks, amid exogenous positive monetary policy shocks, encourage home equity extraction, especially among wealthy HtM households. It delves into the impact of house price declines and interest rate hikes on refinancing activities, referencing Berger and Vavra (2015) and Berger et al. (2018). Unlike previous works relying on proprietary data, this study utilizes publicly available Freddie Mac approvals data to examine HtM status in relation to household liquidity demand during low income periods, revealing strong preliminary evidence in support.[8] The paper briefly discusses refinance denials and home equity extraction restrictions, as documented by DeFusco and Mondragon (2020) and Boar et al. (2017), acknowledging the bias in the observed liquidity demand channel due to sample selection and denials, especially during economic hardships, as further analyzed in Agarwal et al. (2020).[9] Despite this bias, the findings capture the correct directional impact, suggesting actual estimates might be higher.

Lastly but not the least, though the 3 period partial equilibrium approach developed here is primarily to motivate the measurement of HtM based on their decision to extract home equity using a HELOC and/or cash-out refinance, it can be nested in a general equilibrium setup to study the importance of housing as a separate class of illiquid assets and its consequent interaction with other assets (Auclert (2019)) in a possibly 3 asset heterogeneous agent along the lines of Kaplan et al. (2018) who stress the importance of considering 2 asset incomplete markets model

[8]For related fiscal policy insights, see Agarwal et al. (2015).

[9]See Keys et al. (2016) for more on refinance denials.

with heterogeneous MPCs to enrich our understanding about monetary policy transmission & redistribution. To study the role of idiosyncratic collateral constraints, it can be expanded along the lines of the theoretical work of Iacoviello (2005) and the literature that follows emphasizing the dynamic nature of housing debt and its influence on monetary policy.

I also advocate for categorizing housing as a distinct class of illiquid assets in structural models, given its unique utility and role as collateral, unlike other illiquid assets like retirement accounts or 401k plans. These assets, although capable of facilitating income transfers before maturity, lack the direct utility provided by homeownership.[10] The preference for homeownership over solely investing in retirement accounts is mirrored by nearly 65.8% of US households owning homes, marking it as the predominant source of illiquid assets.[11] Furthermore, leveraging a home for loans differs from diminishing other illiquid assets, entailing distinct transaction costs. With a majority (62.9%[12]) of US households owning homes through mortgages, understanding the interplay between mortgages and other illiquid assets is pivotal.

The rest of the paper is structured as follows. Section 3.2 details the data sources and my empirical methodology. Results are presented in Section 3.3. Section 3.4 develops the model and benchmark calibration to rationalize & motivate the empirical measurement for Section 3.2 while Section 3.5 concludes. Relevant empirical results not present in the main text is provided in Appendices C.2 & C.3.

3.2 Empirical Exercise

3.2.1 Quantifying the HtM

I use the Survey of Consumer Finances (SCF) data till 2019 to empirically estimate the share of HtM. Details about the survey are also available in Appendix C.1 of KVW. Here, I present only some features. The study is conducted every three years and it collects all the relevant information. It is sponsored by the Federal Reserve System and the Statistics of Income Division

[10]This diverges from the theory posited by Kaplan and Violante (2014a) and subsequent literature, which acknowledges intermediate transfers from illiquid assets but overlooks the direct utility gains.

[11]Source: US Census Bureau, 2021 https://www.census.gov/housing/hvs/files/currenthvspress.pdf

[12]Source: Zillow Research (2019)

of the Internal Revenue Service (IRS). I follow the procedure of KVW in cleaning the data and determining the selected samples. They examine a narrower definition of net liquid wealth that excludes directly held mutual funds, stocks, and bonds from liquid assets, and a broader one that includes outstanding debt in home-equity lines of credit as liquid debt. Net illiquid wealth in the SCF includes the value of housing, residential and non-residential real estate net of mortgages and home equity loans, private retirement accounts (such as 401(k)s, IRAs, thrift accounts, and future pensions), cash value of life insurance policies, certificates of deposit, and saving bonds. For the empirical study, KVW had used survey data till 2010 for the US. I update the data and present here the results of interest. The methodology is also exactly in line with KVW with minimal changes which I detail in the next paragraph.[13] The SCF is an extensive survey with a very detailed documentation. Some variables of interest are removed/added in every survey. Specifically, I change the definition of illiquid assets slightly by augmenting them with newly introduced variables for quantifying HELOCs. I also add the balance payable after a mortgage is due to the illiquid assets. Similarly, other variables of interest which have been added for later rounds of the survey regarding the amount borrowed/refinanced have been suitably included in the measures for illiquid assets. Categorical variables controlling for the decision to refinance (which proxies for cash-out refinance and/or the decision to extract home equity by taking another HELOC) have also been accommodated. These changes are necessary in keeping with the purposes of the empirical study that aim to get a better estimate in quantifying the interlinkage between household refinance & HtM status.

The theoretical procedure for motivating the classification of households into wealthy HtM and poor HtM depending on their holdings of the illiquid/liquid assets is detailed in KVW Section 3 and Appendix B. I follow their procedure identically. I present here the amended motivation for the need to study the data based on the decision to extract home equity by adopting a three period partial equilibrium framework that underscores the importance of housing.[14]

[13]All the variables are not present every survey the data is missing for these years. This can be observed in the graphs in section 3.3.1.

[14]For more details, see section 3.4.1 which also contains baseline calibration & simple qualitative experiments.

3.2.2 Refinance choice & Collateral Constraint

The chief objective is to observe how the probability of choosing one refinance option over the other varies with a set of commonly used regressors and controls as determined by the literature. My data comes from three sources (all of which are publicly available). First, the Freddie Mac single family data set which is the mainstay of the analysis. The data is available at quarterly frequency and the period of the study is from 1999-2020. Each data set is an exhaustive list of all mortgage loans that were approved for either purchase or refinance along with other information on individual debt-to-income, FICO scores, unpaid loan balance, remaining months to maturity, loan-to-value and combined loan-to-value (which include HELOCs and other second liens). The data is at the Metropolitan Statistical Area (MSA) level. I clean the data following the steps listed in Freddie Mac user guide & combine the quarterly data to get the combined yearly dataset. I merge the resulting data with unemployment data from BLS & FHA home value index, both of which are at the MSA level. After obtaining the cleaned data, I proceed with the empirical analysis using the choice of refinance as my initial dependent variable. Before running a formal logistic regression on the set of regressors, I divide the yearly data into quantiles of 3 and 5 for each of the 8 regressors to study the trends in the cash-out refinance (as a percentage of total refinances) over the years. These simple plots serve to provide added motivation for the choice of regressions. Results for the 3 quantiles have been included in the main text while those for 5 quantiles have been included in Appendix C.3.

I label the event of being approved for a cash-out refinance as a success with the alternative of being approved for a no cash-out refinance as a failure. I estimate yearly logistic regressions at the aggregate level separately for all the twenty two years of data available. I also run the model on separate pooled data to get an estimate of the time fixed effects. Specifically, I carry out the following yearly regressions.

$$\begin{aligned} Pr(cash-out\ \ refinace) = \alpha_1 FICO + \alpha_2 DTI + \alpha_3 UPB + \alpha_4 IR + \\ \alpha_5 LoanAge + \alpha_6 hppc + \alpha_7 unemppc + \alpha_8 HE \quad (3.1) \end{aligned}$$

where home equity has been measured following Beraja et al. (2019) and the yearly percentage changes in the home value index & unemployment rates have been considered. For the pooled logit, equation (3.1) is augmented with the appropriate time dummies to control for the year fixed effects by the term $\sum_{i=2000}^{2020} t_i$ with 1999 being the base year.

Since the data is composed of different units, the stand alone coefficients might give misleading quantitative implications since they cannot be directly compared. Therefore, I also carry out a variance decomposition of the results to get improved estimates for shares of variations in the dependent variable over time and jointly. I begin at the aggregate level and expand by dividing the data further into quantiles of the interested regressors. Results for observing possible regional variations have been included in Appendix C.3. Besides the dummies for controlling the base level estimates, I also include possible interaction effects for the various possible levels. I start off with splitting the data into 3 quantiles before generalizing to 5 quantiles. The results in the main body of the paper pertains to 3 quantiles. Since the data is only till quarter 2 for 2020, the effect for the Covid-19 shock will not be showing up since the impact on refinance decisions due to the corresponding regressors is most likely to be lagged by atleast one or two quarters. Consistent with the household motives for liquidity demand and precautionary savings, the cash-out refinance percentage is likely to pick up pace going forward vis a vis a no cash-out refinance once the full data is available.

3.3 Results

3.3.1 SCF Data

First, I present the relevant results that follow KVW with the modified procedure as detailed in Section 3.2.1 with the pooled data from the 1989-2019 waves of the SCF. Standard error of the estimates for most of the figures have been included in Appendix C.2.

Figure 3.3: For the US from the SCF 1989-2019

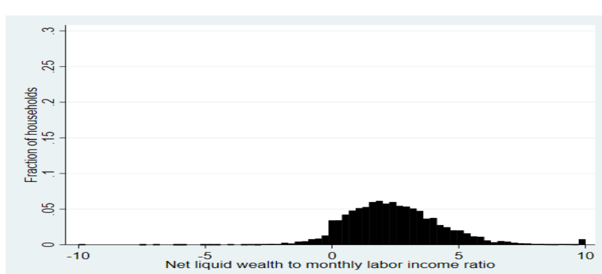


Table 3.5: Descriptive Statistics for the SCF data

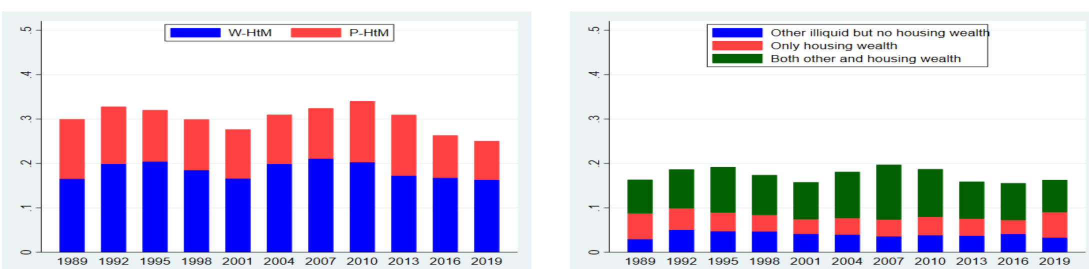
	US: 2010		US: 2019	
	Median	Frac. Pos.	Median	Frac. Pos.
Income (age 22-59)	47040	0.984	55425	0.984
Net Worth	56721	0.883	66820	0.884
Net liquid wealth	1714	0.750	2019	0.752
Cash, checking, saving, MM accounts	2640	0.923	3111	0.923
Directly held stocks	0	0.142	0	0.142
Directly held bonds	0	0.014	0	0.014
Revolving credit card debt	0	0.382	0	0.382
Net illiquid wealth	52000	0.761	61269	0.762
Housing net of mortgages	29000	0.629	34169	0.629
Retirement accounts	1508	0.526	1777	0.526
Life insurance	0	0.186	0	0.186

Figure 3.3 shows that the total share of households with fraction of net liquid wealth to its labor income being negative is pretty low in 2019 perhaps owing to the largest expansion on record post the GFC.[15] The feature of interest in 2019 is shown by Table 3.5. Without classification of households as per their HtM status, it is the rise in housing wealth net of mortgages with the rise being higher than the corresponding rise in retirement account wealth in absolute terms suggesting the growing importance of housing as the economy heads into the Covid-19 recession.

Figure 3.4: Time-series of fraction of HtM households in the U.S

(a) Share of total, wealthy, and poor HtM

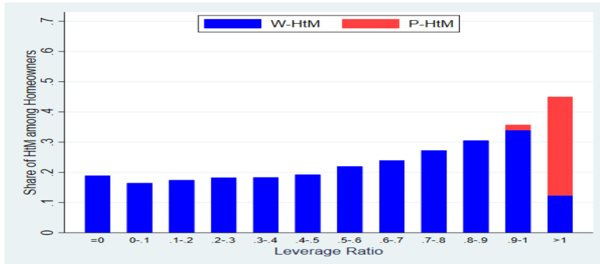
(b) Share of total, wealthy, and poor HtM



The main results that are particularly relevant are given in Figure 3.4 and Figure 3.5. The survey data in 2010 is reflecting the GFC or just post GFC. Predictably, the total share of HtM in the population has declined since then. The last survey in 2019 was also conducted before

[15]The results for Figure 3.3 are not directly comparable with the counterpart in KVW since the data has not been adjusted for tax returns. Doing so would lead to little difference.

Figure 3.5: Share of HtM households among homeowners by leverage ratio, SCF 1989-2019.



the Covid crisis. The wealthy HtM has as a percentage of the total HtM has decreased post the GFC. However, if we are to examine the portfolio decomposition trends post 2010 for the wealthy HtM, we find that the share of housing wealth as a fraction of the illiquid assets held has clearly increased going into 2019 as compared to 2010. This is significant heading into the Covid crisis since the refinance channel has become stronger because there is a significant uptick in the fraction of people who would like to do a cash-out refinance when hit by a sequence of negative income shocks. High household liquidity demand should be the rational behaviour for the wealthy HtM provided the benefits of a refinance are exceeding their costs. Equally significant is the fact that the share of other illiquid assets in the portfolio of the wealthy HtM has decreased implying a greater propensity to use the house (and implicitly mortgage) to tide over the negative income shocks. Figure 3.5 also clearly indicates the majority of wealthy HtM who are homeowners are not highly leveraged implying that they are more likely to be eligible for a cash-out refinance since they are not at their respective borrowing limits. Moreover, higher house prices have been relaxing the collateral constraint for households leading to higher levels of accumulated home equity. The evidence in particularly Figure 3.5 and Figure 3.4 (b) also indicate that the cash-out refinance channel is particularly strong. The standard errors for the estimates are very small in comparison to the size of the means no matter the robustness criteria used in Table 3.6. These preliminary results without further conditioning of the data based on the decision to extract home equity are promising and points to the need to analyze the trends based on the former mentioned decomposition.

Figure 3.6 and Table 3.6 summarizes the sensitivity analysis as followed by the paper depending on the measurement criteria used to produce the estimates for the HtM status. As compared with KVW, using reported credit limit or weighting by the income weighted shares produces similar estimates as the baseline measurement. The reason for the decline in the total fraction of HtM individuals may well be because of the fact that the biggest expansion on record was only

Figure 3.6: Time series of fraction of HtM households in the U.S., alternate definitions.

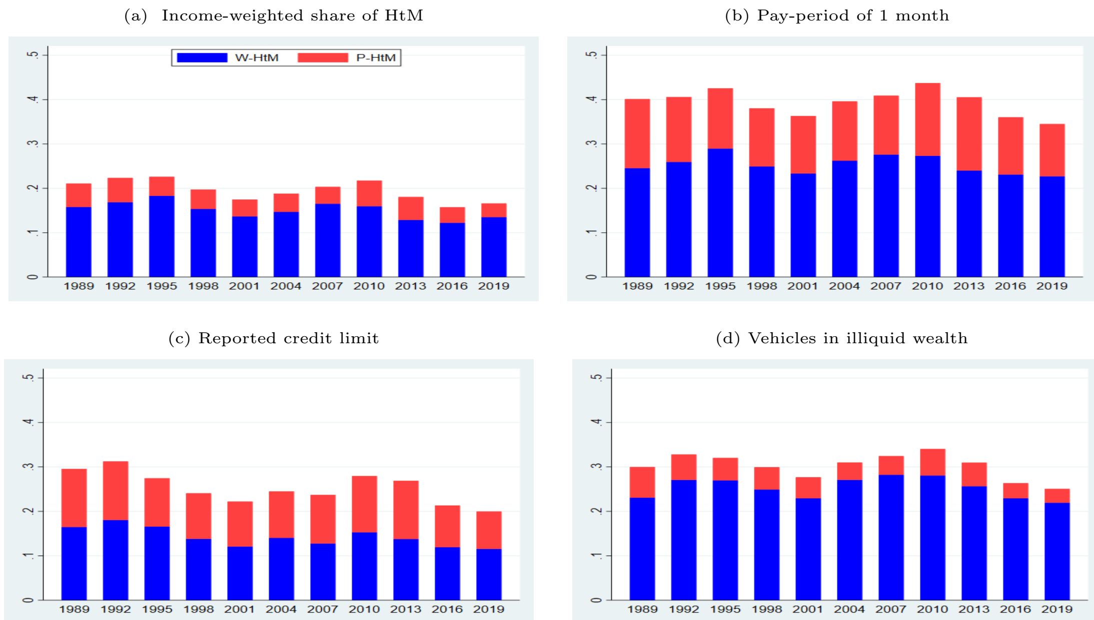


Table 3.6: Robustness results for fraction HtM in each category in the SCF pooled comparison

	1989-2010					1989-2019				
	P-HtM	**W-HtM**	**N-HtM**	**HtM**	**HtM-NW**	**P-HtM**	**W-HtM**	**N-HtM**	**HtM**	**HtM-NW**
Baseline	0.121	0.192	0.687	0.313	0.137	0.116	0.185	0.699	0.301	0.132
Usually c > y	0.089	0.156	0.756	0.244	–	0.088	0.147	0.765	0.235	–
Financially fragile households	0.169	0.316	0.515	0.485	0.203	0.174	0.307	0.519	0.481	0.207
Reported credit limit	0.114	0.148	0.738	0.262	0.126	0.111	0.141	0.749	0.251	0.123
1 year income credit limit	0.102	0.119	0.779	0.221	0.108	0.099	0.113	0.788	0.212	0.104
Weekly pay period	0.106	0.15	0.744	0.256	0.119	0.098	0.144	0.758	0.242	0.112
Monthly pay period	0.141	0.262	0.597	0.403	0.164	0.14	0.253	0.608	0.392	0.163
Higher illiquid wealth cutoff	0.13	0.183	0.687	0.313	0.137	0.125	0.176	0.699	0.301	0.132
Ret. acc. as liquid for 60+	0.121	0.183	0.696	0.304	0.137	0.116	0.174	0.71	0.29	0.132
Businesses as illiquid assets	0.113	0.194	0.693	0.307	0.129	0.11	0.187	0.704	0.296	0.125
Direct as illiquid assets	0.119	0.218	0.663	0.337	0.137	0.115	0.206	0.679	0.321	0.132
Other valuables as illiquid assets	0.117	0.196	0.687	0.313	0.132	0.112	0.189	0.699	0.301	0.128
Excludes cc puzzle households	0.163	0.184	0.654	0.346	0.176	0.155	0.172	0.673	0.327	0.169
HELOCs as liquid debt	0.119	0.182	0.699	0.301	0.135	0.115	0.175	0.71	0.29	0.131
Usual income	0.119	0.198	0.683	0.317	0.136	0.116	0.188	0.697	0.303	0.133
Disposable income - Reported	0.121	0.192	0.687	0.313	0.137	0.116	0.185	0.699	0.301	0.132
Disposable income - Single	0.121	0.192	0.687	0.313	0.137	0.116	0.185	0.699	0.301	0.132
Comm. cons. - beg. of period	0.101	0.166	0.732	0.268	0.116	0.096	0.159	0.745	0.255	0.111
Comm. cons. - end of period	0.149	0.272	0.579	0.421	0.174	0.151	0.263	0.586	0.414	0.176

Note-For details please see corresponding table in KVW.

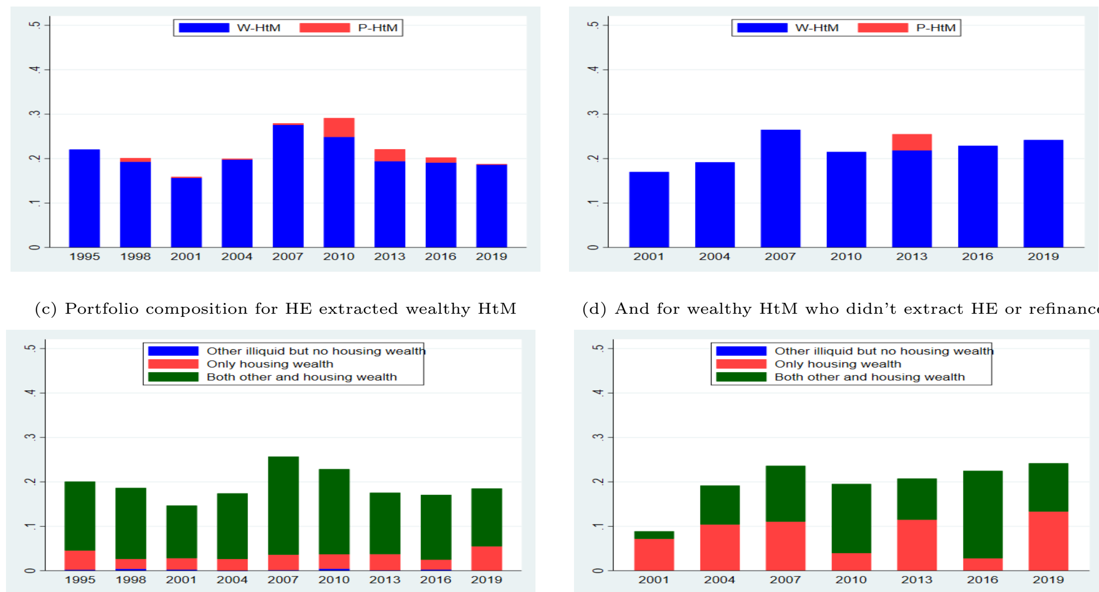
ended by a completely unforeseen crisis. The last survey in 2010 was during or just after the recession and hence picked up a higher HtM share. The trends are pretty similar with KVW across the various definitions. Before I carry out a formal decomposition of the data for explicitly focusing on the home equity extraction channel, I note that the above results provide ample evidence of the importance of housing relative to other illiquid assets for the wealthy HtM from the latest survey data. Coupled with the fact that the majority of the wealthy HtM are still far off from their borrowing constraints, I predict a surge in cash-out refinances among the wealthy HtM which is masked by the overall rise in no cash-out refinance since the majority of the population is non HtM.

The next set of results is selecting only the households who extracted home equity while refinancing and comparing them with the set of household who did not refinance and/or didn't extract home equity. I use the appropriate data after conditioning on the relevant categorical variables. The data is unfortunately not uniformly present for all the years. Figure 3.7 panel (a) and panel (b) show the wealthy HtM among the population who extracted home equity. The poor HtM in this case is measuring the household who have negative home equity as was common during & just after the GFC when house prices collapsed. Panel (b) does not explicitly state whether these individuals decided not to extract home equity or whether their applications were denied.[16] Panels (c) and (d) perform a similar portfolio decomposition as in Figure 3.4 panel (b). As compared to 2010, the share of housing (as a percentage of the illiquid asset holdings) has gone up for the households who did extract home equity. This reinforces the proposed channel as wealthy HtM have a far greater share of their illiquid assets in housing. Similarly, given 2019 was before the Covid shock hit the economy, in next surveys we should see that many wealthy HtM in panel (d) would move to join panel (a) provided they have the necessary resources to get their applications approved. This ties up with the issue of mortgage denials which is weakening the quantitative significance of the channel. This is especially true during recessions when the denial rates would most likely to increase. Both the channels would undeniably lead to a rise in the wealthy HtM shares. Table 3.7 provides the same robustness checks for the former subset of households while Table 3.8 provides the same for the households in the latter group. Analogous to Figure 3.6, the robustness checks for these 2 groups are presented in Figure 3.8.

The last result I present from the SCF is Figure 3.9 which shows the leverage ratio among homeowners who extracted home equity by a refinance against those who did not refinance and/or extract home equity. The poor HtM in this case measures again those household with negative

[16] Or whether due to sample selection, they did not apply. For more details see Boar et al. (2017) as well as DeFusco and Mondragon (2020).

Figure 3.7: HtM households and the portfolio composition of wealthy HtM by refinance decision



(a) Refinanced & extracted home equity

(b) Did not refinance and/or extract HE

(c) Portfolio composition for HE extracted wealthy HtM

(d) And for wealthy HtM who didn't extract HE or refinance

Figure 3.8: Time series of fraction of HtM households in the U.S., alternate definitions, conditioned on Home Equity Extraction

Notes - Based on Income-weighted share of HtM and those with Pay-period of 1 month. Also based on reported credit limit and including vehicles as part of illiquid wealth

home equity. The first indication of denials and sample selection in the approvals data that I present the results in Section 3.3.2 comes to light with the poor HtM being substantially more indebted with the leverage ratio greater than or equal to 0.9. Similarly, the wealthy HtM share is higher at

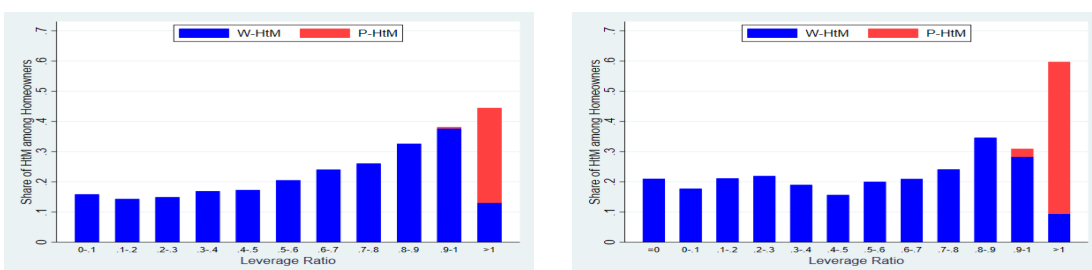
Table 3.7: Robustness results for Refinance in each category in the SCF pooled comparison

	1989-2010					1989-2019				
	P-HtM	**W-HtM**	**N-HtM**	**HtM**	**HtM-NW**	**P-HtM**	**W-HtM**	**N-HtM**	**HtM**	**HtM-NW**
Baseline	0.011	0.22	0.768	0.232	0.023	0.012	0.21	0.778	0.222	0.027
Usually c > y	0.007	0.162	0.831	0.169	-	0.01	0.158	0.833	0.167	-
Financially fragile households	0.015	0.331	0.655	0.345	0.026	0.018	0.321	0.661	0.339	0.031
Reported credit limit	0.006	0.122	0.872	0.128	0.015	0.007	0.119	0.874	0.126	0.021
1 year income credit limit	0.004	0.099	0.897	0.103	0.006	0.006	0.094	0.9	0.1	0.009
Weekly pay period	0.01	0.17	0.82	0.18	0.022	0.01	0.163	0.826	0.174	0.026
Monthly pay period	0.013	0.303	0.683	0.317	0.025	0.016	0.291	0.694	0.306	0.030
Higher illiquid wealth cutoff	0.012	0.219	0.768	0.232	0.023	0.013	0.209	0.778	0.222	0.027
Ret. acc. as liquid for 60+	0.011	0.203	0.786	0.214	0.023	0.012	0.189	0.798	0.202	0.027
Businesses as illiquid assets	0.01	0.218	0.772	0.228	0.020	0.011	0.208	0.781	0.219	0.024
Direct as illiquid assets	0.012	0.255	0.734	0.266	0.023	0.013	0.238	0.749	0.251	0.027
Other valuables as illiquid assets	0.011	0.22	0.768	0.232	0.023	0.012	0.21	0.778	0.222	0.027
Excludes cc puzzle households	0.014	0.19	0.796	0.204	0.026	0.015	0.175	0.81	0.19	0.030
HELOCs as liquid debt	0.01	0.197	0.793	0.207	0.021	0.011	0.189	0.8	0.2	0.026
Usual income	0.011	0.224	0.765	0.235	0.023	0.013	0.213	0.775	0.225	0.027
Disposable income - Reported	0.011	0.22	0.768	0.232	0.023	0.012	0.21	0.778	0.222	0.027
Disposable income - Single	0.011	0.22	0.768	0.232	0.023	0.012	0.21	0.778	0.222	0.027
Comm. cons. - beg. of period	0.01	0.189	0.801	0.199	0.022	0.01	0.181	0.809	0.191	0.027
Comm. cons. - end of period	0.015	0.33	0.655	0.345	0.026	0.018	0.317	0.665	0.335	0.031

Note- The results in the above table are for those agents who did refinanced and extracted home equity. home equity extraction from the mortgage is either through a cash-out refinance or taking additional HELOCs. The rest of the table definitions and notes follow exactly Table 3.6.

Figure 3.9: Time-series of fraction of HtM households in the U.S

(a) Refinanced to extract home equity (b) Did not extract HE by refinance



higher leverage ratios proving that people with higher leverage ratios cannot opt for home equity extraction. Higher house prices would relax the constraints and allow the much needed cash-out refinance during periods of high unemployment quite similar to the situation that the US economy found itself in the Covid crisis.

Table 3.8: Robustness results for those who did not extracted home equity in each category in the SCF pooled comparison

	1989-2010					1989-2019				
	P-HtM	**W-HtM**	**N-HtM**	**HtM**	**HtM-NW**	**P-HtM**	**W-HtM**	**N-HtM**	**HtM**	**HtM-NW**
Baseline	0.13	0.183	0.687	0.313	0.142	0.128	0.184	0.689	0.311	0.14
Usually c > y	0.102	0.181	0.717	0.283	-	0.101	0.181	0.718	0.282	-
Financially fragile households	0.176	0.315	0.508	0.492	0.209	0.174	0.317	0.509	0.491	0.206
Reported credit limit	0.129	0.172	0.698	0.302	0.14	0.127	0.172	0.7	0.3	0.138
1 year income credit limit	0.114	0.128	0.758	0.242	0.119	0.112	0.128	0.76	0.24	0.117
Weekly pay period	0.116	0.14	0.744	0.256	0.126	0.115	0.14	0.745	0.255	0.124
Monthly pay period	0.149	0.253	0.599	0.401	0.169	0.146	0.254	0.6	0.4	0.167
Higher illiquid wealth cutoff	0.14	0.173	0.687	0.313	0.142	0.138	0.174	0.689	0.311	0.14
Ret. acc. as liquid for 60+	0.13	0.178	0.692	0.308	0.142	0.128	0.179	0.694	0.306	0.14
Businesses as illiquid assets	0.119	0.183	0.698	0.302	0.133	0.118	0.184	0.698	0.302	0.131
Direct as illiquid assets	0.129	0.204	0.667	0.333	0.142	0.127	0.205	0.668	0.332	0.14
Other valuables as illiquid assets	0.126	0.187	0.687	0.313	0.138	0.124	0.188	0.689	0.311	0.136
Excludes cc puzzle households	0.174	0.186	0.64	0.36	0.186	0.172	0.186	0.642	0.358	0.184
HELOCs as liquid debt	0.128	0.176	0.696	0.304	0.14	0.126	0.177	0.697	0.303	0.138
Usual income	0	0.218	0.782	0.218	0.002	0.005	0.217	0.777	0.223	0.009
Disposable income - Reported	0.13	0.183	0.687	0.313	0.142	0.128	0.184	0.689	0.311	0.14
Disposable income - Single	0.13	0.183	0.687	0.313	0.142	0.128	0.184	0.689	0.311	0.14
Comm. cons. - beg. of period	0.109	0.159	0.732	0.268	0.12	0.108	0.159	0.733	0.267	0.119
Comm. cons. - end of period	0.154	0.26	0.586	0.414	0.177	0.152	0.261	0.587	0.413	0.174

Note- The results in the above table are for those agents who did not extract home equity and/or did not refinance. home equity extraction from the mortgage is either through a cash-out refinance or taking additional HELOCs. The rest of the table definitions and notes follow exactly Table 3.6.

3.3.2 Freddie Mac Approvals

Before running the regressions to motivate the choice of refinance for households, I present some evidence on cash-out refinance frequency. Figure 3.10 shows how the frequency of cash-out refinance (as a percentage of total refinance) varies with the values of the independent variables used in the regression. The results presented here are obtained by sorting and dividing the data each variable into 3 quantiles for each year.

The results are broadly in line with intuition and serve as checks to indicate that the cash-out refinance channel indicates strong demand for household liquidity if the household is perceived to have a higher debt level as indicated by higher DTI, lower FICO and higher LTV, higher unpaid loan balance. The original interest rate on the loan is becoming more important in recent years. This could be because of monetary policy which has been broadly keeping interest rates consistently low post-GFC indicating that the new interest payments for the increased mortgage amount from opting or choosing a cash-out refinance are going to be lower as compared to pre-GFC.[17] As house

[17]This result can be contrasted with the findings of Bhutta and Keys (2016) who find that changes in interest rate

Figure 3.10: Frequency of Cash-out refinance for 3 quantile levels

price increase, especially pre-GFC, the frequency of cash-out refinances increases. The resulting higher mortgage debt per household probably also contributed to the subsequent defaults. The effect was also pronounced across quantiles during the 2002 recession. Surprisingly on dividing the MSAs by the average unemployment, the effect is muted across quantiles. This might be simply because the average unemployment rate does not matter that much for the decision as compared to the year-on-year percentage changes in unemployment (which is a better proxy for idiosyncratic changes in the household incomes).

were one of the most relevant variables before GFC.

Figure 3.11: Coefficients from yearly regression-1999-2020

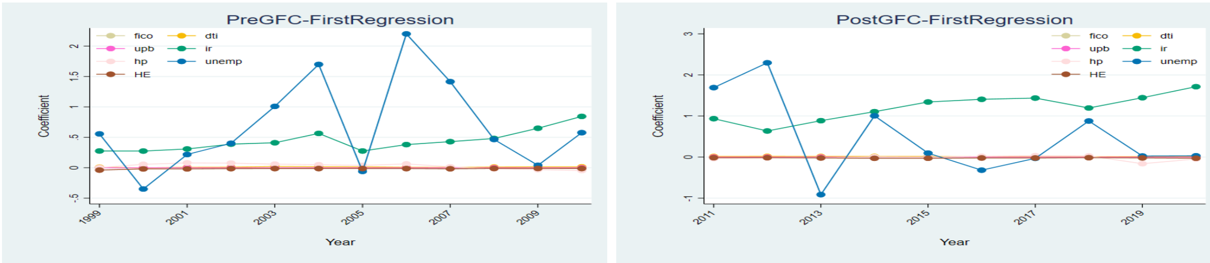
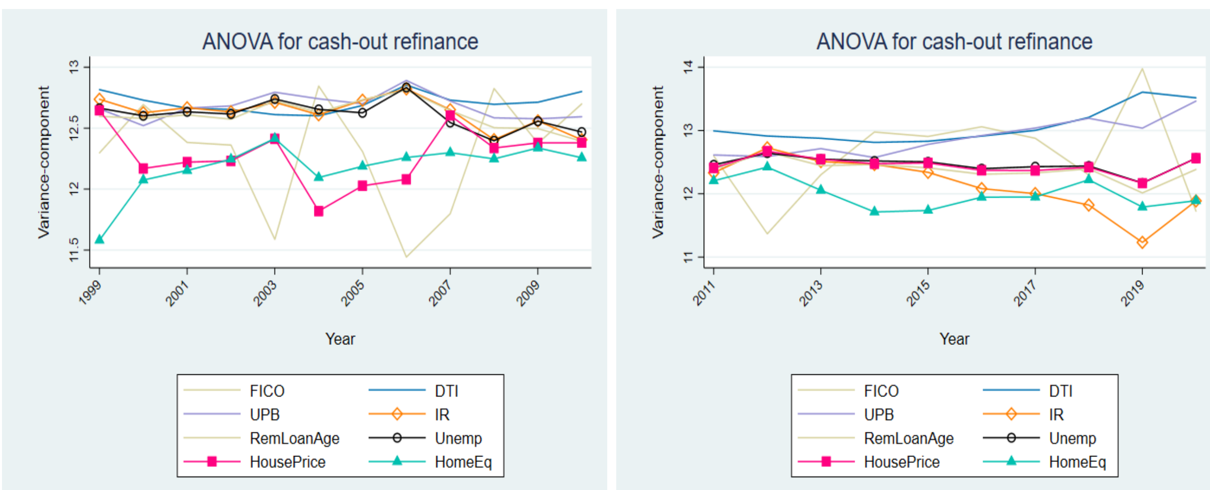


Figure 3.11 shows the value of coefficients. Percentage changes in unemployment had the highest effect on the probability of refinance till almost 2013 showing the strong motive for liquidity. The original interest rate became gradually important over time. This reduces the costs involved with cash-out refinance. The results with region dummies added is presented in Appendix C.3.

Figure 3.12: Variance Decomposition-1999-2020



Since the variables are all in different units to get a broad picture of the amount of variation that each variable is responsible for over the years, Figure 3.12 plots the variations over time. The unemployment channel is accounting for a substantial fraction of the variation for the cash-out refinance before 2010. Post GFC, the effect is slightly muted and coincided with house price. The other interesting channels of home equity and original interest rate appear far less effective confirming that the former are majorly responsible for household liquidity demand aided by higher house prices, working in conjunction with higher unemployment rates.

For the pooled regression over 1999-2020, the time fixed effects is the highest (Table 3.9)

Table 3.9: Pooled data variance decomposition from 1999-2020

Variable	Percentage of Variance Decomposition	Corresponding p-val
FICO	3.60777	0
ODTI	3.55847	0
IR	3.56524	0
UnpaidBalance	3.54332	0
RemLoanAge	3.54812	0
Unemp-%-change	3.55566	0
house price-%-change	3.53427	0
home equity	3.45755	0
Time fixed Effects	41.11557	0
	Coefficient	**Corresponding p-val**
FICO	-0.00416	0
ODTI	0.01393	0
IR	0.00000	0
UnpaidBalance	0.58026	0
RemLoanAge	-0.00158	0
Unemp-%-change	0.06283	0
house price-%-change	0.02044	0
home equity	-0.02001	0

and accounts for a substantial amount of the variation. Even then, the effect of unemployment is the higher than that of home equity and house price. The interest rate effect is only slightly higher. Additional empirical robustness checks are presented in Appendix section 3.3.2.

3.4 Wealthy HtM behaviour: simple 3 period PE model

3.4.1 No other illiquid Asset besides a House

The objective is to develop a theoretical mechanism which motivates a cash-out refinance over a no cash-out in the face of sustained negative income shocks and its interaction with the HtM status of households. As referred earlier, this rationalizes the measurement of wealthy HtM based on their decision to extract home equity as in section 3.2.1. To keep the setup simple, the only illiquid asset available to an agent is a house which needs to be purchased using a mortgage.

The baseline model does not include any income transfer or access to unsecured credit at $t = 1$.[18] Owning a house gives an additional constant non-zero utility and is strictly preferred to not owning a house. It is however always not affordable. Depending on the initial endowment of ω at $t = 0$ they can divide agents into 2 types. Type I is unable to own a house while Type II buys a house offering a lifetime consumption equivalent of H units by purchasing a single fixed rate mortgage (FRM) worth M. To simplify matters, the endowment after purchasing the mortgage for an agent belonging to Type II is equal to the initial endowment of an agent belonging to Type I. In both cases, the value post the decision of purchasing the house is normalized to $\omega = 1$.

Per-period utility for both the agents is log-utility. Consumers earn an income of y_1^k in period 1 and y_2^k in period 2 and consume in periods 1 and 2 where $k = 1, 2$ denotes the group. At $t = 1$, agents decide how much to allocate between liquid assets m_2^k and how much to consume c_1^k. The return on liquid assets is fixed at 1. At $t = 2$, agents do not save and consume their entire income and accumulated savings. Agents owning a house make fixed payments of rM in each of the two periods. In a departure from KVW (2014), Agents of Type I are representative with discount rate ρ^1 while agents of group 2 are heterogeneous with a continuum of discount rates $\rho^{2,j} \in [0, 1]$. Agents of both groups therefore maximize their discounted lifetime utility. Period utility is CES with $\sigma = 1$ or log utility. Since the representative agent of group 1 does not own a house, the discount rate ρ^1 can be controlled independently of $\rho^{2,j}\ \forall\ j \in [0, \infty)$. No matter how impatient/patient an agent j of group 2 is, the utility from owning the house is preferred to not owning one irrespective of the refinance strategy.

Type I: Since Type I does not have the necessary initial endowment to purchase the house, their problem is exactly identical to the setup without illiquid assets as detailed in Appendix A.1 of KVW (2014). The problem faced by the household at $t = 1$,

$$
\begin{aligned}
V^1 &= \max_{c_1, c_2}\ ln\ (c_1^1) + \frac{1}{1+\rho^1}\ ln\ (c_2^1) \\
\text{s.t. } c_1^1 + m_2^1 &= y_1^1 + m_1^1 \\
m_2^1 &\geq 0 \\
c_2^1 &= y_2^1 + m_2
\end{aligned}
$$

[18] Adding these features would lead to more tedious algebra results with gain for motivating the measurement of HtM empirically. See Appendix A.3 & A.4 of KVW.

which has the solution

$$m_2^1 = \max \left\{ \frac{y_1^1 + m_1^1 - y_2^1(1+\rho^1)}{2+\rho^1}, 0 \right\}.$$

The interior solution for m_2^1 implies $c_1^1 = (1+\rho^1)(y_1^1+m_1^1+y_2^1)/(2+\rho^1)$ and $c_2^1 = (y_1^1+y_2^1+m_1^1)/(2+\rho^1)$ where the consumption smoothing result no longer holds due to the introduction of the discount rate. The corner solution remains unchanged with $c_1^1 = m_1^1 + y_1^1$ and $c_2^1 = y_2^1$. Since there are no other illiquid assets available at $t = 0$, $m_1^k = 1$ for both groups, $k = 1, 2$.

Type II: Besides owning the house, each agent has 3 choices. Upon realization of income y_1^2, house prices and the prevailing mortgage rate at $t = 1$, he/she can either decide to refinance their mortgage or not. Upon deciding to refinance, he/she chooses whether to opt for a cash-out over a no cash-out refinance.[19] Opting for a no cash-out refinance would lead to reduced mortgage payments in period 2 which can be treated equivalently as receiving a discounted lump sum transfer at $t = 1$. Alternatively, a cash-out refinance would entail an immediate liquidity transfer at $t = 1$ trading off with higher mortgage payments at $t = 2$. Assuming that an agent owning a house can always undertake a no cash-out refinance once the overall mortgage rate is realized to be lower than the rate at which the mortgage was purchased at $t = 0$ net of transaction costs (which increases overall lifetime utility with certainty), opting for a no cash-out refinance dominates the choice of not refinancing the mortgage at $t = 1$. Therefore, at $t = 1$, once the respective state variables have been realized, agents decide to whether opt for a cash-out or a no cash-out refinance in conjunction with the portfolio allocation decision of their counterparts in Type I. As before, since there is no other illiquid asset available at $t = 0$, $m_1^{2,j} = 1$ for any agent $j, j \in [0, \infty)$.

The problem faced by the household $j, j \in [0, \infty)$, who opts for a no cash-out refinance is given by

$$\begin{aligned} V_{\text{NC}}^{2,j} &= \max_{c_1^{2,j}, c_2^{2,j}} \; ln\ (c_1^{2,j}) + \frac{1}{1+\rho^{2,j}} \; ln\ (c_2^{2,j}) + ln\ H \\ \text{s.t. } c_1^{2,j} + m_2^{2,j} &= y_1^{2,j} + m_1^{2,j} - rM + \frac{1}{1+\rho^{2,j}} \Delta r M \\ m_2^{2,j} &\geq 0 \\ c_2^{2,j} &= y_2^{2,j} + m_2^{2,j} - rM \end{aligned}$$

[19] Since the empirical evidence is based on approvals data, implicitly each agent receives certain approval for their choice of refinance.

which has the solution

$$m_2^{2,j} = \max \left\{ \frac{y_1^{2,j} + m_1^{2,j} + rM\rho^{2,j} + (\Delta rM - y_2^{2,j})(1+\rho^{2,j})}{2+\rho^{2,j}}, 0 \right\}.$$

They are more likely to get an interior solution as the value of Δr increases cet. par. An agent is less likely to be HtM if they opt for a no cash-out refinance and the discounted payments received can act as insurance against negative income shocks experienced at $t = 1$. On the contrary, if the agent is HtM with $m_2^{2,j} = 0$, then $c_1^{2,j} = y_1^{2,j} + m_1^{2,j} - rM + \Delta rM/(1+\rho^{2,j})$ and $c_2^{2,j} = y_2^{2,j} - rM$ again indicating the use of the mortgage as an insurance against unexpected income shocks.

Agents can alternatively opt for a cash-out refinance which is equivalent to borrowing at $t = 1$ using accumulated home equity while repaying higher mortgage payments at $t = 2$ net of transaction costs. In this case, I assume that the future interest rate remains the same as the one in the original mortgage contract post the cash-out refinance. The problem faced by the household who opts for a cash-out refinance is given by

$$\begin{aligned} V_{\mathrm{C}}^{2,j} &= \max_{c_1^{2,j}, c_2^{2,j}} \; ln\,(c_1^{2,j}) + \frac{1}{1+\rho^{2,j}}\, ln\,(c_2^{2,j}) + ln\, H \\ \text{s.t. } c_1^{2,j} + m_2^{2,j} &= y_1^2 + m_1^{2,j} - rM \\ -\theta P \;\leq\; & m_2^{2,j} \;\leq\; 0 \\ c_2^{2,j} &= y_2^2 + rm_2^{2,j} - rM \end{aligned}$$

which has the solution

$$m_2^{2,j} = \max \left\{ -\frac{y_2^2(1+\rho^{2,j}) - y_1^2 - m_1^{2,j} - \rho^{2,j} rM}{r(1+\rho^{2,j})+1}, -\theta P \right\}.$$

The more interesting case is the corner solution where $m_2^{2,j} = -\theta P$ with $c_1^{2,j} = y_1^2 + m_1^{2,j} - rM + \theta P$ and $c_2^{2,j} = y_2^2 - r(M + \theta P)$. The HtM agent opts for higher consumption today by taking an additional loan using the house as a collateral trading off with a lower consumption in the future when the repayment reduces the income available for consumption. More importantly, higher house prices relaxes the collateral constraint and allows greater borrowing irrespective of HtM status for the household indicating the strong demand for liquidity to smooth consumption today in the face of income shocks while settling for a reduced consumption in the future. The mathematical expression indicates that households opting for a cash-out refinance could be more likely to be HtM than their counterparts since the condition for not borrowing upto the limit is harder to satisfy once they have adopted the framework where the income of the agent in period 2 is always the same across groups. Intuitively, such households are likely to be more impatient and have a higher value of $\rho^{2,j}$ and value the future less than those opting for a no cash-out refinance.

The choice at $t = 1$ for a household owning a house is thereby given by the following expression:

$$V^{2,j} = \max \ \{V^{2,j}_{\text{NC}}, V^{2,j}_{\text{C}}\}$$

Even such a minimal departure from the KVW (2014) renders the model analytically intractable and I have to rely on numerical simulations. Given parameter values, the refinance strategy depends on a threshold value of $\rho^{2,j}$, namely $\rho^{2,c}$. Broadly, they have to compare the value functions from the two choices: no cash-out vs cash-out. For $\rho^{2,j} > \rho^{2,c}$, agents opt for a cash-out over a no cash-out & vice-versa. For equality, they are indifferent. As is also clear from the above expressions, the model developed can satisfactorily explain the mechanism at hand intuitively. An agent opting for a no cash-out refinance is less likely to be HtM than his/her counterpart who opts for a cash-out refinance since the former is likely to be more patient valuing the future more than the latter. In either case, the agent is acting rationally maximizing their total lifetime utility.

3.4.2 Benchmark Model Calibration

The first step to calibrating the benchmark model would be determining the shares of the Poor and wealthy HtM for each group of agents. For agent 1 who does not not own a house, the only parameters under my control are the incomes in the two periods. If $m^1_2 > 0$, they are not HtM and vice versa. Choosing a grid of discount rates ρ, I report the values of y^1_1 and y^1_2 in the Table 3.10. Following the SCF 2019 the average Poor HtM not owning a house has been estimated to be 7-8% (row 1, column 3 of Table 3.3). Targeting the share, the representative agent discount rate is fixed to be 0.8911. As mentioned previously, the discount rate ρ^1 can be set independently of $\rho^{2,j}$ $\forall$ $j \in [0, \infty)$.

For agents of group 2, to ensure that they would always derive a lifetime utility which is higher from owning a house to not, I set H=1.6 which ensures that for my chosen grid of ρ the

Table 3.10: For Representative Agent 1 - No House

Parameter	y_1^1	y_2^1	ρ^1	**Target P-HtM (in %)**
Agent 1	6.3	3.8	0.8911	7-8

simulated value function is from opting for a non-cash-out refinance is always higher than not owning a house with the income parameters as defined in the above Table 3.10. To match the share of the HtM among those opting for cash-out refinance the other parameter values that I select for Type II are $y_1^2 = 5.4, y_2^2 = 4.2, \theta = 0.8, M = 7.8, r = 0.1, \Delta = 1.2$ & $P = 1$. This would form my benchmark calibration on which I run certain numerical experiments. The results are as obtained in the first row of Table 3.11. The numbers are motivated by the SCF 2019 estimates.

Table 3.11: For Heterogeneous Agent 2 who owns a house

Experiment	**Cash-out over no cash out ($\rho^{2,j} > \rho^{2,c}$)**	**Total cash-out (in %)**	**Cash-out at limit (in %)**
Baseline	$\rho^{2,j} > 0.81$	20	7
$P \uparrow 10\%$	$\rho^{2,j} > 0.81$	20	5
$\Delta \uparrow 10\%$	$\rho^{2,j} > 0.83$	18	7
$y_1^2 \downarrow 10\%$	$\rho^{2,j} > 0.67$	35	25
All together	$\rho^{2,j} > 0.68$	34	21

The value of the threshold discount rate $\rho^{2,c}$ above which agents are sufficiently impatient to ignore the cost of higher future mortgage payments is determined to be 0.81. The incomes are not the same as the agents in Type I. This would be not be very far from reality since there is a substantial fraction of people who own a house but are not in high paying jobs or have the necessary skill set. Conversely, higher education and being a part of the skilled labor force would not guarantee ownership of the house.Though the setup is purely to motivate the empirical measurement of HtM agents based on their decision to opt for cash-out refinance and/or taking additional HELOcs, I conduct some simple comparative statics below to demonstrate qualitative consistency with currently observed macroeconomic facts.[20]

[20]These results are consistent with an infinitely lived representative agent model with dynamically changing collateral constraints; see Iacoviello (2005) and others.

Experiment 1 - Increase P by 10%: Increasing house price P by 10%, we observe that not surprisingly the percentage of individuals opting for a cash-out refinance over a no cash-out remains as the house price does not affect the cash-out refinance individuals who are not at their borrowing limit explicitly. It only relaxes the borrowing constraint. However the cash-out HtM who are at their borrowing constraint utilize the increased borrowing limits and the total number of cash-out HtM decreases by around 2%. By the design of the setup, the price increase does not affect the agents opting for a no cash-out refinance.

Experiment 2 - Increase Δ by 10%: This predictably increases the no cash-out refinance share and the threshold discount rate $\rho^{2,c}$ increases to 0.83. The share of the HtM in cash-out remains unchanged from the benchmark case. Allowing higher discounted payments at $t = 1$ disincentives the cash-out refinance decision.

Experiment 3 - Decrease y_1 by 10%: The main experiment of interest is reducing the income in period 1 by 10% for an agent of Type II. The results are in line with the proposed mechanism. The number of agents opting for a cash-out refinance in this toy setup almost doubles with the share of HtM going up by more than a factor of 3. Consequently, the threshold value of $\rho^{2,c}$ reduces to only 0.67 as more agents use the "House as an ATM" to get emergency liquidity. In the benchmark model, there is no precautionary savings motive. Suitably altered preference would lead to more enhanced results.

Experiment 4 - Combining Experiments 1-3: The joint shock of 1, 2 and 3 would characterize the economic environment where labor incomes shrank from the shock that originated in the labor markets while house prices have been surging. Aided by a emergency expansionary monetary policy, the mortgage rates have also declined to historically low levels. Given the joint shock, the results suggest that the unemployment shock with the strong urge for emergency liquidity has the maximum impact. More subtly, the house price increase only aids the cash-out HtM. The share reduces by 4% while the the percentage of agents opting for the cash-out refinance more or less remains the same. Stronger well calibrated shocks with state of the art income processes would make the toy setup closer to reality. The only purpose of the benchmark calibration is to ensure that the PE model makes sense and retains the promise of delivering a quantitatively meaningful channel in a more enriched general equilibrium setup even in the absence of any other competing illiquid asset to housing.

3.5 Conclusion

The paper refines the measurement of HtM households by incorporating refinance choice into the classification motivated by substantial heterogeneity in the MPC between households who extract home equity versus those who do not. Employing estimates from the literature reveal a recalibrated aggregate consumption at 9.98% , compared to 16.56% in Kaplan et al. (2014), based on SCF 2019 data. Empirical evidence further demonstrated that the probability of cash-out refinancing increased by 0.06% for every 1% rise in unemployment and by 0.02% for every 1% rise in house prices. These patterns underscore the housing market's critical role in mitigating economic shocks while revealing systemic challenges, such as heightened barriers to accessing equity, that limit the broader financial resilience of households. The research employed a three-period model that endogenized the refinancing decision based on a threshold discount rate, providing a theoretical basis for assessing HtM status. This model effectively showed how economic shocks can influence households' HtM status based on homeownership and refinancing decisions.

To enhance empirical insights, it is recommended to estimate the MPCs for different groups of HtM individuals, both wealthy and non HtM based on those who refinanced and those who did not, using Panel Study of Income Dynamics data first. This not only disciplines the aggregate MPC or consumption dynamics but motivates the need to measure HtM agents based on their refinance choice. These estimates can then be integrated into a partial equilibrium framework within a general equilibrium model, treating housing as an illiquid asset. A significant development links household mortgage positions to Unhedged Interest Rate Exposures (UREs) in Auclert (2019), which, coupled with the decline in real interest rates, suggests potential welfare gains for households with negative UREs holding long-term assets and adjustable-rate mortgages (ARMs). Additionally, the possibility of increasing debt through home equity extraction, such as cash-out refinancing or Home Equity Lines of Credit (HELOCs) for fixed-rate mortgages, could exacerbate UREs and alter the distribution of welfare gains from monetary policy expansions. I leave these dimensions to be explored in structural models for future work.

Bibliography

ACHDOU, YVES, JIEQUN HAN, JEAN-MICHEL LASRY, PIERRE-LOUIS LIONS, AND BENJAMIN MOLL (2022) "Income and wealth distribution in macroeconomics: A continuous-time approach," *The review of economic studies*, 89 (1), 45–86.

AGARWAL, SUMIT, GENE AMROMIN, SOUPHALA CHOMSISENGPHET, TIM LANDVOIGT, TOMASZ PISKORSKI, AMIT SERU, AND VINCENT YAO (2015) "Mortgage refinancing, consumer spending, and competition: Evidence from the home affordable refinancing program,"Technical report, National Bureau of Economic Research.

AGARWAL, SUMIT, SOUPHALA CHOMSISENGPHET, HUA KIEFER, LEONARD C KIEFER, AND PAOLINA C MEDINA (2020) "Inequality During the COVID-19 Pandemic: The Case of Savings from Mortgage Refinancing," *Available at SSRN 3750133*.

ALAN, SULE (2006) "Entry costs and stock market participation over the life cycle," *Review of Economic Dynamics*, 9 (4), 588–611.

ALPANDA, SAMI AND SARAH ZUBAIRY (2019) "Household debt overhang and transmission of monetary policy," *Journal of Money, Credit and Banking*, 51 (5), 1265–1307.

AMPUDIA, MIGUEL, DIMITRIS GEORGARAKOS, JIRI SLACALEK, ORESTE TRISTANI, PHILIP VERMEULEN, AND GIOVANNI VIOLANTE (2018) "Monetary policy and household inequality."

AUCLERT, ADRIEN (2015) "Monetary Policy and the Redistribution Channel."

——— (2019) "Monetary policy and the redistribution channel," *American Economic Review*, 109 (6), 2333–67.

AUCLERT, ADRIEN AND MATTHEW ROGNLIE (2020) "Inequality and Aggregate Demand."

Auclert, Adrien, Matthew Rognlie, and Ludwig Straub (2018) "The intertemporal keynesian cross,"Technical report, National Bureau of Economic Research.

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

Bauluz, Luis and Timothy Meyer (2021) "The Wealth of Generations," *Working Paper*.

Bennett, Julie and YiLi Chien (2022) "The Large Gap in Stock Market Participation Between Black and White Households," *Economic Synopses* (7).

Beraja, Martin, Andreas Fuster, Erik Hurst, and Joseph Vavra (2019) "Regional heterogeneity and the refinancing channel of monetary policy," *The Quarterly Journal of Economics*, 134 (1), 109–183.

Berger, David, Veronica Guerrieri, Guido Lorenzoni, and Joseph Vavra (2018) "House prices and consumer spending," *The Review of Economic Studies*, 85 (3), 1502–1542.

Berger, David and Joseph Vavra (2015) "Consumption dynamics during recessions," *Econometrica*, 83 (1), 101–154.

Bhutta, Neil and Benjamin J Keys (2016) "Interest rates and equity extraction during the housing boom," *American Economic Review*, 106 (7), 1742–74.

Black, Sandra E, Paul J Devereux, Fanny Landaud, and Kjell G Salvanes (2020) "Where does wealth come from?"Technical report, National Bureau of Economic Research.

——— (2022) "The (Un)Importance of Inheritance," Working Paper 29693, National Bureau of Economic Research, 10.3386/w29693.

Boar, Corina, Denis Gorea, and Virgiliu Midrigan (2017) "Liquidity constraints in the US housing market,"Technical report, National Bureau of Economic Research.

Bu, Chunya, John Rogers, and Wenbin Wu (2021) "A unified measure of Fed monetary policy shocks," *Journal of Monetary Economics*, 118, 331–349.

Catherine, Sylvain (2022) "Countercyclical labor income risk and portfolio choices over the life cycle," *The Review of Financial Studies*, 35 (9), 4016–4054.

Chen, Hui, Michael Michaux, and Nikolai Roussanov (2020) "Houses as ATMs: mortgage refinancing and macroeconomic uncertainty," *The Journal of Finance*, 75 (1), 323–375.

Chetty, Raj, John N Friedman, Nathaniel Hendren, Michael Stepner, and The Opportunity Insights Team (2020) *How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data*: National Bureau of Economic Research Cambridge, MA.

Cioffi, Riccardo A (2021) "Heterogeneous Risk Exposure and the Dynamics of Wealth Inequality," *URL: https://rcioffi. com/files/jmp/cioffi_jmp2021_princeton. pdf (cit. on p. 7)*.

Cloyne, James, Clodomiro Ferreira, and Paolo Surico (2020) "Monetary policy when households have debt: new evidence on the transmission mechanism," *The Review of Economic Studies*, 87 (1), 102–129.

Coibion, Olivier, Yuriy Gorodnichenko, Lorenz Kueng, and John Silvia (2017) "Innocent Bystanders? Monetary policy and inequality," *Journal of Monetary Economics*, 88, 70–89.

Colarieti, Roberto, Pierfrancesco Mei, and Stefanie Stantcheva (2024) "The How and Why of Household Reactions to Income Shocks,"Technical report, National Bureau of Economic Research.

Curcuru, Stephanie, John Heaton, Deborah Lucas, and Damien Moore (2010) "CHAPTER 6 - Heterogeneity and Portfolio Choice: Theory and Evidence," in AÏT-SAHALIA, YACINE and LARS PETER HANSEN eds. *Handbook of Financial Econometrics: Tools and Techniques*, 1 of Handbooks in Finance, 337–382, San Diego: North-Holland, https://doi.org/10.1016/B978-0-444-50897-3.50009-2.

DeFusco, Anthony A and John Mondragon (2020) "No job, no money, no refi: Frictions to refinancing in a recession," *The Journal of Finance*, 75 (5), 2327–2376.

Di Maggio, Marco, Amir Kermani, and Kaveh Majlesi (2020) "Stock market returns and consumption," *The Journal of Finance*, 75 (6), 3175–3219.

Elinder, Mikael, Oscar Erixson, and Daniel Waldenström (2018) "Inheritance and wealth inequality: Evidence from population registers," *Journal of Public Economics*, 165, 17–30.

Fagereng, Andreas, Matthieu Gomez, Emilien Gouin-Bonenfant, Martin Holm, Benjamin Moll, and Gisle Natvik (2022) "Asset-Price Redistribution,"Technical report, Working Paper.

Farrell, Diana, Fiona Greig, and Chen Zhao (2020) "Tapping Home Equity: Income and Spending Trends Around Cash-Out Refinances and HELOCs," *Available at SSRN 3742341*.

Favilukis, Jack (2013) "Inequality, stock market participation, and the equity premium," *Journal of Financial Economics*, 107 (3), 740–759.

Feiveson, Laura and John Sabelhaus (2019) "Lifecycle patterns of saving and wealth accumulation."

Gertler, Mark and Peter Karadi (2015) "Monetary policy surprises, credit costs, and economic activity," *American Economic Journal: Macroeconomics*, 7 (1), 44–76.

Glover, Andrew, Jonathan Heathcote, Dirk Krueger, and José-Víctor Ríos-Rull (2020) "Intergenerational redistribution in the great recession," *Journal of Political Economy*, 128 (10), 3730–3778.

Gomme, Paul, B Ravikumar, and Peter Rupert (2011) "The return to capital and the business cycle," *Review of Economic Dynamics*, 14 (2), 262–278.

Gornemann, Nils, Keith Kuester, and Makoto Nakajima (2021) "Doves for the rich, hawks for the poor? Distributional consequences of systematic monetary policy,"Technical report, ECONtribute Discussion Paper.

Greaney, Brian (2020) "The distributional effects of uneven regional growth," *University of Washington, mimeograph.[6]*.

Greenwald, Daniel (2018) "The mortgage credit channel of macroeconomic transmission."

Gruber, Joseph and Robert Martin (2003) "Precautionary Savings and the Wealth Distribution with Illiquid Durables."

Hansen, Gary D (1993) "The cyclical and secular behaviour of the labour input: Comparing efficiency units and hours worked," *Journal of Applied Econometrics*, 8 (1), 71–80.

Hartzmark, Samuel M and David H Solomon (2019) "The dividend disconnect," *The Journal of Finance*, 74 (5), 2153–2199.

Hedlund, Aaron, Fatih Karahan, Kurt Mitman, and Serdar Ozkan (2017) "Monetary policy, heterogeneity, and the housing channel," in *2017 Meeting Papers*, 1610.

Holm, Martin Blomhoff, Pascal Paul, and Andreas Tischbirek (2021) "The transmission of monetary policy under the microscope," *Journal of Political Economy*, 129 (10), 2861–2904.

Hubmer, Joachim, Per Krusell, and Anthony A Smith Jr (2021) "Sources of US wealth inequality: Past, present, and future," *Nber macroeconomics annual*, 35 (1), 391–455.

Iacoviello, Matteo (2005) "House prices, borrowing constraints, and monetary policy in the business cycle," *American economic review*, 95 (3), 739–764.

Jäger, Philipp and Philip Schacht (2023) *The rise and fall of median wealth in the US: A birth-cohort story* (989): Ruhr Economic Papers.

Jappelli, Tullio and Luigi Pistaferri (2010) "The consumption response to income changes," *Annu. Rev. Econ.*, 2 (1), 479–506.

——— (2014) "Fiscal policy and MPC heterogeneity," *American Economic Journal: Macroeconomics*, 6 (4), 107–36.

Johnson, David S, Jonathan A Parker, and Nicholas S Souleles (2006) "Household expenditure and the income tax rebates of 2001," *American Economic Review*, 96 (5), 1589–1610.

Jordà, Òscar, Katharina Knoll, Dmitry Kuvshinov, Moritz Schularick, and Alan M Taylor (2019) "The rate of return on everything, 1870–2015," *The Quarterly Journal of Economics*, 134 (3), 1225–1298.

Kaplan, Greg, Peter Maxted, and Benjamin Moll (2020) "Liquid and Illiquid Assets with Fixed Adjustment Costs," https://benjaminmoll.com/wp-content/uploads/2020/06/liquid_illiquid_numerical.pdf, Accessed: 2022-08-20.

Kaplan, Greg, Benjamin Moll, and Giovanni L Violante (2018) "Monetary policy according to HANK," *American Economic Review*, 108 (3), 697–743.

Kaplan, Greg and Giovanni L Violante (2014a) “A model of the consumption response to fiscal stimulus payments,” *Econometrica*, 82 (4), 1199–1239.

——— (2014b) “A tale of two stimulus payments: 2001 versus 2008,” *American Economic Review*, 104 (5), 116–21.

——— (2020) “The Marginal Propensity to Consume in Heterogeneous Agents Models,”Technical report, Working Paper. Princeton University.

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

Kartashova, Katya and Ben Tomlin (2017) “House prices, consumption and the role of non-Mortgage debt,” *Journal of Banking & Finance*, 83, 121–134.

Kekre, Rohan and Moritz Lenel (2021) “Monetary policy, redistribution, and risk premia,”Technical report, National Bureau of Economic Research.

Keys, Benjamin J, Devin G Pope, and Jaren C Pope (2016) “Failure to refinance,” *Journal of Financial Economics*, 122 (3), 482–499.

Kuhn, Moritz, José-Víctor Ríos-Rull et al. (2016) “2013 Update on the US earnings, income, and wealth distributional facts: A View from Macroeconomics,” *Federal Reserve Bank of Minneapolis Quarterly Review*, 37 (1), 2–73.

Kuhn, Moritz and José-Victor Rios-Rull (2020) “2019 Update on the US Earnings, Income, and Wealth Distributional Facts: A View from Macroeconomics.”

Kuhn, Moritz, Moritz Schularick, and Ulrike I. Steins (2020) “Income and Wealth Inequality in America, 1949–2016,” *Journal of Political Economy*, 128 (9), 3469–3519, 10.1086/708815.

Leombroni, Matteo and Ciaran Rogers (2021) “Household Portfolios, Monetary Policy and Asset Prices,” *Monetary Policy and Asset Prices (November 10, 2021).*

Luetticke, Ralph (2021) “Transmission of monetary policy with heterogeneity in household portfolios,” *American Economic Journal: Macroeconomics*, 13 (2), 1–25.

Maggio, Marco Di, Amir Kermani, and Christopher J Palmer (2020) "How quantitative easing works: Evidence on the refinancing channel," *The Review of Economic Studies*, 87 (3), 1498–1528.

Mertens, Karel and Morten O Ravn (2013) "The dynamic effects of personal and corporate income tax changes in the United States," *American economic review*, 103 (4), 1212–47.

Mian, Atif, Kamalesh Rao, and Amir Sufi (2013) "Household balance sheets, consumption, and the economic slump," *The Quarterly Journal of Economics*, 128 (4), 1687–1726.

Mian, Atif and Amir Sufi (2014) "What explains the 2007–2009 drop in employment?" *Econometrica*, 82 (6), 2197–2223.

Miranda-Agrippino, Silvia and Giovanni Ricco (2021) "The transmission of monetary policy shocks," *American Economic Journal: Macroeconomics*, 13 (3), 74–107.

Monacelli, Tommaso and Roberto Colarieti (2022) "Monetary Policy with Heterogenous Risk."

Paiella, Monica and Luigi Pistaferri (2017) "Decomposing the wealth effect on consumption," *Review of Economics and Statistics*, 99 (4), 710–721.

Paul, Pascal (2020) "The time-varying effect of monetary policy on asset prices," *Review of Economics and Statistics*, 102 (4), 690–704.

Piazzesi, Monika and Martin Schneider (2016) "Housing and macroeconomics," *Handbook of macroeconomics*, 2, 1547–1640.

Piketty, T. (2014) *Capital in the Twenty-First Century*: Cambridge, MA: Belknap.

Plagborg-Møller, Mikkel and Christian K Wolf (2021) "Local projections and VARs estimate the same impulse responses," *Econometrica*, 89 (2), 955–980.

Romer, Christina D and David H Romer (2004) "A new measure of monetary shocks: Derivation and implications," *American Economic Review*, 94 (4), 1055–1084.

Wieland, Johannes F and Mu-Jeung Yang (2020) "Financial dampening," *Journal of Money, Credit and Banking*, 52 (1), 79–113.

Wolff, Edward N and Maury Gittleman (2014) “Inheritances and the distribution of wealth or whatever happened to the great inheritance boom?” *The Journal of economic inequality*, 12, 439–468.

Wong, Arlene (2019) “Refinancing and the transmission of monetary policy to consumption,” *Unpublished manuscript*, 20.

Zhu, Bing, Lingxiao Li, David H Downs, and Steffen Sebastian (2019) “New evidence on housing wealth and consumption channels,” *The Journal of Real Estate Finance and Economics*, 58, 51–79.

Appendix A

Appendix for Chapter 1

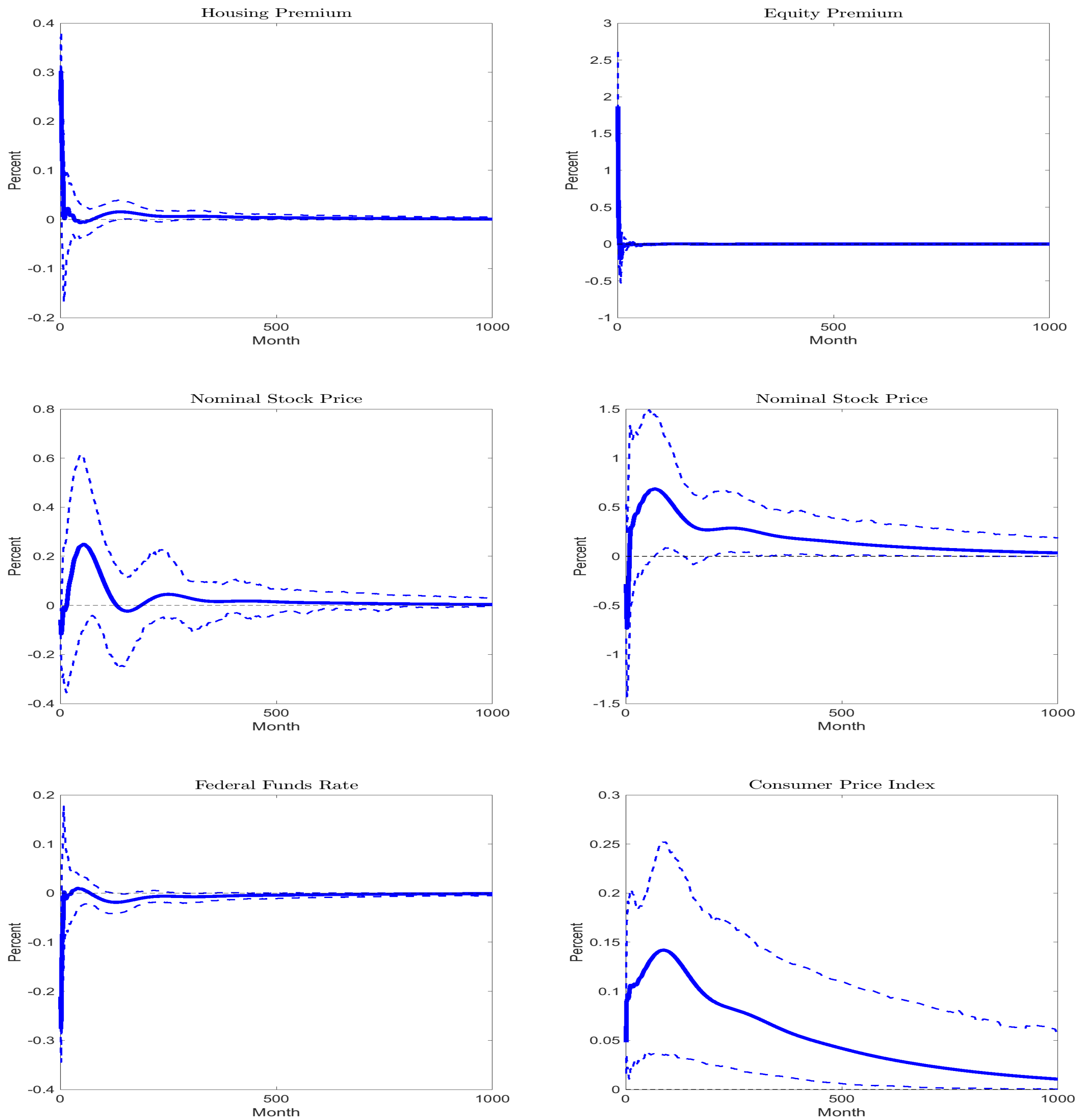
A.1 Robustness to Monetary Policy Shock

A.1.1 Alternate Specifications of SVAR used

The baseline specification in section 1.3.1 uses 7 variables and 7 lags. The *IRFs* for the full horizon of 1000 months ahead is shown in Figure A.1. The choice of the horizon ensures that the *IRFs* are still consistent and the persistence is negligible. The mainstay of my quantitative findings depends on the actual numerical estimates of the present discounted values of the excess premia to housing and equity along with their nominal price changes in Table 1.1. These summarize the conditional impact of the one time shock to a monetary policy surprise for housing and equity.

Robustness to alternate values of the discount factor for the same model with the IRF horizon fixed at 1000 is presented in Table A.1. In general, increasing β leads to higher housing premia and lower equity premia indicating that the changes are more persistent for housing and slower to respond to the shock. This is consistent with the explanation of housing being slower to respond due to its higher degree of illiquidity. Though the values for the nominal prices seem substantially higher, normalized versions are similar. The third row with $\beta = 0.975$ is of significance. Auclert (2019) has two kinds of agents with heterogeneity in discount factor for his structural model. Calibrating to the more impatient agent could tilt the balance of overall gains in favor of housing and will have very different policy implications. On the aggregate, the results will be quantitatively

Figure A.1: *IRFs* for complete horizon of 1000 months ahead for requisite variables for expansionary shock



Note - Derived for a one standard deviation decrease in the monetary policy surprise considered in Gertler and Karadi (2015) for VAR specification in section 1.3.1 which has seven variables and seven lags. The graph for the log of industrial production has not been shown. The first 48 months corresponding to 16 quarters is shown in Figure 1.1. 95 percent confidence bands computed using bootstrapping methods identical to Gertler and Karadi (2015).

Table A.1: Sensitivity of PDV estimates to choice of β.

Present Discounted Value at $t = 0$	Nominal House Price	Housing Premium	Nominal Stock Price	Equity Premium	Nominal House Price	Nominal Equity Price
$\beta = 0.935$	0.26	1.25	0.48	2.63	0.17	0.33
$\beta = 0.965$	2.06	1.23	6.58	2.35	0.67	2.13
$\beta = 0.975$	3.64	1.33	12.39	2.16	0.81	2.76
$\beta = 0.99$	0.80	1.74	38.63	1.37	0.80	3.44

Note - For VAR specification, see section 1.3.1 - $\beta = 0.975$ is the second discount factor used by the structural model in Auclert (2015) besides the benchmark of $\beta = 0.95$ used in the main text. The lag length is fixed at 7. *IRFs* are generated for 1000 months ahead.

stronger since agents with housing tend to have negative *URE* and moderate *NNP*, both of which contribute to higher household *MPC* from the real interest rate and Fisher channels respectively.

Next, I check the sensitivity to choice of lag length in the SVAR specification used in Table A.2. Again, consistent with my explanation for housing being in general slower to respond than equity, I report higher values of housing premia as the lag length reduces. Beyond 9 lags for the 7 variables, the *IRFs* are no longer consistently estimated and tend to diverge as the horizon increases. There is also higher persistence. The overall trend is not very different. The price changes are affected more leading to possibly higher estimates from the Fisher channel. I do not present any results for horizon length. Firstly, even though increasing the number of periods 5 or 10 times hardly makes any difference to the PDVs since the *IRFs* are already converging. Second, for some specifications, this would lead to inconsistent estimation of the *IRFs* at very large horizons.

I analyze alternate specifications of the SVAR in along with different lag lengths. Here I present a subset of my results in Table A.3. I observe that not having all the four variables together leads to higher responses for the stock price and equity premia. However, the changes are less accurate since all the requisite variables are not in the same SVAR. Moreover, there is influence of other variables which are not directly related viz. the excess bond premium. For specification 1, I have a SVAR of 6 variables. The first 4 are the log of consumer price index, log of industrial

Table A.2: PDV estimates using alternate lag lengths for 1000 months ahead

Lag Length used	Nominal House Price (in%)	Housing Premium	Nominal Stock Price (in%)	Equity Premium	Nominal House Price Norm.	Nominal Equity Price Norm.
8	0.74	1.28	3.79	2.34	0.33	1.71
6	0.75	1.29	4.37	2.36	0.30	1.78
4	1.84	1.57	3.81	4.12	0.70	1.45
1	1.65	1.77	2.32	1.41	1.77	2.48

Note - To be compared with results in Table 1.1. Specification used is detailed in 1.3.1. Results with $\beta = 0.95$ and one standard deviation positive monetary policy surprise. Beyond a lag length of 9, the *IRFs* are not consistent and do not converge at the given horizon of 1000 for the given specification.

production, the federal funds rate and the excess bond premium (identical to used in Gertler and Karadi (2015)). The last two are either the asset excess premia or their nominal price changes. For specification 2, I have the SVAR of 5 variables with the four common variables and the last variable can be any of the 4 of interest. For both the cases, I ensure there is little persistence for 1000 months ahead. The *IRFs* are also consistent and do not diverge after a finite horizon. One can envision a specification which involve estimating the 4 requisite variables with the rest of the variables in the specification of Gertler and Karadi (2015). My arguments against this are three fold. First, their motivation was studying credit costs while mine is looking at the conditional impact on asset excess premia & prices, not on their borrowing costs since households do not adjust their portfolios. Secondly, adding extra variables which are not directly expected to be related is counter-intuitive. Thirdly, increasing the number of variables needs shortening of the lag length for consistent *IRFs*. Otherwise, I need to reduce the horizon length drastically which gives PDVs incompatible with the model. Either compromise is not desirable. The effect is more pronounced for housing since the response is slower and more persistent. For all the above robustness checks, the data sources and duration are the same as defined in the main text.

A.1.2 SVAR with exogenous variables and updated data

A recent alternative developed by Paul (2020) to the external instruments SVAR of Gertler and Karadi (2015) is integrating the data for monetary policy surprises directly into the vector

Table A.3: PDV estimates using alternate specifications & lag lengths

Specification and lag length	Nominal House Price (in%)	Housing Premium	Nominal Stock Price (in%)	Equity Premium	Nominal House Price Norm.	Nominal Equity Price Norm.
Alt Spec 1 with 6 lags	1.24	1.26	19.23	4.45	0.48	7.44
Alt Spec 1 with 11 lags	1.25	0.76	17.77	3.63	0.59	8.36
Alt Spec 2 with 5 lags	3.55	1.14	16.44	5.09	2.60	7.06
Alt Spec 2 with 10 lags	6.05	1.17	23.55	3.70	3.45	10.96

Note - For 1000 months ahead using techniques of Gertler and Karadi (2015) - to be compared with results in Table 1.1. The base line specification is explained in 1.3.1. The data is the same. Results with $\beta = 0.95$ and one standard deviation positive monetary policy surprise. Beyond certain lags, *IRFs* no longer consistent as before.

Alt Spec 1 refers to 2 VARs are estimated with the original specification of Gertler and Karadi (2015). For one, commercial spread is replaced with equity premium and mortgage spread is replaced with housing premium. For the second, replace the two by stock price & house price respectively.

Alt Spec 2 refers to a VAR with federal funds rate, consumer price index, industrial production, excess bond premium and a fifth variable. The fifth variable is housing premium, equity premium, nominal house price and nominal stock price.

Table A.4: Present discounted value estimates from VAR based in section A.1.2 using $\beta = 0.95$

Present Discounted Value at $t = 0$	Nominal House Price	Housing Premium	Nominal Stock Price	Equity Premium	Nominal House Price	Nominal Equity Price
Empirical	0.17	1.07	0.77	1.77	3.52	3.71
Normalized (Y/N)	**N (in%)**	Y	**N (in%)**	Y	Y	Y

Note - Monthly data for monetary policy surprises updated till 2017-9. For more details see associated notes in Table 1.1.

autoregressive model as an exogenous variable (VARX). He shows analytically that his approach consistently identifies the true relative impulse responses. This holds even when the surprises contain measurement error that is orthogonal to all other variables. The major advantage is the extension of this constant parameter VARX for estimating a time-varying parameters using standard methods. I restrict my attention for ease of comparison with the constant parameter VARX. I use the same 7 variables used for the specification in section 1.3.1 for monthly frequency. The data is updated till 2017 month 9. Notwithstanding the limitations with the approach as listed in footnote 8, I show the corresponding estimates in Table 1.1 for the same horizon of 1000 months ahead in Table A.4. Aggregate consumption in general equilibrium is 21% higher for a one-time unexpected positive monetary policy surprise of comparable magnitude, of which redistributive effects account for 13%. Among the three redistribution channels, the real interest rate channel accounts for 8% while the Fisher channel accounts for 6%. Asymmetric effects are stronger with a negative surprise producing a 26% smaller decline in aggregate consumption in general equilibrium.

A.1.3 Local Projections

I compare the main quantitative results with the local projection technique that does not rely on an explicit SVAR specified for the underlying data generating process. As mentioned in section 1.1, the biggest drawback is the very short time horizon of less than 100 months ahead for the generated *IRFs*. Since Luetticke (2021) studies similar trends economically for the interested variables, as a comparison I repeat my exercise using his technique and data which I mention briefly here. For more details, see section IV A of his paper. With the exception of the housing premium which is not available at monthly frequency, I follow his definitions and sources at monthly frequency for the main text.

At the aggregate level, to estimate the impact of the monetary policy shock on returns by asset class, Luetticke (2021) requires aggregate quarterly data for stock & house prices, federal funds rate, asset premia along with data on monetary policy shocks. Stock prices is measured by S&P 500. House prices come from the Case-Shiller S&P U.S. National Home Price Index (CSUSHPINSA) divided by the all-items CPI (CPIAUCSL). For the rest, he uses national accounts data provided by the Federal Reserve Bank of St. Louis. The housing premium is measured as the excess realized return on housing. This is composed of the rent-price-ratio, $R_{h,t}$, in t plus the quarterly growth rate of house prices in $t+1$, $\frac{H_{t+1}}{H_t}$, over the nominal rate, R_t^B, (converted to a quarterly rate):

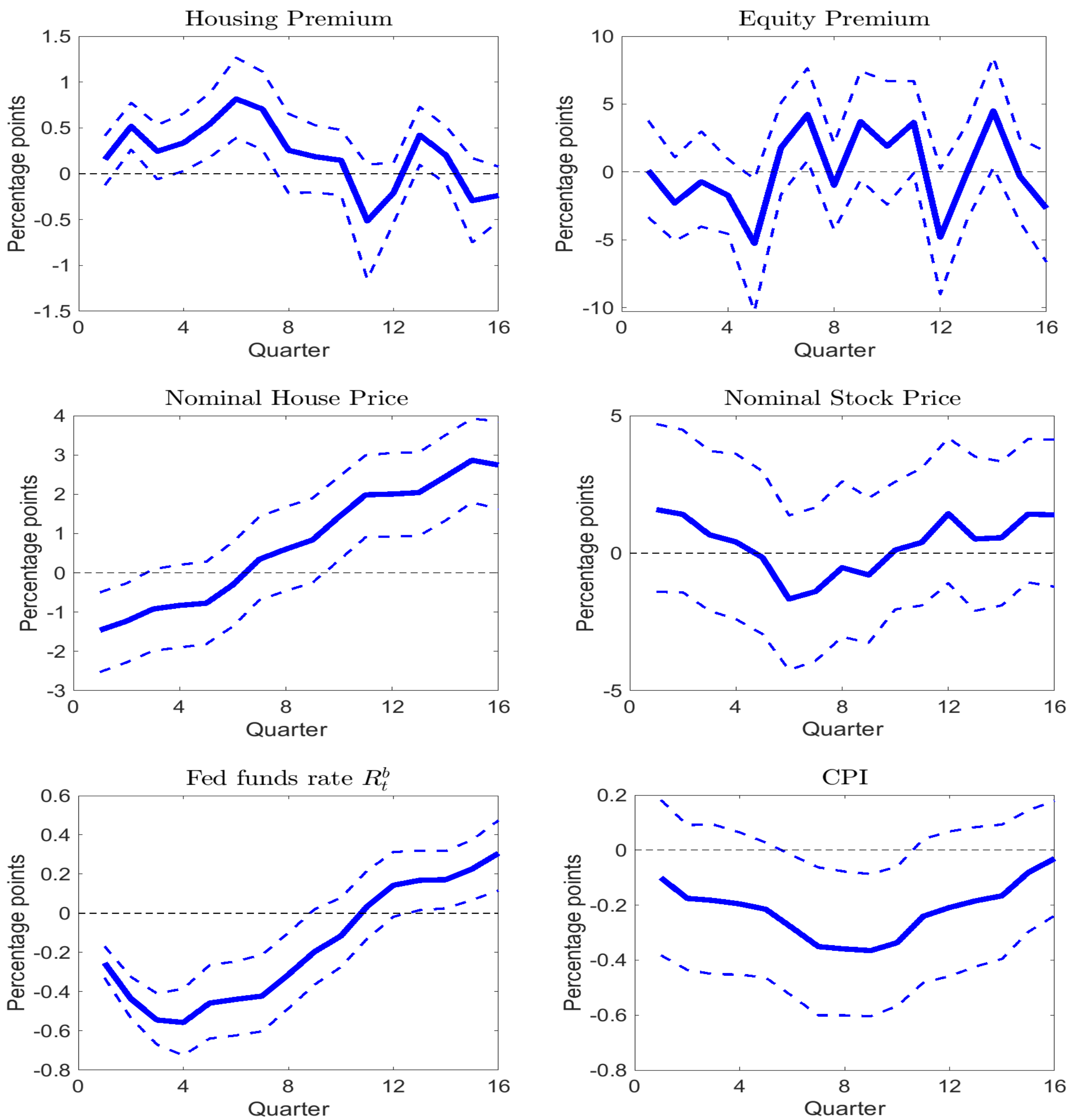
$$LP_t = \frac{R_{h,t}}{H_t} + \frac{H_{t+1}}{H_t} - (1 + R_t^B)^{\frac{1}{4}}$$

Rents are imputed on the basis of the CPI for rents on primary residences paid by all urban consumers (CUSR0000SEHA) fixing the rent-price-ratio in 1983Q1 to 4%. The equity premium is the growth rate of Wilshire 5000 Total Market Full Cap Index (WILL5000INDFC) minus the federal funds rate. Finally, the convenience yield, a measure of liquidity in financial markets, is equal to the Moody's Seasoned Aaa Corporate Bond Yield (AAA) minus 10-Year Treasury Constant Maturity Rate (GS10). He uses monetary shocks identified by Wieland and Yang (2020) that improve on the original shock series by Romer and Romer (2004) for 1983Q1 to 2007Q4. The impulse responses of the endogenous variables Υ at time $t+j$ to monetary shocks, ε_t^R , at time t are estimated using horizon-specific single regressions by local projections, in which the endogenous variable shifted ahead is regressed on the current normalized monetary shock $\overline{\varepsilon}_t^R$ (with standard deviation 1), a constant, time trend, and controls $\mathbf{X_{t-1}}$. These controls are specified as the lagged normalized monetary shock R_{t-1}^B and the log of GDP Y_{t-1} , consumption C_{t-1}, investment I_{t-1}, and of lagged monetary shocks $\varepsilon_{t-1}^R, \varepsilon_{t-2}^R$:

$$\Upsilon_{t+j} = \beta_{j,0} + \beta_{j,1} t + \beta_{j,2} \overline{\varepsilon}_t^R + \beta_{j,3} \mathbf{X}_{t-1} + \nu_{t+j},\ j = 0...15$$

The *IRFs* for the baseline 16 quarters is presented in Figure A.2 for the expansionary shock. The major drawback is the high persistence which impacts the present discounted values substantially since the estimates for 17 quarters and beyond do not have negligible magnitude.

Figure A.2: *IRFs* for equivalent 16 quarters from Luetticke (2021) using local projection method



Note - For a one standard deviation positive monetary policy surprise for the Romer and Romer (2004) shock series. Results to be compared with Figure 1.1. Data range is 1983Q1 to 2007Q4. Bootstrapped 90% confidence bands are shown in the dashed lines (block bootstrap).

Table A.5: Robustness of PDV estimates from local projections

Present Discounted Value at $t = 0$	Nominal House Price (in%)	Housing Premium	Nominal Stock Price (in%)	Equity Premium	Nominal House Price Norm.	Nominal Equity Price Norm.
Luetticke 16 quarters for 1969-2007	4.45	1.14	3.58	-0.31	1.81	1.46
Luetticke 32 quarters for 1969-2007	13.62	1.09	1.19	-2.17	7.11	0.62
Gertler & Karadi 16 quarters for 1990-2012	1.67	0.82	5.01	-1.07	7.26	21.84
BRW Unified 16 quarters for 1994-2015	5.60	1.5249	-33.60	11.12	1.65	-9.88

Note - To be compared with results in Table 1.1. Using local projections technique of Luetticke (2021) with $\beta = 0.95$ for alternate horizons & alternate shock sources. For a one standard deviation positive monetary policy surprise. The estimates for the first row correspond to the *IRFs* in Figure A.2. Monetary policy surprises for the first two rows correspond to Romer and Romer (2004). For the third row it is identical to the one used in this paper. For the fourth row, it uses the estimates in Bu et al. (2021).

Secondly, the inflation seems to decrease for the majority of the time period while the housing premium is larger than the equity premium at $t = 0$. The corresponding PDVs are presented in the first row of Table A.5. The results are counter-intuitive for especially the equity premium. Also, housing tends to respond faster than equity. As an additional sensitivity check, I use alternate measures of monetary policy surprises. A major issue is data availability for the shock and therefore the estimates cannot be widely compared. The motivation for including them is to argue that the robustness checks for the SVAR will produce similar results as the ones in the main text. Using the estimates for local projections could have vastly different quantitative implications and it seems that the SVAR is better suited than a local projection technique for the current question of interest.

However, if I ignore the robustness issues and use the baseline specification of Luetticke (2021) and repeat the exercise with the estimates in the first row of Table A.5, I find that the aggregate results are qualitatively similar. Only the results by asset class are substantially different

Table A.6: σ^* across models for benchmark case with $\sigma = 0.5$ in CE data

Measure	**Shock**	Auclert	Housing + Stock	Housing	Stocks
$\boldsymbol{\sigma^*}$	**Expansionary**	0.36	0.52	0.54	0.30
% Change	**Expansionary**	—	45.55	49.83	-16.08
$\boldsymbol{\sigma^*}$	**Contractionary**	0.36	0.43	0.38	0.32
% Change	**Contractionary**	—	18.60	4.92	-11.66

Note - Using Local projections method of Luetticke (2021) for 16 quarters. First two rows to be compared with first two rows of Table 1.10 while the last two rows are to be compared with first two rows of Table 1.7.

Table A.7: Aggregate consumption for expansionary shock in CE data

Model with estimated *MPCs*	Consumption Response		In corresponding RANK	
	PE	GE	PE	GE
Auclert + House + Stock	0.82	1.26	0.32	0.77
Auclert + House	1.06	1.51	0.32	0.77
Auclert + Stock	0.87	1.33	0.32	0.78
Auclert	0.71	1.17	0.32	0.78

Note - Numbers are in percent with $\sigma = 0.5$ & $\gamma = -0.5$. Using local projections of Luetticke (2021) for 16 quarters. To be compared with Table 1.5. For details on expansionary shock, see notes in Table 1.5.

in keeping with the intuition since the numerical estimates for housing are relatively better to equity, especially for the interest rate channel.

I only present the results for the CE data since this involves changing estimates of *MPCs* which is the quantitatively significant channel. I report that excess sensitivity over a RANK with calibrated *IES* of 0.5 from the real interest rate change reported in Table A.6 declines by roughly 17% as compared to Table 1.10. The general equilibrium consumption response from the first row of Table A.7 is only around 8% higher vs being 15% higher in the main text from Table 1.5.

The asymmetric response is now substantially reduced for the main model with both housing and equity return heterogeneity from the first row of Table A.8. Aggregate consumption would decrease by only around 2% less compared to 12% in general equilibrium in the main text in Table 1.8.

Table A.8: Aggregate consumption for contractionary shock in CE data

Model with estimated *MPCs*	Consumption Response		In corresponding RANK	
	PE	GE	PE	GE
Auclert + House + Stock	0.67	1.15	0.31	0.78
Auclert + House	0.58	1.06	0.31	0.79
Auclert + Stock	0.64	1.10	0.32	0.78
Auclert	0.71	1.17	0.32	0.78

Note - Numbers are in percent with $\sigma = 0.5$ & $\gamma = -0.5$. Using local projections of Luetticke (2021) for 16 quarters. To be compared with Table 1.8. For details on contractionary shock, see notes in Table 1.8.

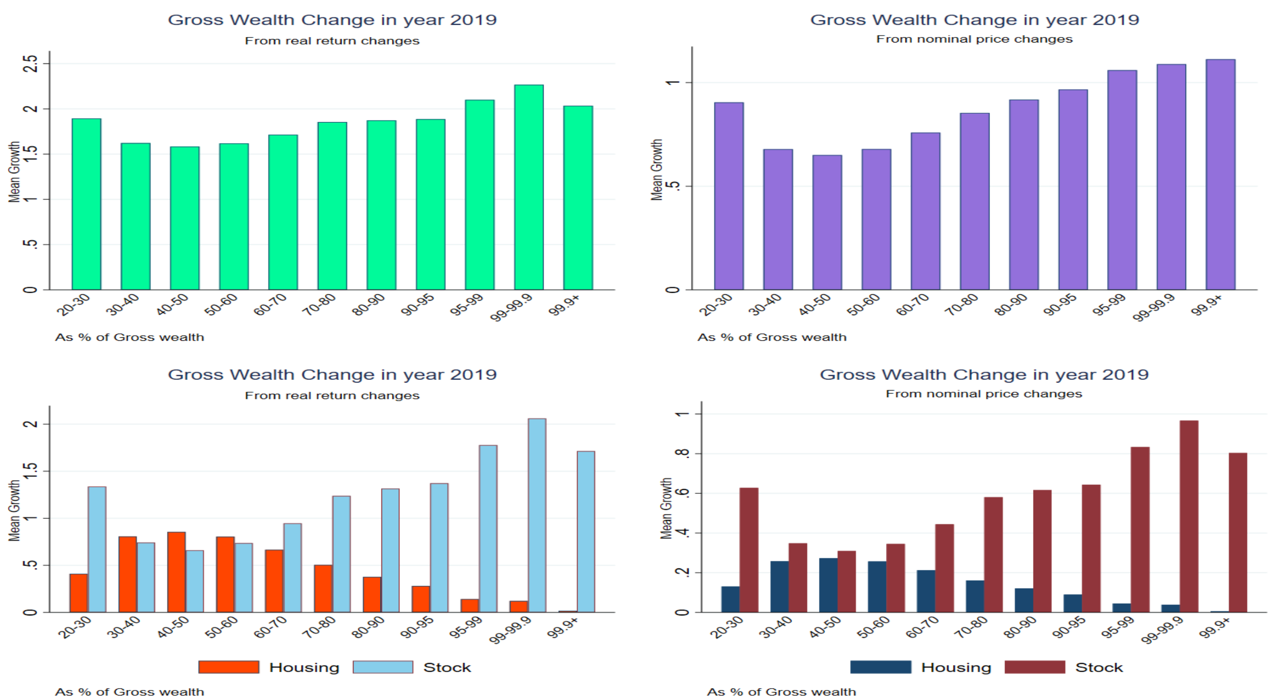
For partial equilibrium, the corresponding numbers are around 6% & 25% respectively. This is true across asset classes. Since housing is responding more relative to equity in this case, the declines in wealth are also more from the increase in the real interest rate. Since agents with majority of housing have higher *MPCs*, they lead to much higher overall consumption decline reducing the magnitude of the asymmetric effect.

A.1.4 Unrealized/Realized wealth changes from SCF data

In this section, I present additional motivating graphs to support my claim that the conditional impact of expansionary monetary policy produces very different impacts across the wealth distribution form the real interest rate and the Fisher channel. It is also not a one off effect in only the interested year of 2001. From Figure A.3, it is clear that even with the latest data, the motivation holds true. Intuitively, since households have different portfolio asset shares, the instantaneous changes reflect the heterogeneity of across class asset holdings. [1] For comparison, I depict the survey reported numbers for realized and unrealized capital gains/losses from the SCF data for the two years 2001 and 2019 in Figure A.4. I also break them down by housing and equity. These are however not the conditional instantaneous impacts for the transitory monetary policy surprise

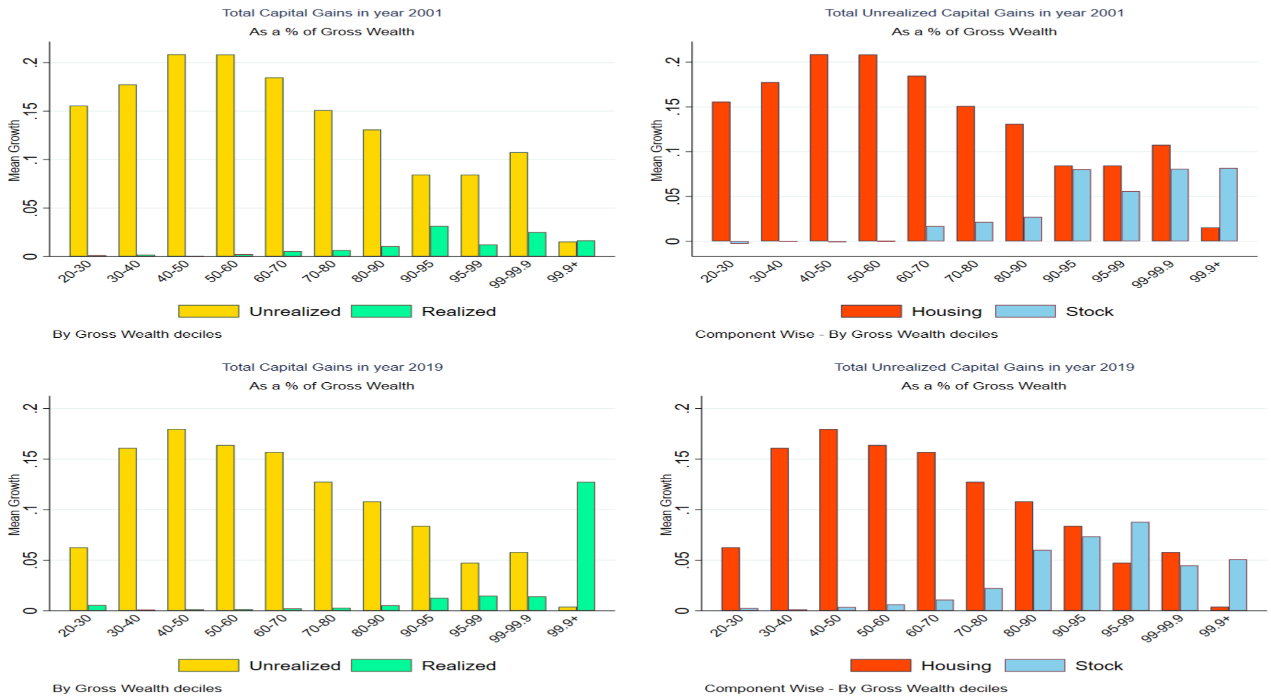
[1] In reality, the returns on debt is different from asset for both housing and equity. Getting similar conditional estimates to reflect within asset class portfolio heterogeneity separately at the aggregate level is hard.

Figure A.3: Estimated Unrealized wealth changes from SCF 2019



Note - From the interest rate & Fisher channels. For more details, see notes in Figure 1.2 and Figure 1.3.

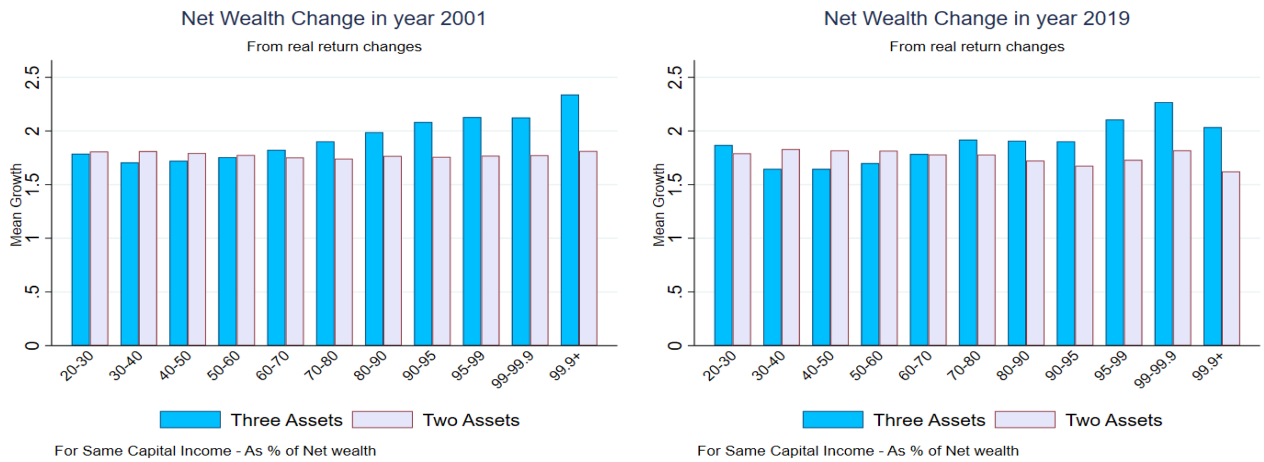
Figure A.4: Survey reported unrealized & realized wealth changes



Note - For the total wealth change and component wise from SCF 2001 & 2019 using the reported numbers in the data. The drawback is that these changes cannot account for the instantaneous monetary policy shock.

and therefore not directly comparable. The motivation behind including them is to show that even under the unconditional setup where ex-ante returns on housing and equity are equal to the liquid asset as in the benchmark results, there is substantial differences across the gross wealth quantiles. It is not uniformly 1 across quantiles. Lastly, the literature on structural modeling has so far treated housing and equity as the same illiquid asset with both earning the same conditional return and experiencing the same price change ex-post the monetary policy surprise. For a concrete example, I refer to the 2 - asset canonical HANK model of Kaplan et al. (2018) who consider only the real interest rate channel. Even then the estimated conditional impacts ex-post are very different for some quantiles, especially for those towards the top of the net wealth distribution as evidenced by Figure A.5. To get the quantitative impact on the aggregate *MPCs* more accurately, we need two separate illiquid assets. There remains significant theoretical and computational hurdles in developing such a model and proves to be exciting for future work.

Figure A.5: Estimated Unrealized wealth changes from SCF data



Note - Three assets are the liquid asset, housing and equity. Two assets are liquid asset and a combined illiquid asset. The return on the latter is the same as the return from the representative portfolio of housing and equity held in equal amounts. The aim is to show that assuming housing and equity to be a single illiquid asset as in Kaplan et al. (2018) leads to underestimation of the gains from the real interest rate channel. See notes in Figure 1.2 for more details.

A.2 Proofs of Results & Theoretical Model Extensions

The experiment presented in section 1.4.2 is essentially listing the changes that occur in the standard representative-agent New Keynesian model following the one-period change in monetary policy. As mentioned in section 1.4.1, the general and flexible approach to representing complex household balance sheets in terms of consolidated nominal claims $\left({}_{-1}B_t\right)$ & real claims $\left({}_{-1}b_t\right)$ at the beginning of each period allows me to extend sufficient statistics to incorporate ex-post returns heterogeneity.

In section A.2.1, I first present the mathematical expressions for arriving at equations (1.4) & (1.5) which lead to the main theoretical result for measuring aggregate consumption in (1.6). I restrict myself to only the principal points of departure in the context of my theoretical framework in section 1.4. Next, I show that the results hold with the addition of durable goods as a percentage of varying expenditure of household consumption in section A.2.2. Finally, I show that these results can also be extended to encompass mafrket incompleteness in section A.2.3. For the complete step by step derivation, see Auclert (2019) appendices A.2 - A.8 for more details. I keep the notation as consistent as possible. Any explicit departures are explained.

A.2.1 Deriving *NURE* and *NNP* for the perfect foresight model

As laid out in section 1.4.2, to incorporate the conditional impact of monetary policy on housing and equity through the differential asset returns. I treat the liquid asset as the benchmark and normalize the corresponding changes in the other two asset classes. Mathematically, the differences to the real interest rate and Fisher channels relevant for household measures of exposures can be captured by the values of $\{\theta_i\}_{i=1}^4$ & $\{\Theta_j\}_{j=1}^2$. Setting all of them to be 1 gives back the original results which acts as the benchmark. As stated in the main text, there is no change in the conditional impact of the idiosyncratic earnings post the transitory monetary policy surprise across asset classes by assumption. They can be incorporated theoretically under this modified setup in a similar manner. Measuring the corresponding estimates are much harder. I therefore focus on only the household exposures summarizing the real interest rate channel which is defined as the *URE* and the one for the Fisher channel which is defined as the *NNP*.

The setup is described mathematically in section 1.4.1. Normalizing $q_{\ell,1} = q_1 = 1$ and letting $q_{\ell,0} = q_0$ vary for the liquid asset as

$$\frac{dq_{\ell,0}}{q_{\ell,0}} = \frac{dq_0}{q_0} = \frac{dR}{R} = \frac{dR_\ell}{R_\ell} \tag{A.2.1}$$

Then at time $t = 0$ when the one time shock is realized, only the values of y_0, w_0 & q_0 vary with the sequence in prices $\{P_{\ell,t} = P_t\}$. Equation (A.2.1) shows that a rise in the relative price of future goods from the positive monetary policy surprise relative to a current good is the same as a fall in the price of that current good relative to all future goods.The corresponding variations for housing and equity are normalized and given by the relations in section 1.4.2. The expenditure function is defined as

$$e(q_0, w_0, \mathcal{U}) = \min \left\{ \sum_t q_t(c_t - w_t n_t) \quad \text{s.t.} \quad \sum_t \beta_t \{u(c_t) - v(n_t)\} \geq \mathcal{U} \right\} \tag{A.2.2}$$

The compensated demands for time 0 consumption and hours are c_0^h & n_0^h. The version of Shepherd's lemma relevant for the proof are

$$e_{q_0} = c_0 - w_0 n_0$$

$$e_{w_0} = -q_0 n_0$$

Ex-ante, the composition of household balance sheets do not matter as reflected by (A.2.3). Ex-post the shock at $t = 0$, the conditional impacts on the prices and returns lead to the following definition of unearned wealth from the variation as in (A.2.4)

$$\begin{aligned}\widetilde{\omega} &\equiv \sum_{t\geq 0} q_t \left(y_t + ({}_{-1}b_t) + \left(\frac{{}_{-1}B_t}{P_t}\right)\right) \\ &= \sum_{t\geq 0} q_t \left(y_t + ({}_{-1}h_t) + \left(\frac{{}_{-1}H_t}{P_t}\right) + ({}_{-1}s_t) + \left(\frac{{}_{-1}S_t}{P_t}\right) + ({}_{-1}\ell_t) + \left(\frac{{}_{-1}L_t}{P_t}\right)\right) \end{aligned} \tag{A.2.3}$$

$$\begin{aligned} d\widetilde{\omega} \;=\; & \left(y_t + ({}_{-1}\ell_0) + \left(\frac{{}_{-1}L_0}{P_0}\right)\right) dq_{L,0} + \left(({}_{-1}h_0) + \left(\frac{{}_{-1}H_0}{P_0}\right)\right) dq_{H,0} + \left(({}_{-1}s_0) + \left(\frac{{}_{-1}S_0}{P_0}\right)\right) dq_{S,0} \\ & + q_0 dy_0 - \sum_{t\geq 0} q_t \left(\frac{{}_{-1}L_t}{P_t}\right)\frac{dP_{L,t}}{P_{L,t}} - \sum_{t\geq 0} q_t \left(\frac{{}_{-1}H_t}{P_t}\right)\frac{dP_{H,t}}{P_{H,t}} - \sum_{t\geq 0} q_t \left(\frac{{}_{-1}S_t}{P_t}\right)\frac{dP_{S,t}}{P_{S,t}} \end{aligned} \tag{A.2.4}$$

Using the normalized relations defined previously and simplifying everything in terms of the change in the benchmark liquid asset.

$$\begin{aligned} d\widetilde{\omega} \;=\; & \left(y_0 + ({}_{-1}\ell_0) + \left(\frac{{}_{-1}L_0}{P_0}\right)\right) dq_{L,0} \\ & + \left(({}_{-1}h_0) + \left(\frac{{}_{-1}H_0}{P_0}\right)\right) \Theta_1\theta_1 q_{L,0}\frac{dq_{L,0}}{q_{L,0}} + \left(({}_{-1}s_0) + \left(\frac{{}_{-1}S_0}{P_0}\right)\right) \Theta_2\theta_2 q_{L,0}\frac{dq_{L,0}}{q_{L,0}} \\ & + q_0 dy_0 - \sum_{t\geq 0} q_t \left(\frac{{}_{-1}L_t}{P_t}\right)\frac{dP_{L,t}}{P_{L,t}} \\ & - \sum_{t\geq 0} q_t \left(\frac{{}_{-1}H_t}{P_t}\right)\theta_3\frac{dP_{L,t}}{P_{L,t}} - \sum_{t\geq 0} q_t \left(\frac{{}_{-1}S_t}{P_t}\right)\theta_4\frac{dP_{L,t}}{P_{L,t}} \end{aligned} \tag{A.2.5}$$

Using the Fisher Equation $\frac{q_t}{P_t} = \frac{Q_t}{P_0}$ and the fact that $\frac{dP_t}{P_t} = \frac{dP}{P}$ is a constant I rewrite $d\widetilde{\omega}$ from (A.2.5) in terms of the household exposures conditioned on the shock.

$$\begin{aligned} d\widetilde{\omega} \;=\; & \left\{ y_0 + ({}_{-1}\ell_0) + \left(\frac{{}_{-1}L_0}{P_0}\right) + \Theta_1\theta_1\left[({}_{-1}h_0) + \left(\frac{{}_{-1}H_0}{P_0}\right)\right] + \Theta_2\theta_2\left[({}_{-1}s_0) + \left(\frac{{}_{-1}S_0}{P_0}\right)\right]\right\} dq_0 \\ & + q_0 dy_0 - \sum_{t\geq 0} q_t \left\{\left(\frac{{}_{-1}L_t}{P_t}\right) + \theta_3\left(\frac{{}_{-1}H_t}{P_t}\right) + \theta_4\left(\frac{{}_{-1}S_t}{P_t}\right)\right\}\frac{dP_t}{P_t} \end{aligned} \tag{A.2.6}$$

The consumer's net nominal position NNP can be defined as the present value of the nominal assets. It summarizes the relevant measure of the household's balance sheet to the nominal price changes from the Fisher channel. The consumer's unhedged interest rate exposure URE can be defined as the difference between all maturing assets and liabilities at a point of time. Analogously, it summarizes the relevant measure of household's balance sheet to the nominal price changes from the real interest rate channel. Conditioned on the transitory unexpected shock, they can be defined as

$$\begin{aligned} NNP &= \sum_{t\geq 0} q_t \left\{ \left(\frac{{}_{-1}L_t}{P_t} \right) + \theta_3 \left(\frac{{}_{-1}H_t}{P_t} \right) + \theta_4 \left(\frac{{}_{-1}S_t}{P_t} \right) \right\} \\ &\equiv \sum_{t\geq 0} Q_t \left\{ \left(\frac{{}_{-1}L_t}{P_0} \right) + \theta_3 \left(\frac{{}_{-1}H_t}{P_0} \right) + \theta_4 \left(\frac{{}_{-1}S_t}{P_0} \right) \right\} \end{aligned} \tag{A.2.7}$$

$$\begin{aligned} URE_0 \equiv & \left\{ \omega_0 n_0 + y_0 + ({}_{-1}\ell_0) + \left(\frac{{}_{-1}L_0}{P_0} \right) \right. \\ & \left. + \Theta_1\theta_1 \left[({}_{-1}h_0) + \left(\frac{{}_{-1}H_0}{P_0} \right) \right] + \Theta_2\theta_2 \left[({}_{-1}s_0) + \left(\frac{{}_{-1}S_0}{P_0} \right) \right] - c_0 \right\} \end{aligned} \tag{A.2.8}$$

Equation (A.2.7) for NNP uses Fisher equation for equivalence with (1.4). Equation (A.2.8) is the URE at time $t = 0$ for equation (1.5) which is defined for any time period. Equation (A.2.6) now can be rewritten as identical to (A.10) in Auclert (2019).

$$d\widetilde{\omega} = (URE + c_0 - w_0 n_0)\, dq_0 + q_0 dy_0 - q_0 NNP \frac{dP}{P} \tag{A.2.9}$$

The corresponding indirect utility function that attains the new $\widetilde{\omega}$ using equation (A.2.2) is also identical to (A.11)

$$V(q_0, w_0, \widetilde{\omega}) = \max \left\{ \sum_t \beta_t \{u(c_t) - v(n_t)\} \quad \text{s.t.} \quad \sum_t q_t (c_t - w_t n_t) = \widetilde{\omega} \right\} \tag{A.2.10}$$

Using the definitions of Shepherd's Lemma with the resulting Marshallian demands, Slutsky's theorems can be applied. After following the steps for aggregation, the final result is given by (1.6) which also holds for persistent changes in the real interest rate with the constant changes being replaced with their time subscripts. Since the transitory monetary policy shock actually produces persistent changes in the real interest rate, the framework can be used to emprically estimate the per period consumption response form each period conditional impacts to the returns and prices instead of using the constant PDVs for the one time instantaneous response. See appendix A.1.3

for one example. I leave it to discretion in selecting the horizon of the consumption IRF cognizant of the assumption that households cannot adjust their portfolios of asset holdings for any of the three assets. The setup is also flexible to alternate utility functions as well as aggregate uncertainty.

A.2.2 Presence of Durable Goods

Keeping the setup identical to A.5, I look at the wealth changes arising from incorporating durable goods in the framework. The consumer durables expenditure does not affect the balance sheet at time $t = 0$ since it is given. Since consumers do not adjust their balance sheets at for the instantaneous response to the shock, durable expenditures theoretically have no bearing on ex-post asset holdings. Empirically, they only alter how consumption will be measured at the household level. Ex-ante, balance sheets and durables expenditure can be correlated but that does not affect my exercise either theoretically or empirically since the starting point is taking the balance sheets at $t = 0$ as given. Before the shock, the composition of balance sheets does not matter.

By expanding the household wealth into the three assets held, let Ω be defined as

$$\Omega \equiv \sum_{t\geq 0} q_t \left\{Y_t + \left({}_{-1}\ell_t\right) + \left({}_{-1}h_t\right) + \left({}_{-1}s_t\right) - C_t - p_t I_t\right\} \tag{A.2.11}$$

where p_t is the price of durables relative to nondurables. The exogenous variation in the benchmark liquid asset for $dR,\ dP\ \&\ dY$ in (A.2.11) produces the change in net wealth as

$$\begin{aligned} d\Omega &= dY - IdP - \sum_{t\geq 0} dq_t \left\{Y_t + \left({}_{-1}\ell_t\right)\frac{dR_\ell}{R_\ell} + \left({}_{-1}h_t\right)\frac{dR_H}{R_H} + \left({}_{-1}s_t\right)\frac{dR_S}{R_S} - C_t - p_t I_t\right\} \\ &= dY - IdP - \sum_{t\geq 0} q_t \left\{Y_t + \left({}_{-1}\ell_t\right) + \left({}_{-1}h_t\right)\theta_1 + \left({}_{-1}s_t\right)\theta_2 - C_t - p_t I_t\right\}\frac{dR}{R} \\ &= dY - pI_0\frac{dp}{p} + \left(\underbrace{Y_0 + \left({}_{-1}\ell_0\right) + \left({}_{-1}h_0\right)\Theta_1\theta_1 + \left({}_{-1}s_0\right)\Theta_2\theta_2 - C_0 - p_0 I_0}_{URE}\right)\frac{dR}{R} \end{aligned} \tag{A.2.12}$$

In (A.2.12), C_0 is specifically consumption of nondurables while $p_0 I_0$ is the consumption of durables. Total consumption is the sum of durables and non durables. (A.2.12) assumes that the relative price of durables to nondurables do not change post the transitory unexpected monetary shock. Since ex-post price of housing is different from the aggregate change in the CPI following section 1.4.2, accommodative monetary policy in my setup causes additional capital wealth loss from the increase in the relative price of durables. While the changes for the nondurables and housing services are not equivalent in terms of utility in general, these two effects could be consolidated into a single one, we can restrict ourselves to variations that feature a constant elasticity of the durable-good price to the nondurable real interest rate

$$\epsilon_{pR} \equiv -\frac{\partial p}{p}\frac{R}{\partial R}$$

which leads to the general definition of URE from (A.2.12)

$$d\Omega = dY + \Bigg(\underbrace{Y_0 + \left({}_{-1}\ell_0\right) + \left({}_{-1}h_0\right)\Theta_1\theta_1 + \left({}_{-1}s_0\right)\Theta_2\theta_2 - C_0 - p_0 I_0 \left(1 - \epsilon_{pR}\right)}_{URE^{\epsilon}} \Bigg) \frac{dR}{R} \tag{A.2.13}$$

Empirically, as in section 1.5, URE is measured with consumption being total sum of durables and nondurables with the benchmark case of $\epsilon_{pR} = 0$. The rest of the derivation and results follow identically consistent with the definition of URE in (A.2.12) & (A.2.13).

A.2.3 Incomplete Markets

The environment for the extension to incomplete markets is identical to section I.C of Auclert (2019). The consumer faces idiosyncratic income uncertainty and restrictions on the number of assets traded. The consumer faces an idiosyncratic process for real wages $\{w_t\}$ and unearned income $\{y_t\}$. The choice variables are consumption c_t and labor supply n_t to maximize the expected utility function. As in the perfect foresight model, the horizon need not be specified.

$$\mathbb{E}\left[\sum_t \beta^t \left\{u(c_t) - v(n_t)\right\}\right]$$

Market incompleteness is modeled in a general form. Ex-ante as in the complete markets setup, the composition of the balance sheets does not matter. Only the measures of household exposures unconditionally are pinned down exactly before the one time unexpected monetary policy surprise at $t = 0$. To consider the changes in consumption from the changes in the current unearned income dy, current real wage dw and the real interest rate dR.

I keep the assumption that this variation in asset prices adjusting to reflect the change in discounting alone given here by (A.2.14) for $j = 1, , ..., N^x$ for any of the N^x, $\forall\, x = \{\ell, H, S\}$ assets that can be considered belonging to the class of assets for liquid, housing and equity.

$$dQ^x/Q^x = dS^x_j/S^x_j = -dR^x/R^x \;\; \forall \;\; x = \{\ell, H, S\} \tag{A.2.14}$$

$$dQ^\ell/Q^\ell = dQ/Q = dS_j/S_j = -dR/R = -dR^\ell/R^\ell = dS^\ell_j/S^\ell_j \tag{A.2.15}$$

$$dS^H_j/S^H_j = -dR^H/R^H = -\theta_1 dR/R \;\;\&\;\; dS^S_j/S^S_j = -dR^S/R^S = -\theta_2 dR/R \tag{A.2.16}$$

$$dP_H/P_H = \theta_3 dP_\ell/P_\ell \;\;\&\;\; dP_S/P_S = \theta_4 dP/P \;\; \text{with} \;\; dP_\ell/P_\ell = dP/P = d\Pi/\Pi \tag{A.2.17}$$

$$Q_H = \Theta_3 Q_\ell = \Theta_3 Q \;\;\&\;\; Q_S = \Theta_4 Q_\ell = \Theta_3 Q \tag{A.2.18}$$

Specifically (A.2.15) refers to the benchmark change for the liquid asset while (A.2.16) - (A.2.18) refers to the normalized relations for housing and equity analogous to section 1.4.2 conditioned on the transitory monetary policy surprise. Additionally, if $MPC = \partial c/\partial y$ and both the marginal propensities to work and save are similarly defined as responses to current income transfers then the final aggregate consumption can be represented in terms of the sufficient statistics by (1.6). My interest in this context is to ensure that amended definitions of household exposures to real interest rate and the Fisher channels to account for the conditional impact in the presence of market incompleteness remain consistent.

The aim is to show that equations (A.53) & (A.54) have to continue to hold analogous to equations (A.19) & (A.20) in the perfect foresight model (as proved in section A.2.1). There are two cases required to be proved separately. In the first case, the consumer is at the binding borrowing limit and spends all income or the consumer is hand-to-mouth. Here, the solution is on the boundary. In the second case, the consumer problem has an interior solution. Two sub cases are to be proved for the second case.

Case I. Binding borrowing limit and hand-to-mouth consumers.

The problem is a static choice between c and n. For ease of comparison, I restate some of the definitions. Q is the nominal price, δ is the nominal bonds holding while λ is the real bonds holding. θ denotes portfolio shares, $\mathbf{d}$ are real dividends while $\mathbf{S}$ denote the real prices. Z is the measure of net wealth of the consumer. The consumption of the agent at the borrowing limit or being hand-to-mouth is given by

$$c = wn + Z \quad \text{where} \;\; Z = z + (1+Q\delta)\frac{\lambda}{\Pi} + \theta\cdot(\mathbf{d}+\mathbf{S}) + \frac{\overline{D}}{R} \tag{A.2.19}$$

Using $d\mathbf{S} = -\frac{S}{R}dR, dQ = -\frac{Q}{R}dR$ and $d(\frac{1}{\Pi}) = -\frac{1}{\Pi^2}d\Pi = -\frac{1}{\Pi}\frac{dP}{P}$ along with relations (A.2.15) - (A.2.18), if the agent is at the borrowing limit then splitting the household balance sheets by asset class.

$$\begin{aligned} Z &= z + (1 + Q_\ell S_\ell + Q_H\delta_H + Q_S\delta_S)\left(\frac{\lambda_\ell+\lambda_H+\lambda_S}{\Pi}\right) + \theta(\mathbf{d}+S_\ell+S_H+S_S) + \frac{\overline{D}}{R} \\ \implies \quad dZ &= dz \;\; + \;\; \text{Price Effect} \;\; + \;\; \text{Real Interest Rate Effect} \end{aligned} \tag{A.2.20}$$

The price effect in (A.2.20) for the Fisher channel is derived as

$$\begin{aligned} \text{Price Effect} &= -\left(1 + Q_\ell\delta_\ell\frac{dP_\ell}{P_\ell} + +Q_H\delta_H\frac{dP_H}{P_H} + Q_S\delta_S\frac{dP_S}{P_S}\right)\frac{\lambda}{\Pi} \\ &= -\frac{\lambda}{\Pi}\left\{1 + (\delta_\ell + \theta_3\Theta_3\delta_H + \theta_4\Theta_4\delta_S)\right\}\frac{dP}{P} \\ &= -\underbrace{\frac{\lambda}{\Pi}(1+\delta_{m_1}Q)}_{\text{NNP}}\frac{dP}{P} \end{aligned} \tag{A.2.21}$$

The real interest rate effect in (A.2.20) for the rela interest rate channel is derived as

$$\begin{aligned} \text{Price Effect} &= \frac{\left(\lambda_\ell\frac{dR_\ell}{R_\ell} + \lambda_H\frac{dR_H}{R_H} + \lambda_S\frac{dR_S}{R_S}\right)}{\Pi}Q\delta \\ &\quad + \frac{\lambda}{\Pi}\left(Q_\ell\delta_\ell\frac{dR_\ell}{R_\ell} + Q_H\delta_H\frac{dR_H}{R_H} + Q_S\delta_S\frac{dR_S}{R_S}\right) + \theta\cdot\mathbf{S} - \frac{\overline{D}}{R} \\ &= \left(Q\delta\frac{(\lambda_\ell + \lambda_H\theta_1 + \lambda_S\theta_2)}{\Pi} + \frac{\lambda}{\Pi}(\delta_\ell + \theta_1\Theta_3\delta_H + \theta_2\Theta_4\delta_S)\,\theta\cdot\mathbf{S} - \frac{\overline{D}}{R}\right)\left(-\frac{dR}{R}\right) \\ &= \underbrace{\left(\lambda_m\delta\frac{Q}{\Pi} + \delta_{m_2}\lambda\frac{Q}{\Pi} + \theta\cdot\mathbf{S} + \frac{\overline{D}}{R}\right)}_{-\text{URE}}\left(-\frac{dR}{R}\right) \end{aligned} \tag{A.2.22}$$

Using (A.2.21) & (A.2.22), the variation in income given by (A.2.20) is given by

$$dZ = dz - \underbrace{\frac{\lambda}{\Pi}\left(1+\delta_{m_1}Q\right)}_{\text{NNP}}\frac{dP}{P} + \underbrace{\left(\lambda_m\delta\frac{Q}{\Pi} + \delta_{m_2}\lambda\frac{Q}{\Pi} + \theta\cdot\mathbf{S} + \frac{\overline{D}}{R}\right)}_{-\text{URE}}\left(-\frac{dR}{R}\right) \tag{A.2.23}$$

If the agent is hand-to-mouth, then (A.2.23) still applies for (A.2.24) as the consumer is still making a static choice for consumption and labor supplied given the budget constraint in (A.2.19) and $MPS = 0$. The rest of the steps are identical.

$$dZ = dz \quad \& \;\; NNP = URE = 0 \tag{A.2.24}$$

Case II. a) Interior solution with $N = 0$, all variables changing

The derivation till equation (A.65) is identical. The borrowing constraint is not binding and the value function is concave at the interior optimum. For this case, the updated notation to show that (1.6) still holds is given by the mapping

$$q \equiv Q, \;\; z \equiv y + \frac{\lambda}{\Pi}, \;\; a = \lambda', \;\; b_1 = \delta_{m_1}\frac{\lambda}{\Pi}, \;\; b_2 = \delta_{m_2}\frac{\lambda}{\Pi}$$

Using the benchmark relation for the liquid asset $\frac{dP}{P} = \frac{d\Pi}{\Pi}$ and $\frac{dQ}{Q} = -\frac{dR}{R}$ gives

$$dz = dy - \frac{\lambda}{\Pi}\frac{dP}{P}, \;\; db_1 = -\delta_{m_1}\frac{\lambda}{\Pi}\frac{dP}{P}, \;\; db_2 = -\delta_{m_2}\frac{\lambda}{\Pi}\frac{dP}{P} \;\text{ and }\; \frac{dq}{q} = -\frac{dR}{R}$$

Then, the variation in the net wealth change from the two channels is given by

$$\begin{aligned} dz + qdb_1 - (a-b_2)dq &= dy - \frac{\lambda}{\Pi}\frac{dP}{P} - q\delta_{m_1}\frac{\lambda}{\Pi}\frac{dP}{P} - \left(\lambda' - \delta_{m_2}\frac{\lambda}{\Pi}\right)dQ \\ &= dy - \underbrace{\frac{\lambda}{\Pi}\left(1+\delta_{m_1}Q\right)\frac{\lambda}{\Pi}}_{\text{NNP}}\frac{dP}{P} + \underbrace{\left(\lambda' - \delta_{m_2}\frac{\lambda}{\Pi}\right)Q}_{\text{URE}}\frac{dR}{R} \end{aligned} \tag{A.2.25}$$

(A.2.25) is essentially of the form of (A.2.23) where the borrowing limit does not bind and can be directly used to derive the result form (A.63) & (A.65).

Case II. b) For $N > 0$, only interest rate changing and no bonds

For this case, there is no change in the wages and all the change in consumption come from the balance sheet changes. The result for the final consumption change of the form in (1.6) is proved by considering the following Lemma structured analogously to Lemma A.2.

Lemma: *Let (θ, Y, R, Θ) be the solution to the following consumer choice problem under concave preferences over current consumption $u(c)$ and initial balance sheet holdings $W(\theta')$*

$$\max_{c,\theta'} \quad u(c) + W(\theta') \;\; s.t. \;\; c + (\theta' - \theta)\Theta\mathbf{S} = Y + \theta\mathbf{d} \;\; \text{where} \;\; \frac{dS}{dR} = -\frac{\mathbf{S}}{R},$$

$$(\theta' - \theta)\Theta\mathbf{S} = \sum_j s_j(\theta^j - \theta'^j)\theta_j, \quad \theta_j \in \{\theta_\ell = 1, \theta_H = \theta_1, \theta_S = \theta_2\}$$

$$\underline{\text{Then, to the first order}}, \quad dc = MPC\left(dY + URE\frac{dR}{R}\right) - \sigma(c)c(1 - MPC)\frac{dR}{R}$$

$$\textit{where} \;\; \sigma(c) \equiv -\frac{u'(c)}{cu''(c)} \;\; \textit{is the local IES} \;\&\; MPC = \frac{\partial c}{\partial Y} \;\; \textit{and} \;\; URE = Y + \theta\mathbf{d} - c$$

The first order conditions characterizing the solution are given by

$$S^i u'(Y + \theta\mathbf{d} - (\theta' - \theta)\Theta\mathbf{S}) = W_{\theta^i}(\theta') \;\; \forall\, i = 1, 2, ..., N \tag{A.2.26}$$

First considering the increase in income alone and differentiating along (A.2.26) gives

$$S^i u''(c)\left(1 - \sum_j \underbrace{S^j \theta_j \frac{d\theta'^j}{dY}}_{\eta^j}\right) = \sum_j W_{\theta^i\theta^j}(\theta')\frac{d\theta'^j}{dY} \;\; \forall\, i \implies \sum_j \left(\frac{1}{S^i S^j} W_{\theta^i\theta^j}(\theta') + u''(c)\right)\eta^j = u''(c) \tag{A.2.27}$$

Defining matrix M with elements m_{ij}, the system can be represented in matrix form as

$$m_{ij} \equiv \frac{1}{S^i S^j} W_{\theta^i\theta^j}(\theta') + u''(c) \implies M\eta = u''(c)\mathbf{1} \implies \eta = u''(c)M^{-1}\mathbf{1}$$

$$\text{where} \;\; \sum \eta^j = \sum S^i \theta_j \frac{d\theta'^j}{dY} = \frac{d}{dY}\sum S^j(\theta^j - \theta'^j)\theta_j$$

which now leads to identical equations (A.68) and (A.69) as follows

$$MPC = \frac{dc}{dY} = 1 - \sum_j \eta^j = 1 - u''(c)m \tag{A.2.28}$$

$$\text{where } m \text{ is defined as } \; m \equiv \mathbf{1}M^{-1}\mathbf{1} \tag{A.2.29}$$

Considering a change in the real interest rate by dR. Differentiating along (A.2.26) by separately considering the three asset classes in the the household balance sheet.

$$\frac{dS^i}{dR}u'(c){+}S^i u''(c)\left\{-\sum_j S^j\frac{d\theta'^j}{dR} - \frac{dS^\ell}{dR^\ell}(\theta'^\ell - \theta^\ell)\right.$$
$$\left. - \frac{dS^H}{dR^H}(\theta'^H - \theta^H) - \frac{dS^S}{dR^S}(\theta'^S - \theta^S)\right\} = \sum_j W_{\theta^i\theta^j}(\theta')\frac{d\theta'^j}{dR} \;\; \forall\, i \tag{A.2.30}$$

Using the subset of the relations assumed in equation (A.2.14) relevant for the real interest rate channel

$$\frac{dS^L}{S^L} = -\frac{dR}{R}, \;\; \frac{dS^H}{S^H} = -\frac{dR_H}{R_H} = -\theta_1\frac{dR}{R}, \;\; \frac{dS^S}{S^S} = -\frac{dR_S}{R_S} = -\theta_2\frac{dR}{R} \tag{A.2.31}$$

substituting the conditional impacts from (A.2.31) in (A.2.30) and rewriting as

$$\frac{dS^i}{dR}u'(c) + S^i u''(c)\left\{-\sum_j S^j\frac{d\theta'^j}{dR} - \sum_j \frac{S^j}{R}(\theta'^j - \theta^j)\theta_j\right\} = \sum_j W_{\theta^i\theta^j}(\theta')\frac{d\theta'^j}{dR} \;\; \forall\, i \tag{A.2.32}$$

Defining $\gamma^j \equiv S^j\frac{d\theta'^j}{dR}$ such that it solves

$$\sum m_{ij}\gamma^j = -\frac{1}{R}u'(c) + u''(c)\sum_j \frac{S^j}{R}(\theta'^j - \theta^j)\theta_j \;\; \forall\, i$$

$$\text{In matrix form, } \; M\gamma = \left(\frac{1}{R}u'(c) + u''(c)\sum_j \frac{S^j}{R}(\theta'^j - \theta^j)\theta_j\right)\mathbf{1}$$

$$\implies \gamma = \left(\frac{1}{R}u'(c) + u''(c)\sum_j \frac{S^j}{R}(\theta'^j - \theta^j)\theta_j\right)M^{-1}\mathbf{1} \tag{A.2.33}$$

Differentiating with respect to R in the budget constraint defined as $c + (\theta' - \theta)\Theta\mathbf{S} = Y + \theta\mathbf{d}$,

$$\frac{dc}{dR} = -\sum_j S^j \frac{d\theta'^j}{dR} + \sum_j \frac{S^j}{R}(\theta'^j - \theta^j)\theta_j = -\sum_j \gamma^j + \sum_j \frac{S^j}{R}(\theta'^j - \theta^j)\theta_j \tag{A.2.34}$$

Substituting (A.2.33) and using $m = M^{-1}\mathbf{1}$ from (A.2.29), (A.2.34) can be rewritten as

$$\frac{dc}{dR} = -\left(\frac{1}{R}u'(c) + u''(c)\sum_j \frac{S^j}{R}(\theta'^j - \theta^j)\theta_j\right)m + \sum_j \frac{S^j}{R}(\theta'^j - \theta^j)\theta_j \tag{A.2.35}$$

Substituting $u'(c) = -c\sigma(c)u''(c)$ in (A.2.35) and rearranging terms,

$$\frac{dc}{dR} = -\sigma(c)\frac{c}{R}u''(c)m + \sum_j \frac{S^j}{R}(\theta'^j - \theta^j)\theta_j(1 - u''(c)m) \tag{A.2.36}$$

Substituting the expression for MPC from (A.2.28), (A.2.36) can be written as

$$\frac{dc}{dR} = \sigma(c)\frac{c}{R}(1 - MPC) + \sum_j \frac{S^j}{R}(\theta'^j - \theta^j)\theta_j MPC \tag{A.2.37}$$

The second term on the RHS of (A.2.37) can be simplified using the defined budget constraint $c + (\theta' - \theta)\Theta\mathbf{S} = Y + \theta\mathbf{d}$ as follows

$$\begin{aligned}\sum_j \frac{S^j}{R}(\theta'^j - \theta^j)\theta_j MPC &= \frac{1}{R}\sum_j S^j(\theta'^j - \theta^j)\theta_j MPC = \frac{1}{R}\left[(\theta' - \theta)\Theta\mathbf{S}\right] MPC \\ &= \frac{1}{R}\left[Y - \theta\mathbf{d} - c\right] MPC = \frac{1}{R}URE \cdot MPC\end{aligned} \tag{A.2.38}$$

where I have used the consistent definition of URE being the net wealth defined by considering all present and future assets & liabilities. Now, using (A.2.38), the real interest rate impact on consumption from (A.2.37) can be written as

$$\frac{dc}{dR} = \sigma(c)\frac{c}{R}(1 - MPC) + \frac{1}{R}URE \cdot MPC \tag{A.2.39}$$

Now considering the entire change from the simultaneous income and real interest rate, using (A.2.28) along with (A.2.39), the lemma is proved

$$dc = MPC\left(dY + URE\frac{dR}{R}\right) - \sigma(c)c(1 - MPC)\frac{dR}{R} \tag{A.2.40}$$

Using the result of the lemma from (A.2.40), the result for labor supply dn can be proved analogously. Given the restrictions of fixed balance sheets and only transitory shocks, following appendix A.7 using the lemma for both consumption and labor supply, the aggregation follows identically. This proves that (1.6) holds under general market incompleteness and completes all the required proofs for model extensions.

A.3 Sufficient Statistics - Additional Results

A.3.1 Redistribution elasticities relative to benchmark

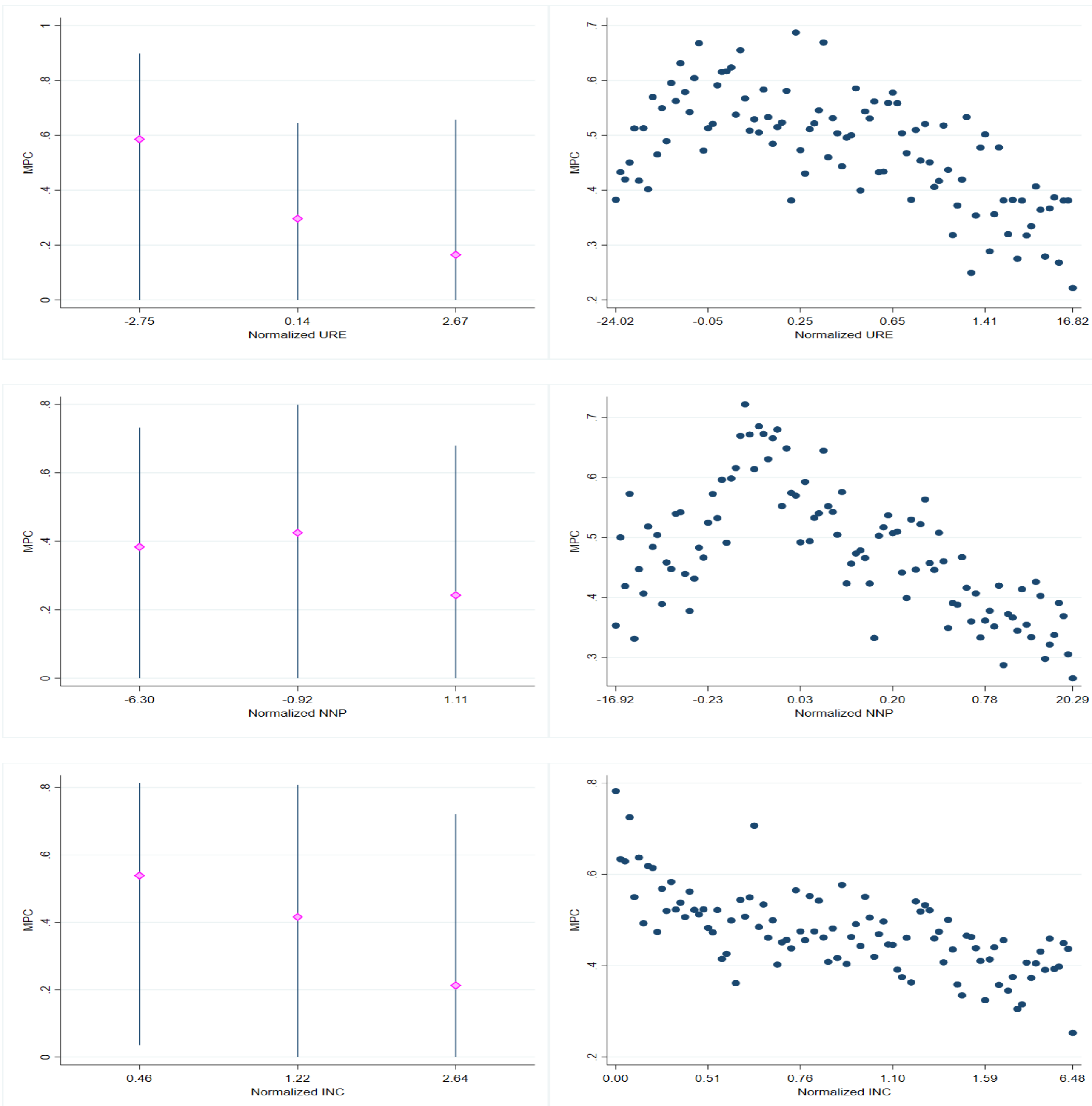
The differential impacts on prices & returns to housing and equity leads to the entire distribution of household exposure from both the real interest rate and Fisher channels to flatten. The capturing of longer tails not only makes them more accurate but also amplifies the exposures as revealed by panel (a) of Figure A.6 for the CE data.[2] The distribution for earnings shifts slightly to the left. It is consistent since the survey reported numbers for unrealized capital gains are not included as they do not reveal any information about transitory monetary policy. Panel (b) compares the response in SHIW data assuming that agents face the exact same shock and are not directly comparable. However, both the panels visually indicate that there is a negative correlation between *URE, NIC* & associated *MPCs* when conditioned on the shock. The relation is slightly less pronounced for *NNP*. The majority of US households own housing despite having mortgages and the net position on housing is likely to be positive. They occupy the middle quantiles of wealth distribution and are expected to have higher *MPCs*. I maintain the benchmark assumptions regarding asset maturity and number of bins used to estimate the *MPCs* from CE data. The estimates along with their 95% confidence interval for the two surveys are presented in Table A.9. Compared to previous results, the point estimates are considerably larger for the two channels of interest. The earnings heterogeneity channel remains more or less same since it uses reported measures. The focus here is on the unrealized conditional changes on household balance sheets. The standard substitution and wealth effects present in a RANK do not show any appreciable improvement. On average, the confidence intervals admit more negative values for the *URE* & *NNP*

[2] Looking at Figure A.6 seems it is possible to have similar graphs for only housing or equity wealth. However, following the same empirical method to estimate *MPCs* could involve substantial error on ignoring significant parts of household portfolio. Differences across the distribution in that case would be erroneously attributed to asset maturity. I comment on this issue in section 1.1.

Figure A.6: Marginal Propensities to Consume and Redistribution Channels in survey data

(a) For CE data

(b) For SHIW data



Note - The normalization follows the definition of 1.12 for both the datasets. In SHIW, *MPCs* are self-reported. The number of bins to estimate *MPC* in CE as a function of household exposure is 3.

Table A.9: Cross - sectional moments for the two surveys corresponding to Figure 1.5

Survey:	CE		SHIW	
	Estimate	95 percent CI	Estimate	95 percent CI
$\widehat{\varepsilon_R}$	-0.38	[-0.94,0.17]	-0.07	[-0.15,0.01]
$\widehat{\varepsilon}_R^{NR}$	-0.38	[-0.94,0.18]	0.08	[0.00,0.16]
$\widehat{\mathcal{S}}$	0.65	[0.38,0.92]	0.56	[0.52,0.59]
$\widehat{\varepsilon_P}$	-0.13	[-0.90,0.63]	-0.06	[-0.13,0.02]
$\widehat{\varepsilon}_P^{NR}$	-0.85	[-1.75,0.06]	-0.10	[-0.17,-0.03]
$\widehat{\varepsilon_Y}$	-0.12	[-0.34,0.10]	-0.05	[-0.06,-0.03]
$\widehat{\mathcal{M}}$	0.44	[-0.06,0.94]	0.49	[0.47,0.51]

Note - The final version of the model in section 1.4 is used which includes separate conditional impact to both houses and equity. The robustness is ensured by re-sampling the panel 100 times with replacement to reduce errors.

channels. Even larger negative covariance between *MPCs* & interest rate channels is possible. This leads to bigger consumption responses conditioned on these unrealized changes arising from the differential effects to housing & equity. In general, expansionary monetary policy tends to benefit agents who have more liabilities (primarily with longer maturities eg mortgages - negative *URE*) than assets (with shorter maturity eg stocks and bonds - positive *URE* since the former have higher *MPCs* than the latter. On the contrary, once the *MPCs* are not allowed to change, the new estimates of redistribution elasticities are much smaller in absolute value. In this case, unrealized increases in wealth without corresponding increase in MPC, for majority of the distribution, mechanically reduces the negative covariance. Results in Table A.10 highlight the relative importance of the asset maturity channel for $\widehat{\varepsilon}_R$. The updated results show no major changes in the overall trend on comparison with the original estimates. Consistent with the previous explanation, the estimates diminish in SHIW data. The role of asset returns enhances the impacts across horizons only when associated *MPCs* are changing. Even at quarterly horizon, commonly assumed in most structural models, not accounting for returns heterogeneity underestimates the targeted moment by almost 100 percent. Structural models would atleast need to match the updated sufficient statistics to get an accurate aggregate impact. If the model is misspecified, then the errors would simply

Table A.10: Variation of redistribution elasticity estimated with asset maturity assumption

		Duration scenario				
		Quarterly	Short	Benchmark	Long	Annual
$\widehat{\varepsilon_R}$	CE	-0.99	-0.56	-0.38	-0.38	-0.39
		[-2.29,0.31]	[-1.40,0.29]	[-0.94,0.17]	[-0.81,0.04]	[-0.80,0.01]
	SHIW	-0.08	-0.14	-0.07	-0.05	-0.03
		[-0.27,0.12]	[-0.25,-0.03]	[-0.15,0.01]	[-0.11,0.01]	[-0.10,0.03]

Note - exactly similar process as described in Table A.9. See corresponding notes for more details. For description of maturities, see Auclert (2019) Table 2.

compound. This holds even if the model is not relevant for analyzing policy initiatives from the incorporation of return heterogeneity. Another striking result from Table A.9 is the vastly improved performance with respect to the no-rebate numbers. These act as the lower bound for these point estimates. Accounting for the measurement error leads to even higher magnitudes while preserving the expected sign and prevents counter-intuitive positive covariances that sometimes appear in Auclert (2019). A requisite discussion in this context has been included in section 1.6.2. Additional results are included in section A.3.2.

A.3.2 Additional results for comparing aggregate changes

To get an idea of the impact of asset maturity on aggregate consumption, one can directly see the impact on the redistribution elasticity from the real interest rate which is the only changing sufficient statistic on altering the maturities. The first two rows of Table A.11 correspond to length of assets being shorter than the benchmark while the last two rows correspond to lengths being higher. Compared to the main text results in Table 1.10, the impact increases by around 15% in the quarterly horizon. This is of interest to structural models which typically assume quarterly or shorter asset maturities. The direct effects rise as asset maturity shortens and is robust in general to changing thee asset maturity. Surprisingly, the effects are almost equal at the short horizon. I also present the corresponding estimates keeping the MPC fixed in Table A.12 and find as before there is much lesser variation and in fact the effects decline when compared to the benchmark.

Table A.11: Sensitivity of σ^* to Asset Maturity under expansionary policy in CE

Measure	Maturity	Auclert	Housing + Stock	Housing	Stocks
σ^* / % Change	Quarterly	0.86	1.52	1.28	1.50
		–	77.23	48.59	74.55
	Short	0.75	0.86	0.89	0.85
		–	14.87	18.97	13.13
	Long	0.34	0.58	0.42	0.58
		–	70.07	20.84	67.49
	Annual	0.36	0.60	0.45	0.59
		–	66.96	24.15	64.43

Note - Results with $\sigma = 0.5$. To be compared with the first two rows of Table 1.10. See associated table notes for
more details.

Table A.12: Sensitivity of σ^* to Asset Maturity under expansionary policy in SHIW

Measure	Maturity	Auclert	Housing + Stock	Housing	Stocks
σ^* / % Change	Quarterly	0.29	0.14	0.13	0.31
		–	-50.89	-57.03	6.25
	Short	0.36	0.09	0.23	0.36
		–	-75.45	-36.16	0
	Long	0.13	0.25	0.07	0.15
		–	96.43	-43.88	14.29
	Annual	0.11	0.05	0.04	0.13
		–	-50.89	-67.26	16.67

Note - Results with $\sigma = 0.5$. To be compared with the last two rows of Table 1.10. See associated table notes for more details.

Table A.13: Cross - sectional moments corresponding to Figure 1.5 for a contractionary shock

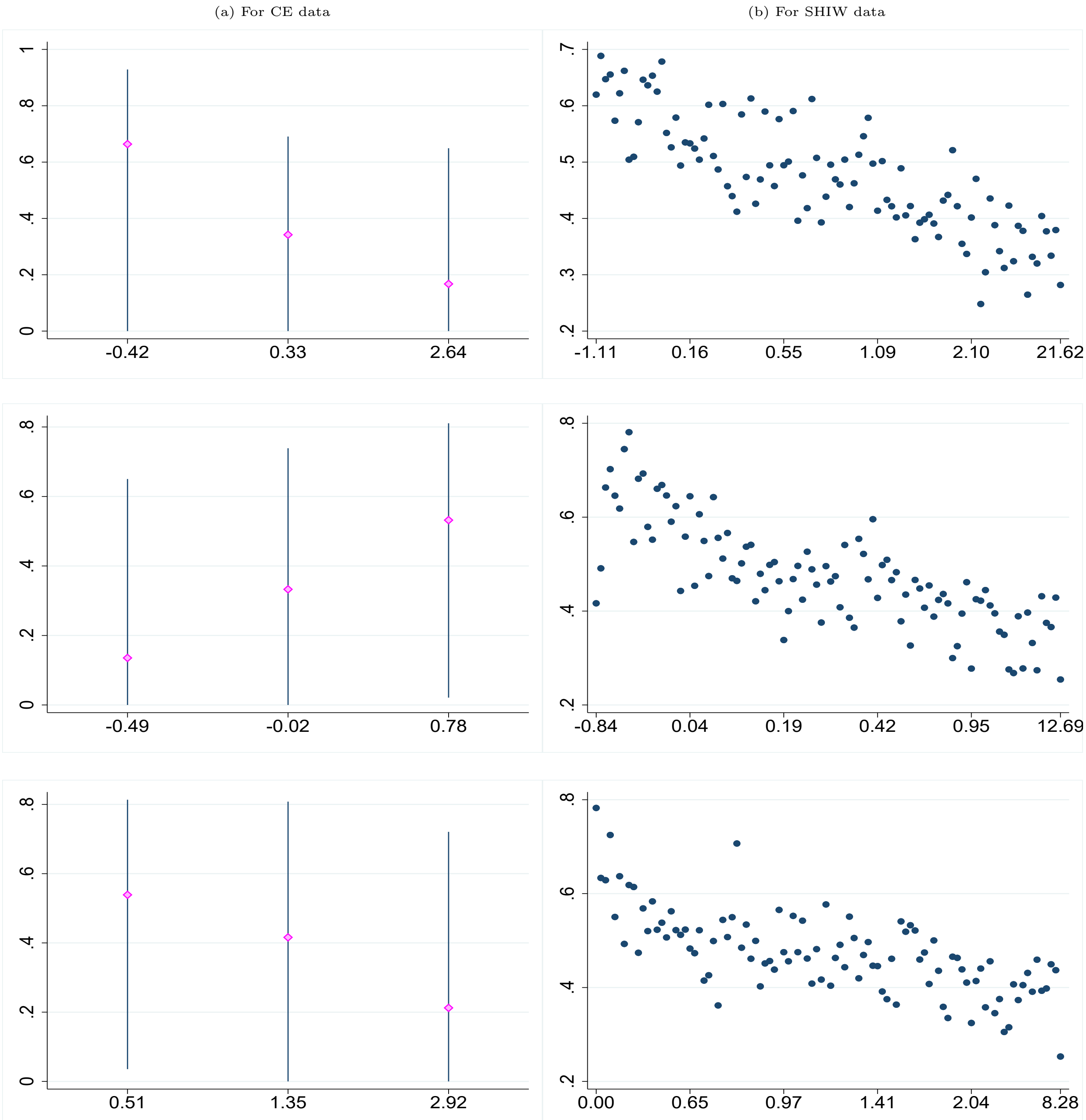
Survey:	CE		SHIW	
	Estimate	95 percent CI	Estimate	95 percent CI
$\widehat{\varepsilon_R}$	-0.24	[-0.55,0.07]	-0.14	[-0.18,-0.10]
$\widehat{\varepsilon}_R^{NR}$	0.09	[-0.33,0.51]	0.54	[0.49,0.58]
$\widehat{\mathcal{S}}$	0.61	[0.33,0.89]	0.55	[0.53,0.58]
$\widehat{\varepsilon}_P$	0.08	[-0.03,0.20]	-0.08	[-0.10,-0.05]
$\widehat{\varepsilon}_P^{NR}$	0.11	[-0.01,0.24]	0.24	[0.22,0.26]
$\widehat{\varepsilon_Y}$	-0.13	[-0.38,0.11]	-0.06	[-0.08,-0.04]
$\widehat{\mathcal{M}}$	0.49	[-0.06,1.94]	0.60	[0.60,0.65]

Note - Contractionary shock uses PDV estimates for one standard deviation rise in the monetary policy surprise. See associated notes in Table A.9 for more details.

For the sake of completeness, I present the results analogous for the contractionary shock. From Figure A.7, the trend for the *URE* is similar while the trend for the *NNP* reverses since the entire distribution shifts leftward by a large magnitude from the wealth declines from the Fisher channel. The data for the SHIW now show clearer patterns of declining *MPC* with increased *URE* & *NNP* as intuitively expected. As stated before, since the two data sources are not strictly comparable, this would not qualify as an improvement. Comparing the redistribution elasticities for the negative shock in Table A.13 with the ones in Figure 1.5, the asymmetric response is felt strongly for both the real interest rate and the Fisher channels. Owing to the new distribution of the *NNP* with its associated *MPC*, there is an increase in the consumption on raising the interest rate through the Fisher channel. The final impact on the aggregate consumption depends on the interaction of all the channels and is explained in section 1.6.3.

Since the asymmetric response to the interest rate channel is the strongest and intuitive, I look at its sensitivity to asset maturity. Shortening the time frame leads to far less reduction in aggregate consumption from direct effects across maturities. On comparing with Table A.10, the differences are most pronounced for the quarterly and short horizons. The asymmetric response to consumption increases in strength as the asset maturity shortens which is another feature of

Figure A.7: *MPC* vs Redistribution Channels in survey data for contractionary shock



Note - Contractionary shock uses PDV estimates for one standard deviation rise in the monetary policy surprise. For more details, see associated notes in Figure A.6

Table A.14: Comparison for expansionary shock with $\sigma = 0.5$ & $\gamma = -0.5$ for no-rebate numbers

Model Consumption Response	Estimated *MPCs*		Fixed *MPCs*	
	PE	GE	PE	GE
Auclert + House + Stock	1.62	2.06	0.33	0.82
Auclert + House	1.68	2.12	0.21	0.70
Auclert + Stock	0.61	1.07	0.10	0.65
Auclert	0.93	1.39	0.01	0.47

Notes - No rebate numbers refer to withholding the instantaneous transfers post the windfall transfer by other sector of the economy from the household sector. For more details see notes in Table 1.5.

Table A.15: Comparison for contractionary shock with $\sigma = 0.5$ & $\gamma = -0.5$ for no-rebate numbers

Model Consumption Response	Estimated *MPCs*		Fixed *MPCs*	
	PE	GE	PE	GE
Auclert + House + Stock	0.17	0.66	-0.48	0.16
Auclert + House	1.00	1.49	0.21	0.84
Auclert + Stock	0.89	1.35	-0.17	0.38
Auclert	0.93	1.39	0.01	0.47

Note - Contractionary shock refers to the transitory unexpected one percent increase in the real interest rate accompanied by a decrease in overall price level & aggregate income by one percent. See notes in Table A.14 for more details.

Table A.16: Variation of $\widehat{\varepsilon_R}$ with asset maturity assumption for a contractionary shock

		Duration scenario				
		Quarterly	Short	Benchmark	Long	Annual
$\widehat{\varepsilon_R}$	CE	-0.14	-0.07	-0.24	-0.17	-0.21
		[-0.73,0.45]	[-0.6,0.46]	[-0.55,0.07]	[-0.41,0.07]	[-0.42,0.00]
	SHIW	-0.27	-0.27	-0.14	-0.10	-0.08
		[-0.35,-0.20]	[-0.34,-0.19]	[-0.18,-0.10]	[-0.13,-0.07]	[-0.11,-0.06]

Note - Contractionary shock uses PDV estimates for one standard deviation rise in the monetary policy surprise. See associated notes in Table A.10 for more details.

interest for structural models.

The value of γ is expected to be negative since idiosyncratic incomes are expected to be countercyclical. I take a wide range of permissible values and check the percentage change in the general equilibrium consumption from the main model which features separate returns to both housing and equity. I compare the baseline and the no-rebate numbers for both the shocks. The numbers in Table A.17 also indicate the magnitude of the asymmetric response with varying γ. In general as incomes become strongly counter-cyclical, the overall aggregate consumption response weakens since the net change from the income effects from the earnings heterogeneity channel start opposing the added substitution effects from equation (1.9). The degree of asymmetric response depends on the updated elasticities and gamma doe snot play any significant role since the earnings heterogeneity channel is almost similar to the original results.

A.4 Comparing *MPC* estimates with previous results

The consumption at the household level from the one time unexpected monetary policy surprise is essentially product of the household income times its *MPC* out of income. We can decompose this total effect into five separate channels as in (1.6). Each channel is again the product of the aggregate change times its associated *MPC*. The economy wide aggregate *MPC* out of income is the first two terms of the same equation. I compare these estimates with existing

Table A.17: Sensitivity of general equilibrium consumption to value of γ

	Expansionary		Contractionary	
Value of γ	**Baseline**	**No-rebate**	**Baseline**	**No-rebate**
-1.5	-15.33	-9.94	10.04	8.58
-1.25	-11.79	-7.62	7.72	6.58
-1.00	-8.07	-5.20	5.28	4.48
-0.75	-4.14	-2.67	2.71	2.29
-0.40	1.72	1.10	-1.13	-0.95
-0.25	4.38	2.78	-2.87	-2.40
-0.1	7.14	4.52	-4.67	-3.90
-0.01	8.83	5.59	-5.78	-4.82

Note - Calculates the percentage changes relative to the general equilibrium consumption for the main model described in section 1.4 for the CE data with $\gamma = -0.5$. Numbers for negative shock show improved response if positive. The second and third columns use the results from the first row in Table 1.6 & Table A.14 respectively. Similarly, the fourth & fifth columns correspond to Table 1.9 & Table A.15 respectively. For more details, see associated notes.

results for the *MPC* out of fiscal transfers.[3] The aggregate *MPC* out of income is 44% (vs 46% in the benchmark). Common estimates in the literature range from 15-25% . The higher numbers are primarily due to the enhanced effects of unrealized wealth changes from the separate redistribution channels on the household estimate of *MPC* out of income.

One of the assumptions regarding the theoretical exercise is that consumers cannot adjust their portfolios post the shock. Therefore, they cannot directly realize the wealth gains in exchange of transaction costs. The effect of balance sheets on the *MPC* out of income are a result of wealth changes from holdings of housing, equity and/or liquid assets. I also compare the aggregate *MPC* out of income with the estimates of *MPC* out of realized wealth changes for both housing and equity. I lay out previous numerical estimates in footnotes 3 and 6. Owing to large transaction costs, *MPC* out of home-equity based borrowings are much smaller than corresponding estimates out of realized wealth changes from equity. Estimating unrealized wealth changes from housing wealth is quite infeasible. Besides other estimates, Hartzmark and Solomon (2019) also estimate

[3] The estimation of MPCs requires a one time unexpected fiscal transfer. So these estimates are directly comparable. See section 1.5 for more details, specifically (1.12).

that the *MPC* out of dividends (equivalent to *MPC* out of realized wealth changes in equity) is 40-60% for top 50% of the wealth distribution.

I compare the model-implied elasticity of consumption to house price shocks as developed by Berger et al. (2018) given by

$$\eta = \frac{dC}{d(PH)} \times \frac{PH}{C} \equiv MPC \times \frac{(1-\delta)PH}{C} \tag{A.4.1}$$

which is the sufficient statistic. For permanent house price changes of 4.59% ad $\delta = 2\%$, they calculate the theoretical elasticity to be $\in \ (0.23, 0.3)$. For my model with an implied aggregate *MPC* out of income of 44% , using the permanent house price change of 4.59% leads to $\eta = 0.45$. If I use the estimated housing price change rather than the permanent shock in housing prices then estimate of $\eta = 0.36$, both being more or less similar.

Lastly, I also compare the estimates of *MPC* out of income with the *MPC* out of realized housing wealth changes in Mian and Sufi (2014). They find that the elasticity of consumption from housing net worth shock is 0.6 - 0.8 across counties when they have the housing net worth shock of

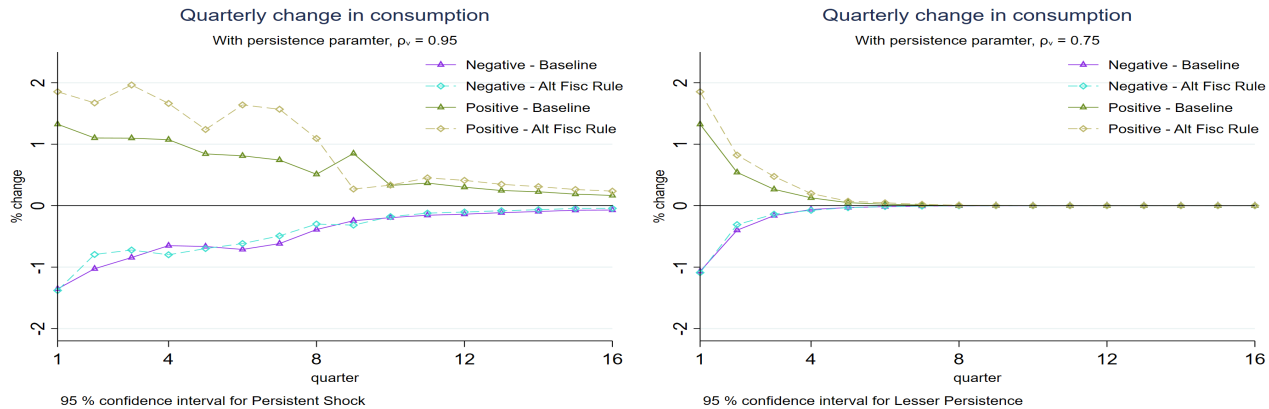
$$\text{HNW\_shock} = \left(\Delta \log p^{H,i}_{06-09} \times H^{i}_{2006}\right) / NW^{i}_{2006} \quad \approx \quad 10\% / NW^{i}_{2006} \tag{A.4.2}$$

Their average marginal *MPC* out of housing wealth is 5-7 cents. The most comparable estimates are for a negative shock and using a model with only housing returns heterogeneity and without any income change is roughy 0.59.

A.5 Implied aggregate consumption ***IRFs***

The flexibility of the sufficient statistics approach allows for measuring implied *IRFs* in line with the theoretical results in appendix A.2.1 beyond the instantaneous response in section 1.6.2 from the same transitory unexpected monetary policy surprise. The key assumption is that households cannot adjust their portfolios during the entire horizon of the response. A major motivation is the need to have *IRFs* for interested aggregate variables without relying on structural models that can study only a subset of the myriad redistribution channels. Empirically, this might be inconsistent with the evidence for households in especially top 10% of the wealth distribution.

Figure A.8: General equilibrium aggregate consumption response for different shocks

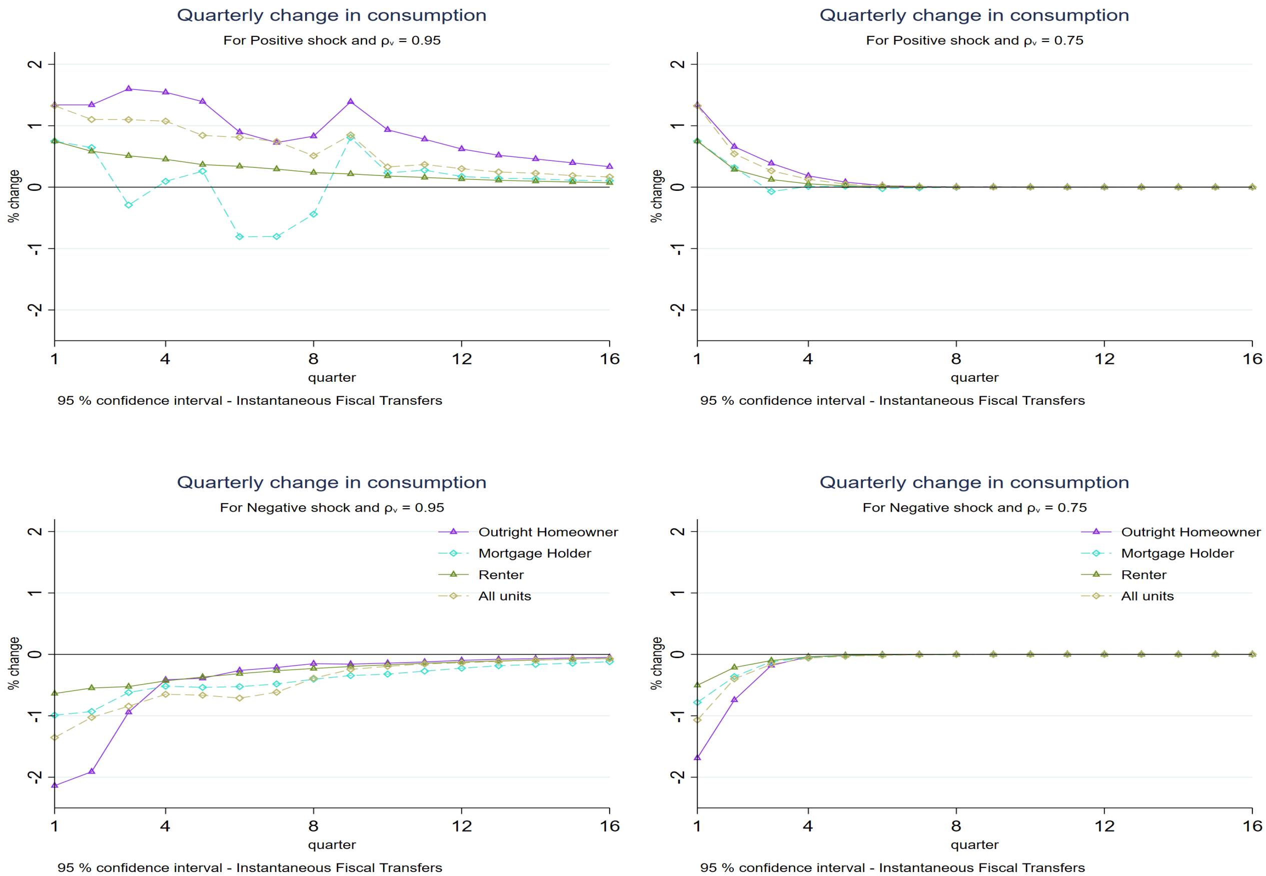


Note - Consumption change is corresponding to (1.9) for the model presented in section 1.4. Positive shock refers to the decline in the real interest by one percent for $t = 1$. Negative shock analogously refers to the increase in the real interest rate by one percent for $t = 1$. From $t = 2$, the one time change declines by ϕ in absolute magnitude. Inflation and aggregate income both change by the same amount as the change in the real interest rate for all $t \geq 1$. Baseline refers to the benchmark model where fiscal transfers are instantaneously rebated. Alt Fisc Rule refers to the case where fiscal transfers are not instantaneously rebated.

Since substantial proportion of the households have a major fraction of their wealth tied up in housing with high transaction costs, their portfolio rebalancing is much less frequent. I present the results here for 16 quarters ahead.

To estimate the results, firstly I need the PDV estimates for each of the 16 quarters ahead. One way to obtain them would be using the local projections approach detailed in appendix A.1.3. It is more robust than a SVAR for smaller time horizons. However, due to the nature of the exercise involved (section 1.4.2), the SVAR remains a superior method since consumers are theoretically forecasting infinitely ahead in the future for each quarter. Second, I need externally specified exogenous changes for the real interest rate, inflation and aggregate income for 16 quarters ahead. I start with unit changes as used in section 1.4.4 for the instantaneous response. From the second quarter onwards, the one time change declines by a common persistence parameter ϕ for all the three changes. As an extension to section 1.6.1, I also follow the same process to derive the implied *IRFs* for additional dimensions of heterogeneity. The purpose of this section is demonstrate the flexibility and usefulness of the sufficient statistics approach. Other possible specifications for exogenous changes in the aggregate real interest rate, inflation and income can be used. An interesting example in this context would be Taylor rules where the consumption deviations proxy

Figure A.9: General equilibrium aggregate consumption *IRFs* by housing tenure



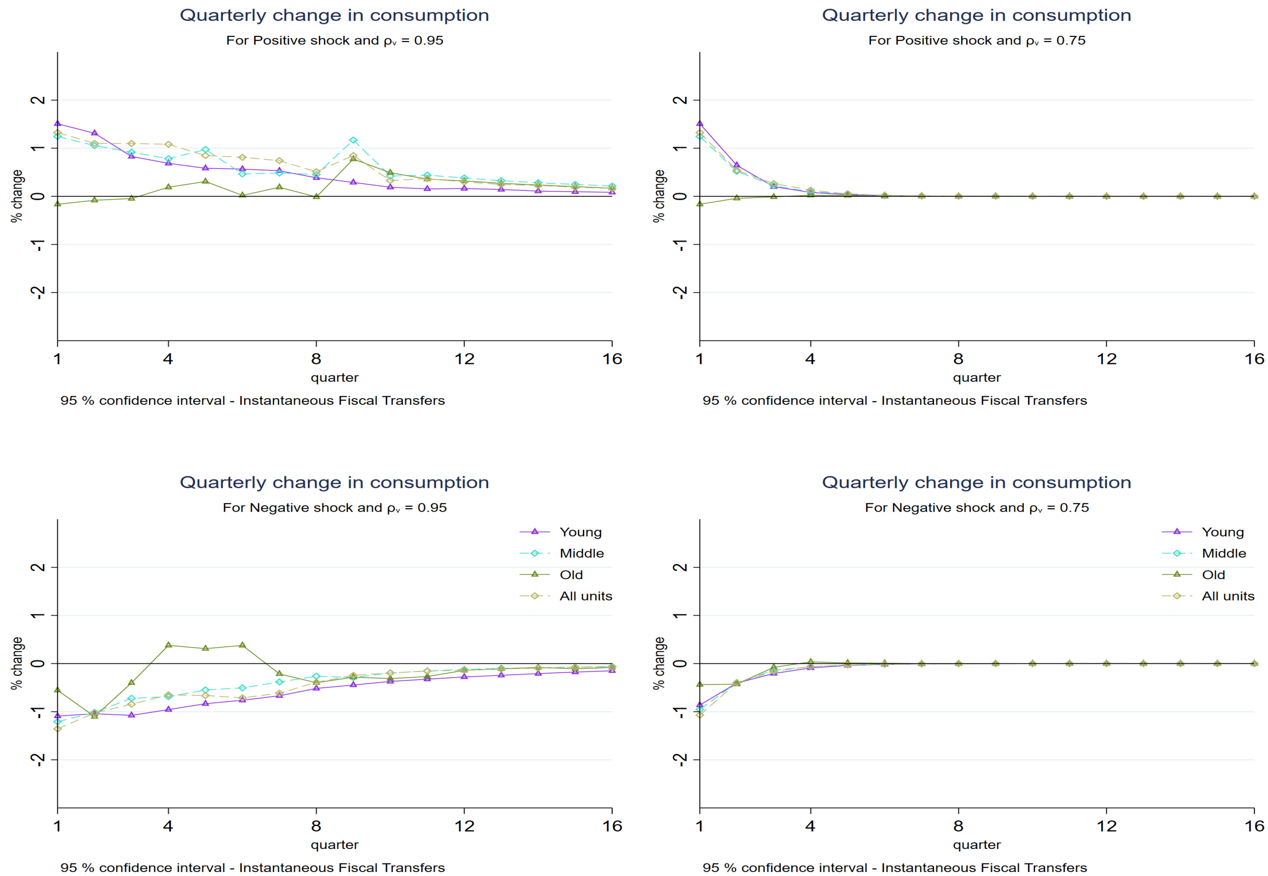
Note - For all the cases, fiscal transfers are instantaneously rebated. Housing tenure is as defined in section 1.6.1. For more details see associated notes in Figure A.8.

for the output gap. In the interest of space and brevity, I do not include these additional results here. In summary, conditional on ex-post returns heterogeneity, sufficient statistics can be used in computing the aggregate general consumption for any quarter post the one time unexpected shock provided we maintain the assumption that consumers do not alter their balance sheets. I contrast the results for shocks of different persistence in Figure A.8 using the general equilibrium aggregate consumption elasticity to the nominal interest rate. The increase in consumption declines slowly for the first year post the shock before dampening by the end of three years for a highly persistent shock in the left panel. The revaluation of consumer balance sheets is different for each individual quarter compared to the cumulative response for the instantaneous response. As can be seen from Figure 1.1, the increased valuation of stock and housing assets is higher immediately post the shock before declining gradually. Consumers, especially those who are unconstrained, would realize these gains at some point in the future leading to a rise in consumption today. The gains would be quantitatively large for the initial number of quarters. The logic is exactly the same as with the instantaneous response, the only exception being that the quantitative differences are different for each individual quarter.

The asymmetries are also sharper when comparing with the response for the negative shock. Consumption declines far less for the first two years from the shock. Since the revaluation affects both the debt and asset side of the balance sheets, consumers experience smaller declines in net wealth depending on both across and within class heterogeneity in their asset holdings leading to a far smaller decline in consumption. Both the results pertain to the baseline model where the government instantaneously refunds the transfers. The responses do not show the typical hump shape response oft observed empirically from VAR analysis where consumption responds with a lag and increases post a few quarters after the shock. Withholding fiscal transfers from households however does not solve the problem and produce a hump-shaped response in consumption despite being expected to constrain households and dampening the increase in consumption. The results also depend on the persistence of the shock. If the persistence is less, the wealth changes are smaller and taper off sooner. Subsequently, consumption responses are dampened across shocks irrespective of the nature of fiscal policy in the model. There is also very little asymmetry for the negative shock of equal magnitudes.

Analogous to section 1.6.1, I present the results by housing tenure in Figure A.9. I only use the baseline model where fiscal transfers are instantly rebated to households. Since outright homeowners are expected to be having higher positive liquid asset holdings, they are significantly less constrained. Similarly, mortgage holders are expected to be more constrained compared to the former. Accordingly, the consumption response for the same increase in returns & prices ex-post for the three classes of assets produces higher unrealized wealth gains for the former. Outright homeowners have a consistently higher response than the aggregate while for mortgage holders, the consumption response is similarly below aggregate. For a negative shock of exact same magnitude, the response is now strongly asymmetric with homeowners reducing their consumption higher since they see the largest decrease in their asset values. Being substantially closer to the borrowing limit prevents a similar consumption reduction for mortgage holders due to inherently higher *MPCs*. The intuition and results for section 1.6.1 applies here as well. Renters have much

Figure A.10: General equilibrium aggregate consumption *IRFs* by demographics



Note - For all the cases, fiscal transfers are instantaneously rebated. Demographics is as defined in section 1.6.1. For more details see associated notes in Figure A.8.

smaller changes and their consumption response is essentially uniform across quarters and depends only on the aggregate decrease in the real interest rate, increase in inflation and earnings quarter by quarter. Their response displays almost negligible asymmetry. Reducing the persistence of the shock understandably dampens the overall deviations from the steady state.

Analogous results by demographics are presented in Figure A.10. The differences from the aggregate response are far less compared to the response by housing tenure. The response for old people is also highly asymmetric as observed for the negative shock in the bottom left panel. Young are expected to much more constrained than middle while old is expected to be the least constrained. The behavior of the old is kind of an outlier. In the left panel for the highly persistent shock, the response for the old is the least. Accordingly, the logic should have led to old people having the highest consumption elasticities. One possible reason could be bequests which means old do not increase consumption despite lesser savings. Reducing the persistence of the shock leads to nearly indistinguishable responses from the aggregate. The model is far less successful in exploiting the balance sheet differences based on age.

A.6 Results for Policy Experiments

I explore the interaction between wealth inequality and the presence of returns heterogeneity, conditional on the shock, using simple experiments. I restrict to comparing instantaneous responses only. The results for this section can be similarly presented in line with the methodology for section A.5. I target the household portfolios using SCF data for 2007 before the GFC and then again for 2019 before the pandemic. Specifically, I adjust the shares for housing, equity and liquid assets relative to the mean for both positive and negative asset positions. Since the results in sections 1.6.2 and 1.6.3 confirm that the household consumption change is primarily from the MPC channel, I restrict myself to the CE data. I focus only on the general equilibrium consumption response. Since the share of redistribution in partial equilibrium is always higher, quantitatively significant results in general equilibrium is always the lower bound for corresponding estimates in partial equilibrium. Higher the share of redistribution in overall aggregate consumption response, greater is the underestimation relative to the benchmark without returns heterogeneity. Of course, I assume that the consumption expenditures are similar across the time periods under consideration.

I report the results for the one time unexpected decline in the real interest rate by 1% in Table A.18 for both the years. Columns 2 and 3 maintain the assumptions of the benchmark results in how to measure household debt. Unless a mortgage is explicitly specified as ARM, it is not treated as such. Columns 4 and 5 assumes that all mortgages are ARMs. In times of monetary easing, ARMs would lead to greater consumption responses since the pass through towards overall transmission is higher from the automatically declining mortgage rate. Intuitively, the reverse is expected to be true for negative monetary policy surprise. The responses for 2007 and 2019 are broadly similar and display a roughly 17% & 16% increase. The main result for a substantial increase in the aggregate consumption in the presence of the additional channel of returns heterogeneity stays robust for different time periods under consideration. Restricting to quarterly frequency increases them by 26% & 24% respectively. As mentioned in section 1.6.5, the exposures from the real interest

Table A.18: Predicted aggregate consumption responses under expansionary shock for $\sigma = 0.5$ & $\gamma = -0.5$

In General Equilibrium	**All Mortgages**				**Only ARMs**			
	Benchmark		Quarterly		Benchmark		Quarterly	
	2007	2019	2007	2019	2007	2019	2007	2019
Auclert + House + Stock	1.52	1.50	2.38	2.23	1.76	1.75	4.07	3.48
Auclert + House	1.45	1.34	2.34	2.18	1.45	1.48	2.34	3.86
Auclert + Stock	1.30	1.52	1.82	1.88	1.69	1.73	2.66	2.70
Auclert	1.30	1.29	1.88	1.80	1.41	1.34	2.26	2.27

Note - Columns 2 and 3 refer to baseline calculations for all types of mortgages. Columns 4 and 5 assumes all mortgages are only adjustable rate. The baseline model (Row 4) differs only by the addition of the required returns heterogeneity. Rows 1 - 3 refer to the updated model with separate returns for the three assets, either present together or one at a time. The wealth distribution is approximated using SCF 2007 and 2019 by using average asset positions (positive & negative) for the entire distribution relative to the information provided in CE 2001. See notes in Table 1.5 for more details. The final general equilibrium estimate is comparable to column 3. The only sufficient statistic that varies with asset maturity assumption is $\widehat{\varepsilon_R}$. See Table 2 in Auclert (2019) for details regarding asset maturities.

rate channel are stronger which drives up the increase in consumption. Interestingly, having only separate returns for housing would lead to corresponding 24% & 22% against -3% & 4% for equity at quarterly maturity. Housing becomes more important for consumption since the bulk of the distribution who won housing wealth typically also hold mortgages. It leads to a negative *URE* which is associated with a higher *MPC*. The findings support the aggressive quantitative easing by the Fed at the start of the pandemic. Though, its primary aim was to prevent financial panic, the support for equity & housing markets rationalizes an even faster recovery in consumption.

Similar results follow through for 2007 before the GFC. An expansionary policy during the housing bubble is of course not the policy recommendation. If households had relatively more housing wealth, they would experience bigger consumption gains in comparison with households who held more equity. The findings should be interpreted as the influence of a temporary decline in wealth gini on aggregate consumption with/without returns heterogeneity. What matters is not only the magnitude of overall gains but also who receives the larger share of these gains. The consumption responses are slightly higher in comparison to 2019 where the wealth gini increased.

Table A.19: Predicted aggregate consumption responses under contractionary shock for $\sigma = 0.5$ & $\gamma = -0.5$

In General Equilibrium	**All Mortgages**				**Only ARMs**			
	Benchmark		Quarterly		Benchmark		Quarterly	
	2007	2019	2007	2019	2007	2019	2007	2019
Auclert + House + Stock	1.18	1.13	1.43	0.88	0.86	0.87	0.79	1.18
Auclert + House	1.12	1.16	0.86	0.93	0.95	0.89	1.09	1.04
Auclert + Stock	1.13	0.98	1.11	0.95	0.85	0.85	1.06	1.06
Auclert	1.30	1.29	1.88	1.80	1.41	1.34	2.26	2.27

Note - Numbers are negative elasticities of aggregate consumption. See notes in Table 1.8 & Table A.18 for more details.

To check the robustness of this result, I focus on the importance of within class heterogeneity for housing on the aggregate consumption elasticity. Columns 5 - 8 report the analogous estimates if all mortgages are assumed to be ARMs. The benchmark maturity estimates for 2007 and 2019 increase to 25% & 30*-0.1cm. Restricting to quarterly frequency would lead to 80% & 53% corresponding increases. The numbers on isolating the returns to housing or equity are considerably lower. The numbers for an expansionary policy in 2007 show that ARMs allow stronger redistribution from housing relative to equity. Since the majority of the distribution who hold considerably more housing wealth have higher *MPCs*, the consumption response is progressively higher. The difference depends on the extent of the excess gains relative to equity despite overall lower returns on housing. The estimates are surprisingly powerful and motivate the need to consider the interaction of returns heterogeneity & wealth inequality for aggregate demand in the short run. As intuitively expected, fiscal and mortgage design policies should focus on reducing the costs associated with refinancing across the wealth distribution. Formally, this is akin to assuming all mortgages to be ARMs at short maturities. Priority would be expediting aid during times of need like at the onset of the pandemic for the more vulnerable sections who don't have enough liquid assets to avail the refinancing. The results show that the consumption recovery could be vastly improved. [4]

[4]The findings support both empirical and structural results in the literature on refinancing frictions. See DeFusco and Mondragon (2020) and Chen et al. (2020) for more details respectively.

The same exercise is repeated for contractionary policy and the numbers are reported in Table A.19. Keeping with the intuition explained before in section 1.6.3, consumption would have dropped 10% & 12% lesser for 2007 and 2019 with benchmark maturity. The corresponding numbers are 24% & 51% lesser for quarterly. Having only housing returns lead to 54% improvement in 2007 vs 41% for equity emphasizing the importance of housing before the GFC. Further assuming all mortgages are ARMs with quarterly maturity would have improved aggregate consumption by 65% & 48%. As mentioned in section 1.6.5, the results for the asymmetric response are counter-intuitive when viewed in terms of a contractionary policy in 2007. Either way, the predicted results demonstrate that structural models need to take returns heterogeneity more seriously for calibrating the aggregate consumption response correctly.

Appendix B

Appendix for Chapter 2

B.1 Model

Demographics: The economy is populated by a unit mass of finitely-lived households. We index a household's age by $j \in [0, J]$, where J is the maximum age. Age-j households die at rate $\psi(j)$. When a household dies, it is replaced by a new one , so there is no population growth. New households draw their initial labor endowment from the invariant distribution and their initial wealth from a distribution Γ_t^0. Γ_t^0 is such that total inheritances equal total bequests.

Preferences: Households derive utility from consumption of a numeraire consumption good c and housing services $\mathbf{h}$. Their flow utility function is

$$u(c, \mathbf{h}) = \frac{(c^{1-\eta}\mathbf{h}^{\eta})^{1-\gamma}}{1-\gamma}$$

Housing services can be obtained either through the rental market or by occupying owner-occupied housing. Renting and owning simultaneously is prohibited. We denote the quantity of rental housing by h^r and the quantity of owner-occupied housing by h^o. The amount of housing services a household enjoys is

$$\mathbf{h}(h^r, h^o) = h^r + \chi h^o$$

The parameter χ captures non-pecuniary benefits of homeownership, and helps us to match the homeownership rate. Households discount the future at rate ρ and have warm-glow bequest preferences

$$v(\omega) = \vartheta_0 \frac{(\vartheta_1 + \omega)^{1-\gamma}}{1-\gamma}$$

where ω is liquid wealth held at death.

Labor Income: Households work from birth until the retirement age J_r. They receive a stochastic stream of labor endowments l, which they supply inelastically at wage w_t. Labor endowments consist of a deterministic lifecycle component $\bar{l}(j)$ and an idiosyncratic component ℓ:

$$\log l = \bar{l}(j) + \ell$$

During the working life, the idiosyncratic component of l follows an Ornstein-Uhlenbeck process:

$$d\ell_t = -\theta \ell_t dt + \sigma_\ell dW_t \tag{B.1.1}$$

where W_t is a Weiner process. The parameter θ determines the persistence of earnings, while σ_ℓ determines the volatility.

Upon reaching retirement, ℓ remains fixed for the remainder of the household's life. Retired households receive a pension benefit $\flat_t(\ell)$, which is a function of their labor endowment at retirement. We denote earnings and pensions, which we refer to as "labor income" by

$$y_t(\ell, j) = \begin{cases} w_t e^{\bar{l}(j)+\ell} & \text{if } j < J_r \\ \flat_t(\ell) & \text{if } j \geq J_r \end{cases}$$

Housing: We denote the price of owner-occupied housing by p_t and the rental price by p_t^r. Renters can freely adjust their quantity of rented housing. Homeowners can change their quantity of owner-occupied housing at any time, but they face transaction costs to do so. Whenever a household changes its quantity of owner-occupied housing, it must pay fraction f_s of the value of its old house and fraction f_b of the value of its new house. Housing depreciates at rate δ^h.

Financial Wealth: In addition to housing wealth, households can accumulate liquid financial wealth. We denote a household's financial wealth by a. There is a collateral constraint which limits borrowing to a fraction ϕ of housing wealth:

$$a \geq -\phi p_t h^o$$

Households with $a < 0$ have mortgage debt and no assets. For households with $a > 0$, financial wealth is divided into a risk-free asset and risky public equity. Following Hubmer et al. (2021), we assume that while the household is free to choose its overall financial wealth, the fraction invested in each of the two financial assets is an exogenous function of a. Specifically, fraction $f_e(a)$ is invested in equity and the remainder in the risk-free asset.

The interest rate on mortgage debt is r_t^m and the interest rate on the risk-free asset is r_t^f. The return on an individual's public equity portfolio, $\tilde{r}_t^e$, follows the stochastic diffusion

$$d\tilde{r}_t^e = r_t^e dt + \sigma_e dW_t$$

where W_t is a Wiener process. The expected equity return is r_t^e, and its volatility is determined by the parameter σ_e. The expected return on non-housing wealth is

$$r_t(a) = \begin{cases} r_t^m & \text{if } a < 0 \\ [1 - f_e(a)]r_t^f + f_e(a)r_t^e & \text{if } a \geq 0 \end{cases}$$

Taxes: Households must pay an income tax of rate τ. The income tax applies to labor earnings, pensions, and capital income. Homeowners are allowed to deduct mortgage interest payments.

Household's Problem: It is convenient to work with the state variable

$$x = a + \phi p_t h^o$$

which is financial wealth held in excess of the borrowing limit. From now on, we refer to x as "liquid wealth." Using this notation, the collateral constraint is $x \geq 0$ and the expected return on non-housing wealth is $r_t(x, h^o) \equiv r_t(x - \phi p_t h^o)$. The household's state variables are x, owner-occupied housing h^o, idiosyncratic labor endowment ℓ, and age j.

Households pay an income tax of rate τ, which applies to earning, pension benefits, and capital income. Homeowners are allowed to deduct mortgage interest payments from their taxable income. In between housing adjustments, the expected change in x is

$$\dot{x}_t(a, h^o, \ell, j, c, h^r) = (1-\tau)[y_t(\ell, j) + r_t(a)a] - c - p_t^r h^r - [\delta^h p_t - (1+\phi)\dot{p}_t]h^o$$

Denote the user cost of housing by

$$p_t^o(x, h^o) \equiv [\delta^h + (1-\tau)r_t(x, h^o)\phi]p_t - (1+\phi)\dot{p}_t$$

The budget constraint can then be written as

$$\dot{x}_t(x, h^o, \ell, j, c, h^r) = (1-\tau)[y_t(\ell, j) + r_t(x, h^o)x] - c - p_t^r h^r - p_t^o(x, h^o)h^o$$

Liquid wealth after adjusting owner-occupied housing from h^o to $h^{o\prime}$ for a household with pre-adjustment liquid wealth x is

$$x'(x, h^o, h^{o\prime}) = \begin{cases} x & \text{if } h^{o\prime} = h^o \\ x + (1 - f_s - \phi)p_t h^o - (1 + f_b - \phi)p_t h^{o\prime} & \text{if } h^{o\prime} \neq h^o \end{cases}$$

Denote the vector of state variables by $\Omega \equiv (x, h, \ell, j)$. The household's value function satisfies the Hamilton-Jacobi-Bellman (HJB) equation

$$[\rho + \psi(j)]V_t(\Omega) = \max_{c,h^r} \underbrace{u(c, \mathbf{h}(h^r, h^o))}_{\text{flow utility}} + \underbrace{\partial_x V_t(\Omega)\dot{x}_t(\Omega, c, h^r)}_{\text{expected change in } x} + \underbrace{\frac{1}{2}\partial_{xx} V_t(\Omega)[\sigma_e f_e(\Omega)a(\Omega)]^2}_{x \text{ volatility}} \qquad \text{(B.1.2)}$$

$$+ \underbrace{\dot{V}_t(\Omega)}_{\text{time derivative}} + \mathbf{1}(j < J_r)\left[\underbrace{\partial_\ell V_t(\Omega)(-\theta\ell + \sigma_\ell^2/2)\ell}_{\text{expected change in } \ell} + \underbrace{\frac{1}{2}\partial_{\ell\ell} V_t(\Omega)(\sigma_\ell \ell)^2}_{\ell \text{ volatility}}\right]$$

$$\text{subject to} \quad \dot{x}_t(\Omega, c, h^r) \geq 0 \text{ if } x = 0$$

$$h^r h^o = 0$$

$$V_t(\Omega) \geq \max_{\tilde{h}^o : x'(x, h^o, \tilde{h}^o) \geq 0} V_t(x'(x, h^o, \tilde{h}^o), \tilde{h}^o, \ell, j)$$

with boundary condition $V_t(x, h^o, \ell, J) = v(x + (1 - f_s - \phi)p_t h^o)$.

Density of State Variables: Denote the density of state variables by $g_t(\Omega)$. Without owner-occupied housing adjustments, the density of state variables evolves according to the Kolmogorov Forward (KF) equation [1]

$$\dot{g}_t(\Omega) = \underbrace{-\partial_x[\dot{x}_t(\Omega)g_t(\Omega)]}_{\text{expected change in } x} + \underbrace{\frac{1}{2}\partial_{xx}[(\sigma_e f_e(\Omega)a(\Omega))^2 g_t(\Omega)]}_{x \text{ volatility}} - [1 - \psi(j)]g_t(\Omega)$$
$$+ \mathbb{1}(j < J_r)\left(\underbrace{-\partial_\ell[(-\theta\ell + \sigma_\ell^2/2)\ell g_t(\Omega)]}_{\text{expected change in } \ell} + \underbrace{\frac{1}{2}\partial_{\ell\ell}[(\sigma_\ell \ell)^2 g_t(\Omega)]}_{\ell \text{ volatility}}\right) \quad \text{(B.1.3)}$$

Government: The government collects the income tax and uses the proceeds to fund the social security system and other government spending G_t, which does not affect household utility. We assume that the government always runs a balanced budget.

B.2 Calibration

B.2.1 Externally Calibrated Parameters

Many model parameters are taken directly from previous literature or data. Table B.1 provides a summary of the externally calibrated parameters. Unless otherwise noted, all values are annual. Without loss of generality, we normalize median earning of working-age households in the initial steady state to 1.

Preferences and Demographics and Preferences: We set the coefficient of relative risk aversion to $\gamma = 2$. Households live for $J = 60$ years, from age 20 to 80. They retire at age 65 ($J_r = 40$). Based on evidence from Wolff and Gittleman (2014), we assume that 30% of households receive an inheritance at birth. We further assume that every household who receives an inheritance receives the same amount.

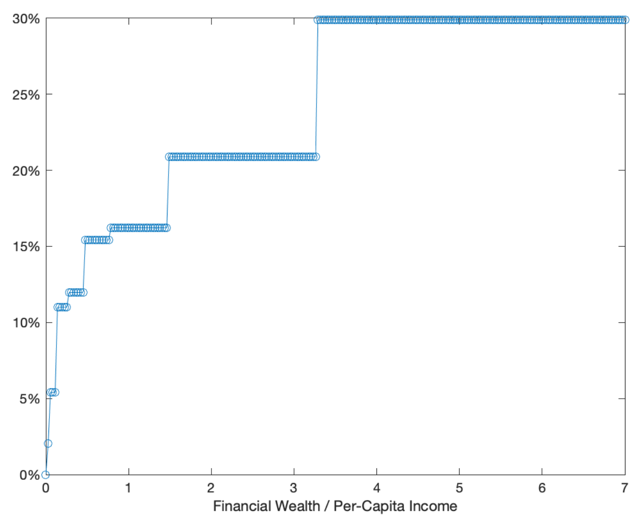
[1] As discussed by Kaplan et al. (2020), KF equations of optimal stopping time problems are not straightforward. For expositional clarity, here we show the KF equation without housing adjustments. It is, however, straightforward to describe how housing adjustments are dealt with in our numerical algorithm.

Earning: Following Achdou et al. (2022), we set the persistence parameter of (B.1.1) to $\theta = 0.95$ and the volatility parameter to $\sigma_\ell = 0.064$.[2] We take the deterministic lifecycle component of earnings $\bar{l}(j)$ from Hansen (1993). We assume that the pension benefit is 50% of earning at retirement in the initial steady state. The income tax rate τ is fixed at 20%.

Housing: We set the housing transaction costs equal to the median costs estimated by Gruber and Martin (2003). The selling cost is $f_s = 7\%$ of the house's value, and the buying cost is $f_b = 2.5\%$. Consistent with the range of commonly used values discussed by Piazzesi and Schneider (2016), we set the housing depreciation rate to $\delta^h = 2\%$ and the collateral constraint to $\phi = 0.8$.

Financial Wealth: We obtain the portfolio schedule $f_e(a)$ from Hubmer et al. (2021). This schedule is displayed in Figure B.1. The returns on each asset class are computed using the same methodology as Hubmer et al. (2021).

Figure B.1: Portfolio Share Schedule



Notes: This figure displays the fraction of financial wealth invested in equity by financial wealth level. Financial wealth is divided by per-capita income.

Government: The ratio of total government spending (including pensions) to per-capita income in the initial steady state is XX. We assume that the tax rate remains fixed at the rate from the initial steady state, with G_t adjusting accordingly over time to ensure government budget

[2] See Appendix F of Achdou et al. (2022). With these parameter values, the standard deviation of ℓ is 0.2.

balance.[3]

Table B.1: Externally Calibrated Parameters

Parameter	Description	Value	Source
γ	Risk aversion	2	
J	Lifespan	60	
J_r	Retirement age	40	
F_t	Initial wealth distribution	See text	
θ	ℓ persistence	0.95	Achdou et al. (2022)
σ_ℓ	ℓ volatility	0.064	Achdou et al. (2022)
$\bar{l}(j)$	Lifecycle labor		Hansen (1993)
$b(\ell)$	Pension	$0.5w_0e^{l(J_r)}$	
f_s	House selling cost	7%	Gruber and Martin (2003)
f_b	House buying cost	2.5%	Gruber and Martin (2003)
δ^h	House depreciation	2%	Piazzesi and Schneider (2016)
ϕ	Collateral constraint	0.8	Piazzesi and Schneider (2016)
$f_e(a)$	Portfolio schedule		SCF 1967
σ_e	Equity volatility	0.16	
τ	Tax rate	0.20	
pr_{inh}	Probability of receiving inheritance	13%	

Notes: This table displays the parameter values which are externally calibrated. The tax rate is no longer endogenous.

B.2.2 Internally Estimated Parameters

The remaining parameters of the model are internally estimated. These are the fraction of end-of-life wealth that is bequested f_{beq}, the housing services preference weight η, the homeownership preference parameter χ, the discount factor ρ, the bequest motive ϑ. Table B.1 provides a summary of the externally calibrated parameters.

[3] We verify ex-post that $G_t > 0$, so that government revenue is always sufficient to cover the costs of the social security system.

Table B.2: Internally Estimated Parameters

Parameter	Description	Value	Target
f_{beq}	Fraction of wealth bequested	0.1352	Average wealth, 20-25: 0.43
η	Housing preference weight	0.1455	House wealth share (owners): 52%
χ	Ownership preference	1.2489	Homeownership rate: 68%
ρ	Discount factor	0.0240	Average wealth: 3.81
ϑ	Bequest motive	14.16	Average wealth, 75/60: 0.64

Notes: This table displays the parameter values which are internally estimated.

B.3 Calibration targets across different generations

The model is currently calibrated to SCF+ 1967. We can try other alternative targets in reference to Hubmer et al. (2021). A summary of such targets is listed in Table B.3.

Table B.3: Compare Targets Across Generations

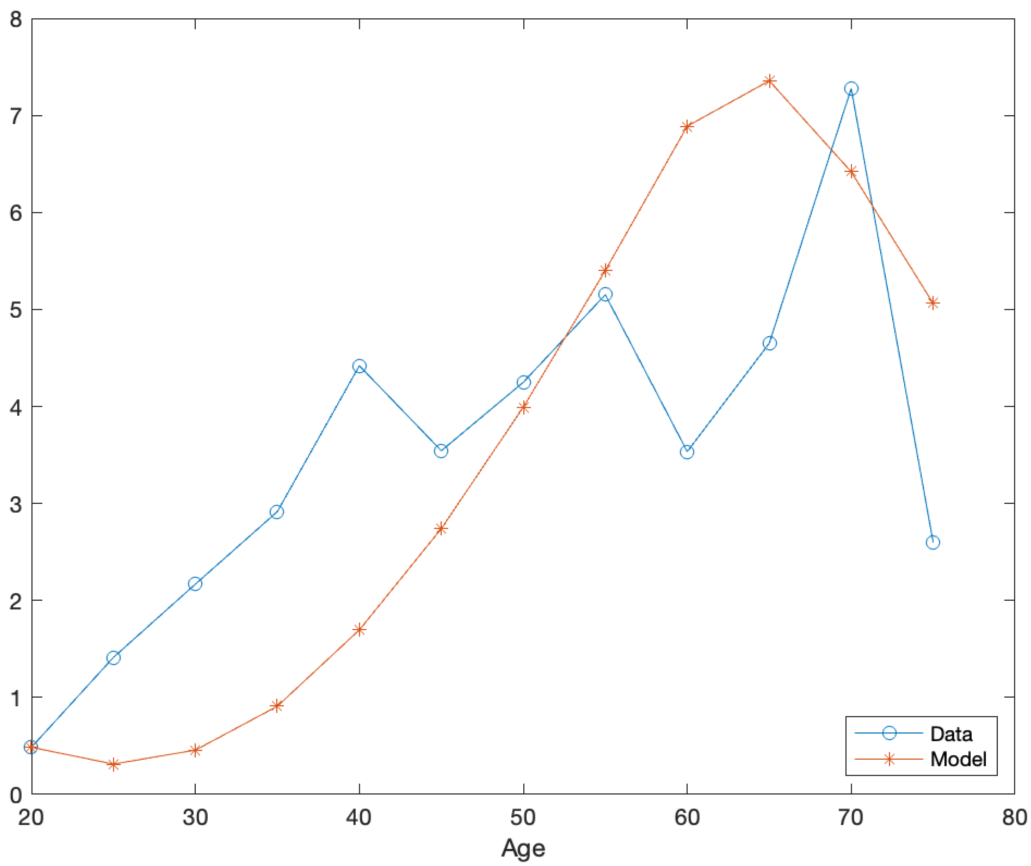
Target	SCF+ (1967)	SCF+ (1970)	SCF+ (1977)	SCF (1989)	SCF(2004)
Average wealth, 20-25	0.55	0.37	0.85	0.43	0.65
House wealth share (owners)	56.93%	61.15%	61.7%	52%	53.91%
Homeownership rate	68%	70%	71.56%	68%	72.71%
Average wealth	2.70	2.35	2.79	3.81	4.92
Average wealth, 75/60	0.63	0.88	0.52	0.64	0.68

Notes: Choosing SCF+ 1970 or 1977 for Boomers, SCF 1989 for Gen X and SCF (2004) for Millennials. Model is calibrated to SCF+ 1967.

B.4 Untargeted Moments from Model Calibration

Figure Figure B.2 displays statistics by wealth decile. It compares observed data from SCF and a model's predictions on average wealth (normalized by per-capita income) across different age groups, displayed in five-year intervals. Both the observed data and model show wealth accumulation increasing with age, peaking around age 65 before declining. The model closely follows the data trends until around age 60, where it then underestimates the peak and subsequent drop seen in the actual data, indicating that while the model captures the general trend of increasing wealth with age, it does not fully align with the sharp increase and rapid decline in wealth accumulation observed in the later years.

Figure B.2: Average Wealth relative to per-capita income by Age

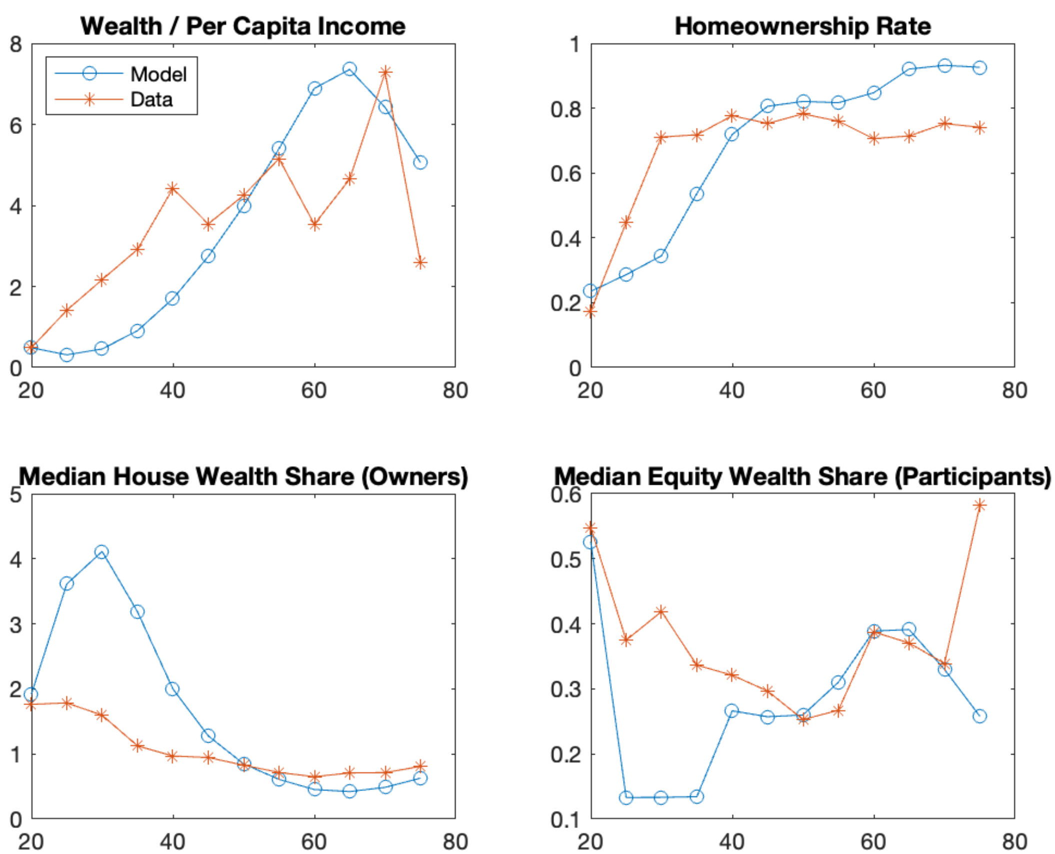


Notes: This figure displays average wealth (divided by per-capita income) by 5-year age groups.

B.4.1 Statistics across the Lifecycle

Figure Figure B.3 displays statistics across the Lifecycle regarding the housing and equity markets. It offers an in-depth look at financial dynamics through various life stages, contrasting actual observed data with theoretical model predictions regarding wealth accumulation and the distribution of assets across different age groups. The wealth graph shows a pattern of wealth relative to per-capita income increasing with age, peaking in the 60s, and then declining. Both the observed data and the model capture this trend, though the model slightly underestimates wealth accumulation in later years, suggesting it might not fully account for the nuances of post-retirement financial dynamics. Another graph illustrates the homeownership rate, which rapidly increases from

Figure B.3: Portfolios by Age Group



Notes: This figure displays statistics by 5-year age groups.

early adulthood and stabilizes around the early 40s. The model mirrors this pattern but projects a stabilization at about 80% , slightly higher than the actual data's level around 70% , indicating an overestimation of homeownership among older demographics. Additionally, the graphs showing median house wealth share and equity wealth share highlight discrepancies between the model's predictions and actual data, with the former depicting a sharper decline in housing wealth and the latter showing unexpected rises in equity participation in later years. These differences underscore the model's challenges in accurately reflecting real-world economic behaviors and the variability in financial decisions among older adults.

B.4.2 Statistics across the Wealth Distribution

Figure Figure B.4 displays statistics by wealth decile. The graphs offer insights into homeownership and asset distribution trends across life stages. Both model and observed data illustrate a steep rise in homeownership rates during early adulthood, peaking in later years, with the model initially overestimating homeownership compared to actual data. The house wealth share graph similarly shows a significant decline in housing's contribution to total wealth as homeowners age, with the model reflecting a less pronounced reduction. In contrast, the mortgage-to-wealth ratio

Figure B.4: Statistics by Wealth Decile

Notes: This figure displays statistics by wealth decile.

graph reveals a consistent decrease in mortgage burden relative to wealth over time, aligning closely between model and data. The equity wealth share graph, however, shows fluctuating investment trends, particularly a mid-life dip and recovery that the model exaggerates compared to smoother trends observed in the data. This highlights potential model oversensitivity to economic cycles or investor behaviors not as clearly mirrored in real-world data. These graphs effectively demonstrate the evolution of financial obligations and asset balances throughout different life stages.

B.5 Quantitative Analysis

B.5.1 One time permanent change in equity and house prices

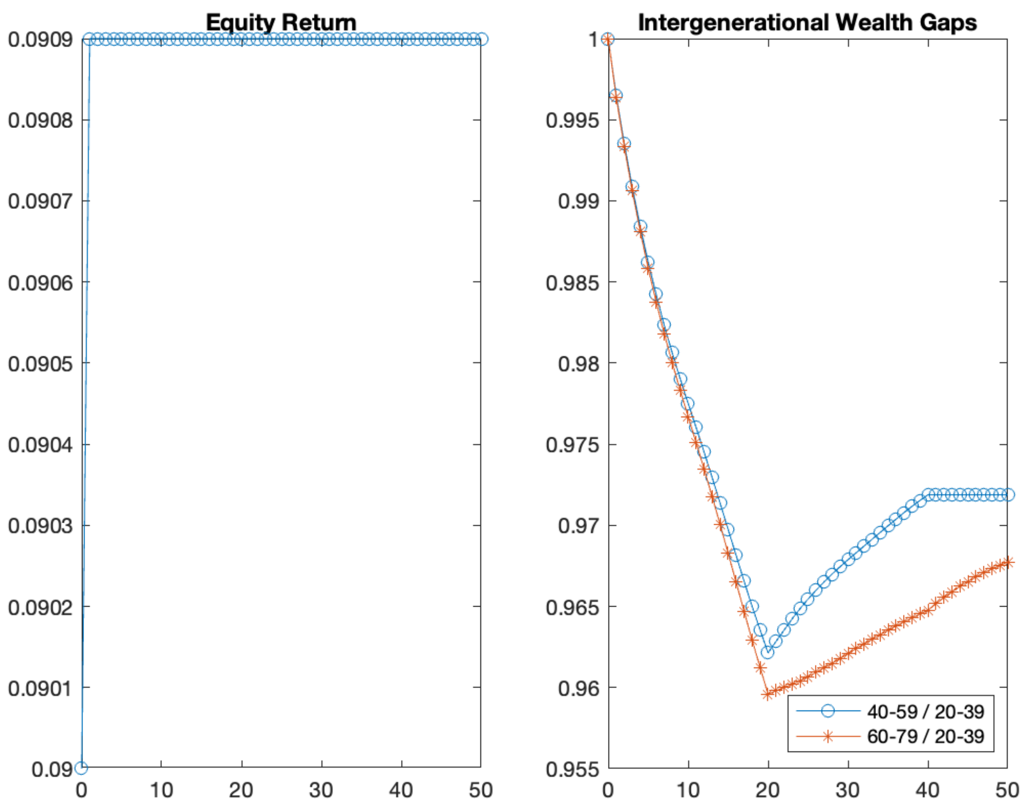
Preliminary quantitative impulse response to permanent asset price increase are shown in Figure B.5 and Figure B.6. The graphs present a comparative analysis of equity and house price stability, which remain consistent over time, alongside the dynamics of inter-generational wealth gaps between different age cohorts. Both asset classes show minor price fluctuations, maintaining near constant levels. In contrast, the wealth gap analysis indicates initial alignment followed by increasing disparities between the younger (20-39) and older (40-59 and 60-79) cohorts, particularly highlighted in house prices where a sharp peak and subsequent decline suggest significant shifts in wealth accumulation over the lifecycle. This pattern reveals how generational wealth disparities evolve and later stabilize as younger cohorts age.

B.5.2 Changes in equity and house prices calibrated to Hubmer et al. (2021)

Figure B.7, Figure B.8 and Figure B.9 provide a detailed analysis of equity and house price trends along with inter-generational wealth gaps, demonstrating significant variations in asset growth and generational wealth disparities over time. In the first figure, equity returns show a marked upward trajectory, indicating robust growth over time, reflecting potentially higher investment returns for stakeholders. The corresponding panel on inter-generational wealth gaps illustrates that wealth disparities between the 40-59 age group and the 20-39 age group initially narrow, then widen significantly before stabilizing, suggesting fluctuating economic advantages between generations at different life stages.

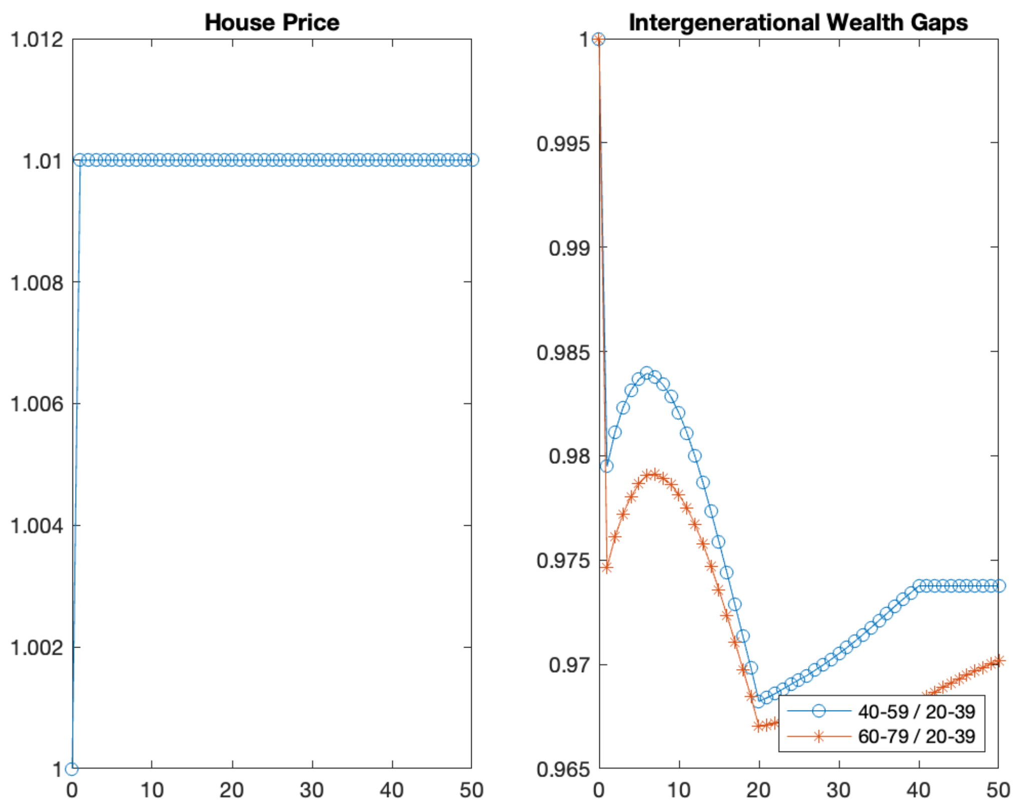
The exponential growth in house prices underscores the sharp increase that benefits older cohorts, possibly due to longer-term investments in real estate. The wealth gap graph for house

Figure B.5: A 10% permanent increase in equity returns



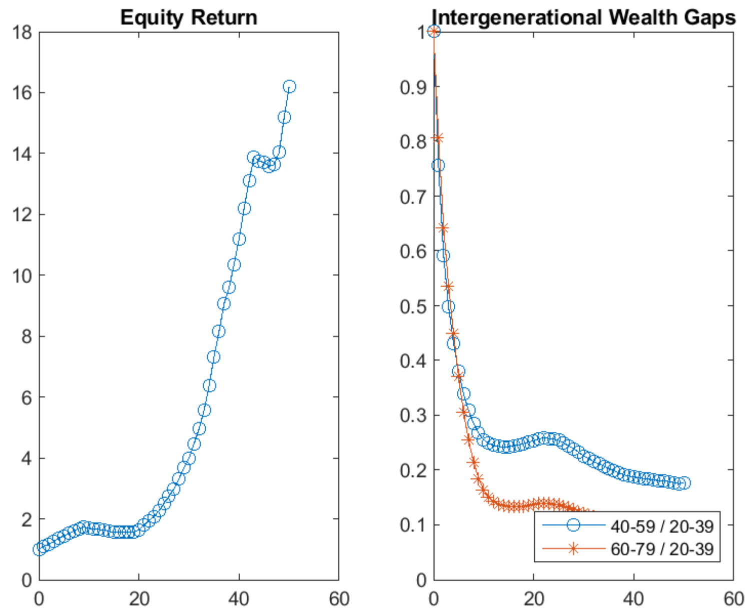
Notes: This figure displays the annual evolution from 1967 onwards

Figure B.6: A 10% permanent increase in house price



Notes: This figure displays the annual evolution from 1967 onwards

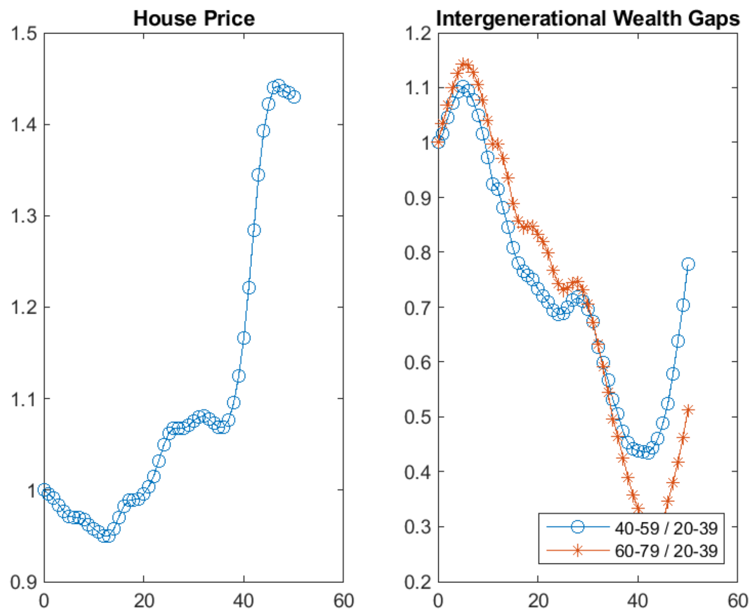
Figure B.7: Changes in equity returns calibrated to HKS



Notes: This figure displays the annual evolution from 1967 onwards

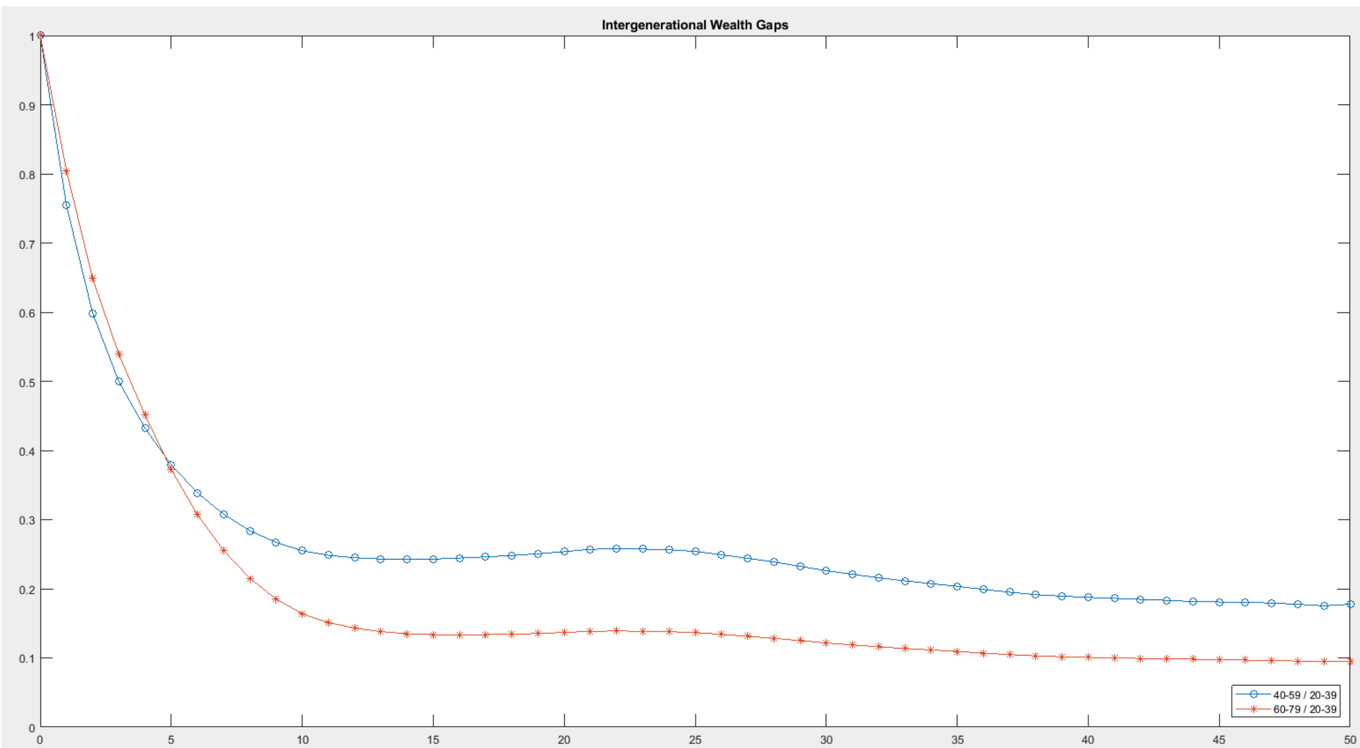
prices shows a more dramatic fluctuation, with gaps initially widening dramatically as the older cohort's investments appreciate before narrowing as market conditions change, reflecting the volatile nature of real estate markets. The third graph simplifies the view on wealth gaps, indicating a steady decline in the wealth ratio over time as younger generations fail to catch up, stabilizing at a lower level, which portrays a sustained economic divide that could influence future policy considerations and financial planning for younger cohorts.

Figure B.8: Changes in equity returns calibrated to HKS



Notes: This figure displays the annual evolution from 1967 onwards

Figure B.9: Changes in equity and house returns calibrated to HKS



Notes: This figure displays the annual evolution from 1967 onwards. The changes in equity and house price are the combined price changes in Figure B.7 and Figure B.8.

Appendix C

Appendix for Chapter 3

C.1 Aggregate Consumption back of the envelope calculation

Using the estimates of SCF 2019 from the first row in Table 3.3 and the MPC estimates from Table 3.1, we can calculate the aggregate weighted consumption for Kaplan et al. (2014) as follows

$$
\begin{aligned}
C_{\text{P-HtM}} &= 0.2507 \times (1 - 0.6513) \\
&= 0.0212 \\
C_{\text{W-HtM}} &= 0.2507 \times 6513 \times 0.301 \\
&= 0.0491 \\
C_{\text{N-HtM}} &= (1 - 0.2507) \times 0.127 \\
&= 0.0952
\end{aligned}
$$

Adding the three gives the total consumption of the economy to be 0.1655 or around 16.55% . Similarly based on the estimates of SCF 2019 from the second and third rows in Table 3.3 and the MPC estimates from Table 3.2 which are from Zhu et al. (2019) Table 5, we can calculate the approximate weighted consumption as follows

Housing Consumption (Share = 0.35)

$$
\begin{aligned}
C_{\text{from HE extraction}} &= 0.1871 \times 0.307 + (1 - 0.1871) \times 0.079 \\
&= 0.1217 \\
C_{\text{from not extracting HE}} &= 0.089 \times 0.2418 + 0.037 \times (1 - 0.2418) \\
&= 0.050j \\
\text{Total Housing Consumption} &= 0.35 \times (0.1217 + 0.05)
\end{aligned}
$$

Non-Housing Consumption (Share = 0.65)

$$
\begin{aligned}
C_{P-HtM} &= (1 - 0.6513) \times 0.2507 \times 0.243 \\
&= 0.021 \\
C_{W-HtM} &= (0.6513 \times 0.2507 - 0.35 \times 0.1871) \times 0.078 \\
&= 0.0076 \\
C_{N-HtM} &= (1 - (1 - 0.6513) \times 0.2507 - 0.098) \times 0.04 \\
&= 0.0326 \\
\text{Total Non-Housing Consumption} &= 0.65 \times (0.021 + 0.0076 + 0.0326)
\end{aligned}
$$

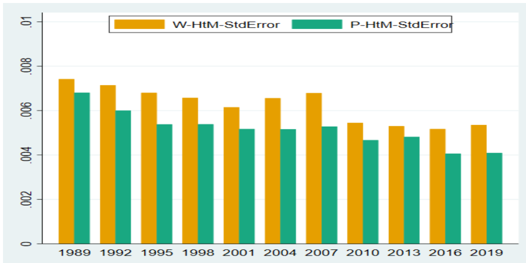
Adding the two gives the total consumption of the economy to be 0.099875 or around 9.98% .

C.2 HtM Estimate Standard Errors

I present here the standard errors of the HtM estimates as a robustness check analogous to Figures 3.4, 3.5, 3.6, 3.7 & 3.8 to in the main text. Figure 3.6 has been split into 2 parts: Figure C.3 and Figure C.4. In all the figures, the standard errors are extremely low suggesting the measurement for the mean estimates is accurate enough for empirical purposes.

Figure C.1: SE of estimates for the time-series of fraction of HtM households in the U.S

(a) Share of total, wealthy, and poor HtM



(b) Share of total, wealthy, and poor HtM

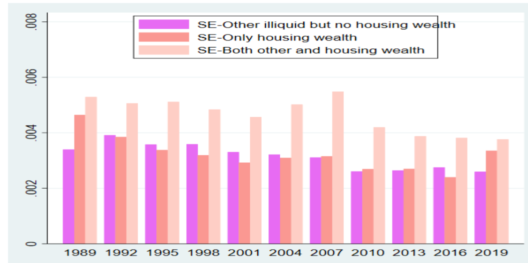


Figure C.2: SE of estimates for the share of HtM households among homeowners by leverage ratio, SCF 1989-2019.

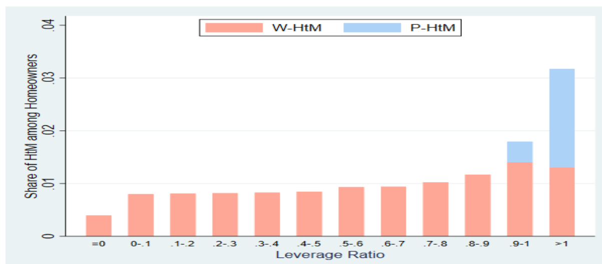
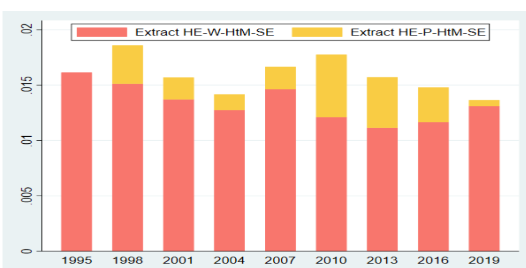
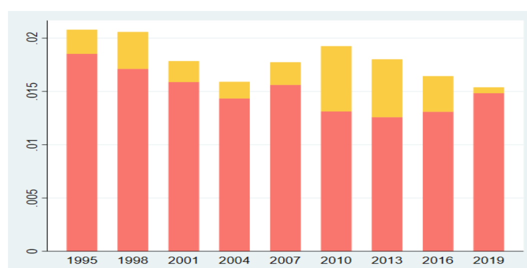


Figure C.3: SE of estimates for the time series of fraction of HtM households in the U.S. who extracted Home Equity, alternate definitions.

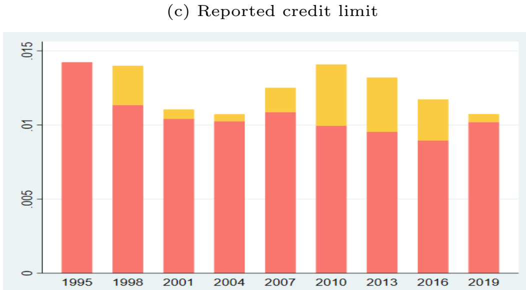
(a) Income-weighted share of HtM



(b) Pay-period of 1 month



(c) Reported credit limit



(d) Vehicles in illiquid wealth

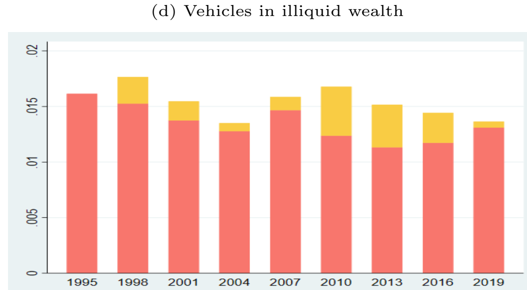
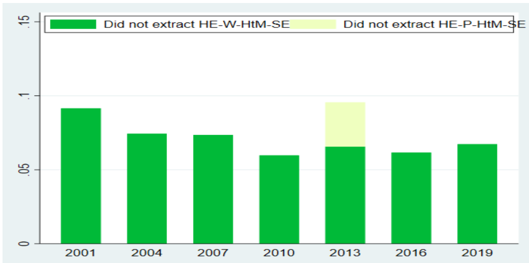
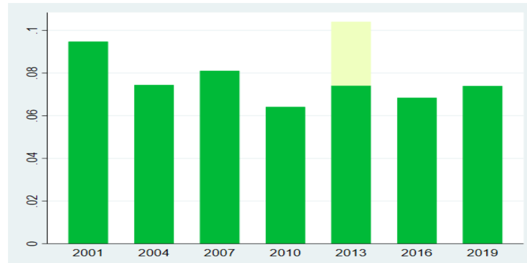


Figure C.4: SE of estimates for the time series of fraction of HtM households in the U.S. who did not extract Home Equity, alternate definitions.

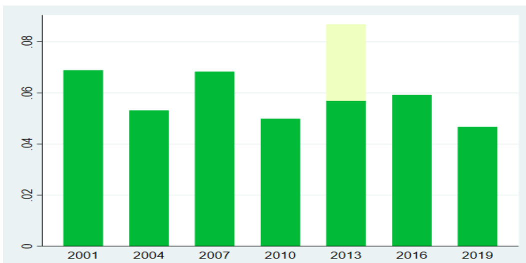
(a) Income-weighted share of HtM



(b) Pay-period of 1 month



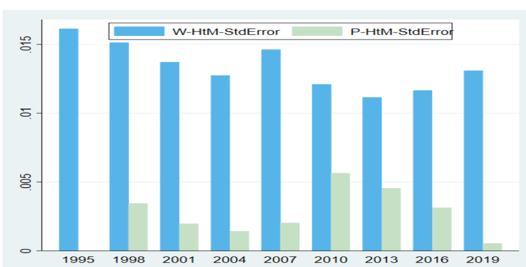
(c) Reported credit limit



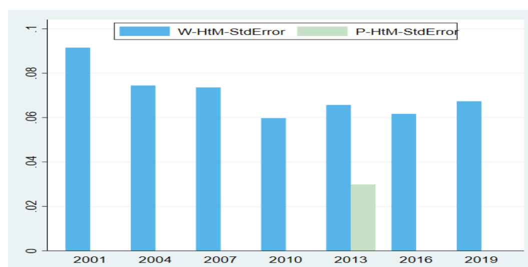
(d) Vehicles in illiquid wealth

Figure C.5: SE of estimates for the HtM households and the portfolio composition of wealthy HtM by refinance decision

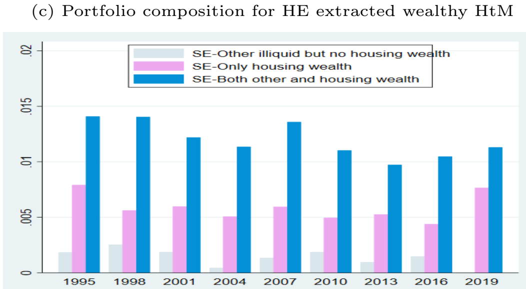
(a) Refinanced & extracted home equity



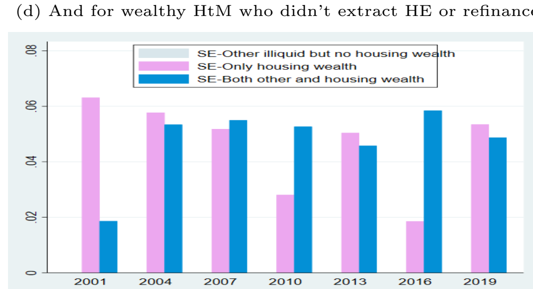
(b) Did not refinance and/or extract HE



(c) Portfolio composition for HE extracted wealthy HtM



(d) And for wealthy HtM who didn't extract HE or refinance



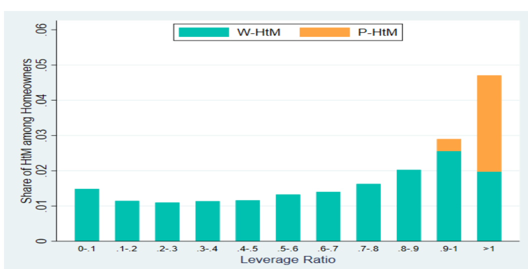
For some of the figures, since the variable denoting the refinancing choice is not present every survey, the values are absent for some survey years, inline with the figures in the main text.

Figure C.6: SE of estimates for the time series of fraction of HtM households in the U.S., alternate definitions. conditioned on Home Equity Extraction

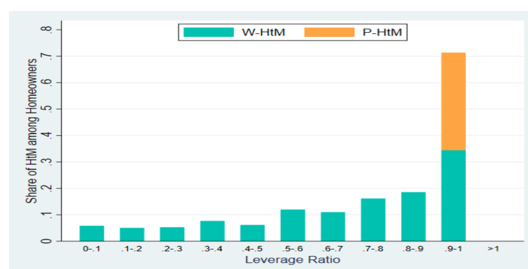
Notes - Based on Income-weighted share of HtM and those with Pay-period of 1 month. Also based on reported credit limit and including vehicles as part of illiquid wealth

Figure C.7: SE of estimates for the time-series of fraction of HtM households in the U.S

(a) Refinanced to extract home equity



(b) Did not extract HE by refinance



C.3 Freddie Mac Approvals

This section contains the detailed results for the Freddie Mac data that motivates the importance of unemployment percentage changes in proxying for idiosyncratic income shocks. The results serve to broaden the evidence of how the same can be used to map to the individual collateral constraint.

Additionally, I present the results conditioned on various quantiles presented in Figures Figure C.8 and Figure C.10. I choose 3 quantiles. The base level and two added dummies for each of the variables that I choose to condition on. The coefficients give similar results as shown by the level variables at the aggregate. Unemployment and interest rates are the only regressors with substantial variation. This effect is consistent with the interest rate effect picking up off late and the unemployment effect reducing in the recent years. The dummy values indicate the trends that are seen with the frequency of refinancings in Figure 3.10. Higher DTI, lower FICO and higher LTV, higher unpaid loan balance all lead to higher dummy values indicating stronger probability of cash-out refinance across the MSAs.

Figure C.8: Coefficient values-3 quantiles

From Figure C.9, I infer that the most important variables governing the decision to undertake a cash-out refinance over a no cash out are the debt-to-income, FICO and unpaid balance. Surprisingly, higher unpaid balance leads to a greater propensity to undertake a cash-out refinance which may well be because the interest rates on the new mortgage amount would be far lesser owing to mortgage rates being at their historic lows. [1] Moreover, I can safely claim that these variables are positively correlated with unemployment changes (proxying for the idiosyncratic income shocks at the individual level). This would increase the true variation captured by the percentages changes in the MSA level unemployment rates. These variables are less correlated with the aggregate changes in the house prices. Interest rate changes and the amount of available home equity explain less of the variation. This effect is consistent across quantiles. The results further strengthen the House

[1] This is in contrast to results obtained by Chen et al. (2020).

Figure C.9: ANOVA for Coefficient values-3 quantiles

Figure C.10: Dummy values-3 quantiles

as ATM channel with changes in unemployment & being a significantly important driver for the choice of refinance activity. On the other hand, the original interest rates are significantly less effective.

If I further study the interaction effects across quantiles as presented in Figures Figure C.12 and Figure C.14, I find that the unemployment percentage changes is the most significant across the various quantiles and this is true for both levels 2 and 3 for the various regressors and variables

Figure C.11: ANOVA for Dummy values-3 quantiles

that have been divided into various quantiles. The interest rates also have become quantitatively significant off late as observed previously. The results confirm my hypothesis that the choice of refinance can be used as an imperfect substitute to proprietary data in studying the incentives for home equity extraction without explicitly relying on the exact amount of home equity extracted per loan. This is sufficient for the interests of the current paper with the strong evidence for household liquidity demand in the face of idiosyncratic income shocks given by the percentage changes in unemployment at the MSA level. The same is also exacerbated if the erstwhile household debt levels are higher as indicated by the various levels of the dummy especially for FICO scores and the debt-to-income along with larger unpaid balances.

To get a better picture about the importance of each regressor of interest in accounting for the interaction and base level effects, I study the corresponding variance decomposition effects for the two dummy levels across quantiles in Figure C.11 (analogous to Figure C.10) followed by the interaction effects of interest for the mid and high level in Figures Figure C.13 & Figure C.15 (analogous to Figures Figure C.12 & Figure C.14) respectively.

Looking at the variance decomposition for the middle quantile (Figures Figure C.11 & Figure C.13) we find that the effects are more or less similar for all the quantile variables except the levels for original loan to value (LTV). Having a larger LTV would mean the effect of unemployment changes is much greater than the effects of changes in house prices & interest rates). This result

Figure C.12: Interaction effects-Quantile 2

Figure C.13: ANOVA for Interaction effects-Quantile 2

seem to slightly surprising suggesting that agents who seem to be more constrained have greater urge to undertake cash-out refinance. Since the data indicates only approvals, the explanation that more constrained agents getting approved for a cash-out refinance that would further increase their LTVs holds and the initiation for the same is coming from negative income shocks indicated or proxied by the unemployment percentage changes.[2] Overall, there does not seem to be any

[2]This could be also due to the endogeneity with increasing house prices. Chen et al. (2020) find that a looser LTI constraint can also enable more households to become homeowners or switch to a bigger house, which would relax the LTV constraint and further increase the amount of borrowing and the results are broadly consistent.

significant changes across the middle quantile. The order of magnitude of the variations are all the same for both the base level coefficients and the diff-in-diff effects captured by the dummy & interaction terms for various quantiles as evidenced by Figures Figure C.9, Figure C.11 and Figure C.13 suggesting little heterogeneity across agents for the middle level.

Figure C.14: Interaction effects-Quantile 3

Similarly, if we are to look at the variation for the third level (denoted by high) we find the results to be significantly different. This is evidenced by Figures Figure C.11 (for the third level) & Figure C.15. The interaction effects are quantitatively different for the quantiles of the debt-to-income, average house prices, FICO score and Home Equity. Higher DTI & FICO scores (both indicating agents who are expected to be significantly constrained comparatively) have higher sensitivity to the unemployment rates and individual interest rates over home equity & house price changes. This further reinforces the fact that wealthy HtM having received higher income shocks has a greater propensity to opt for a cash-out refinance corroborating the significance of my proposed mechanism for a significant fraction of agents whose main illiquid asset is the house that they own through mortgages. The importance of the evidence is especially relevant under the current crisis where we would like to have more precise estimates of the proportion of people who are HtM and can use their house to get an emergency liquidity transfer.

Figure C.16 indicates that there are very slight differences on expanding the number of quantiles. Reassuringly, the results are intuitive and in line with the ones obtained for 3 quantiles

Figure C.15: ANOVA for Interaction effects-Quantile 3

in Figure 3.10 in the main text.

I have excluded home equity and unemployment quantiles since the results were more or less identical to the ones given in the main text for 3 quantiles. Analogous to Figure C.8, Figure C.17 shows the value of coefficients for 5 quantiles. The graphs look almost identical for the case of 3 quantiles suggesting very little improvement in adding more quantiles. There is surprisingly little variation across quantiles. This effect is carried over to the dummy values and the interaction terms for the various quantile levels.

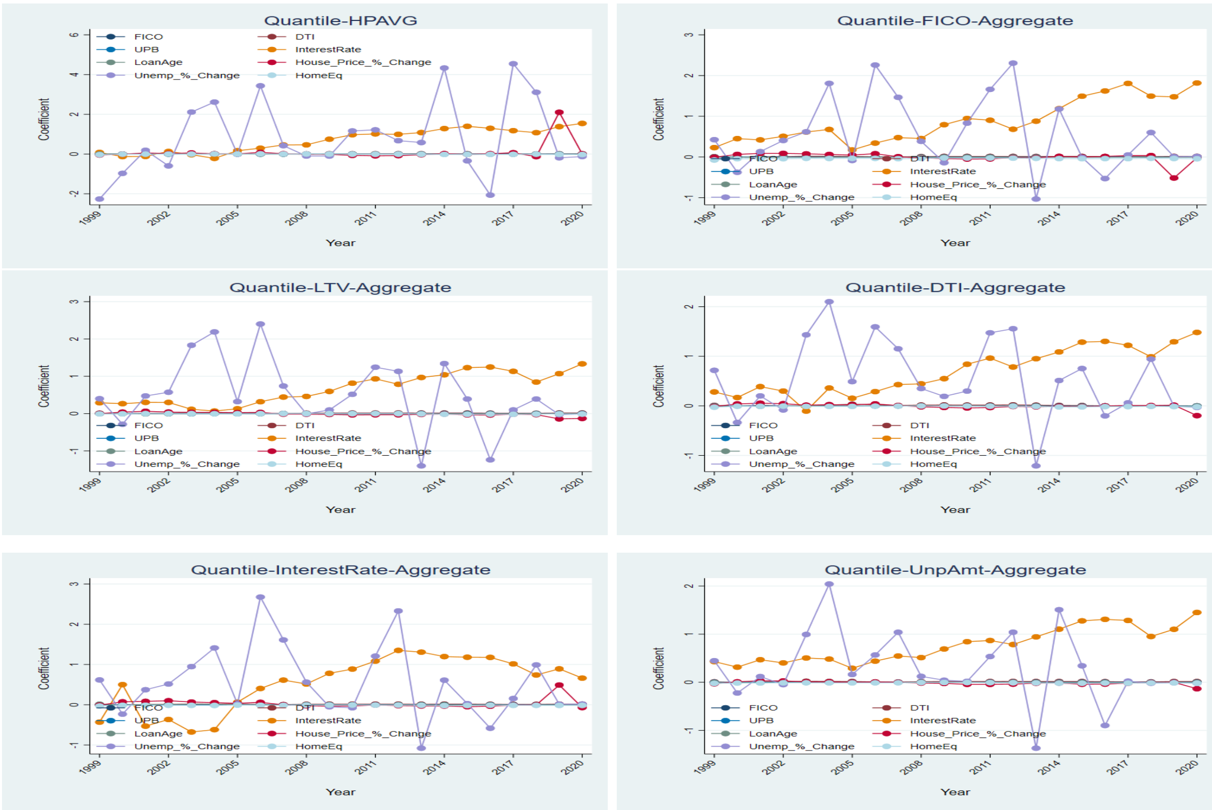
Observing, it can be claimed that Figure C.18 is quite different from Figure C.10 in terms of the magnitudes of the values. The effects are qualitatively and intuitively similar to the corresponding results in the main text with some important exceptions. Within the quantiles, when the data is divided based on the loan-to-value, there is little difference except during the crisis in 2008. Interestingly, the interest rate effect stays muted except for the GFC period. This once again reinforces the main results in the text and is consistent with the HtM status of such households. Interest rate changes are not an important determinant of the probability in preferring a cash-out refinance.

The effects of interest rate increase when considering 5 quantiles. The major effect is still the unemployment percentage change as in the main text suggesting the effects of sudden negative shocks to labor income are stronger in reality. This augments both my theoretical model

Figure C.16: Frequency of Cash-out refinance for 5 quantile levels

that motivates the measurement and the motivation behind measuring the hand-to-mouth status. Figure C.19 and Figure C.20 show the interaction effects for the second and third quantile. Comparing with Figure C.12 & Figure C.14, the magnitude of the interest rate is significantly different from near zero. However, the impact of the unemployment percentage change does not diminish in any way and the results survive on considering different quantiles. Additionally, Figure C.21 & Figure C.22 show the impacts due to the interaction effects for the fourth and fifth quantiles. Observing the panels for interest rate, the impact of further changes in the mortgage rate are inconsequential and the effects are again linked with changes in the unemployment rates.

Figure C.17: Coefficient values-5 quantiles



Lastly, for completeness and for understanding the importance of regional factors, I present the results for various regions in Figure C.23. The effect of unemployment remains strong for all quantiles while the effects of interest rate are strongest only for South. This suggests region specific factors are possibly heterogeneous. I carry out the analogous exercises to the aggregate level for the various regions. However, I observe that the heterogeneity is not that significant. I therefore do not include the figures for rest of the results for the four regions in the interest of space.

Figure C.18: Dummy values-5 quantiles

Figure C.19: 5 quantiles: Interaction Effects for quantile 2

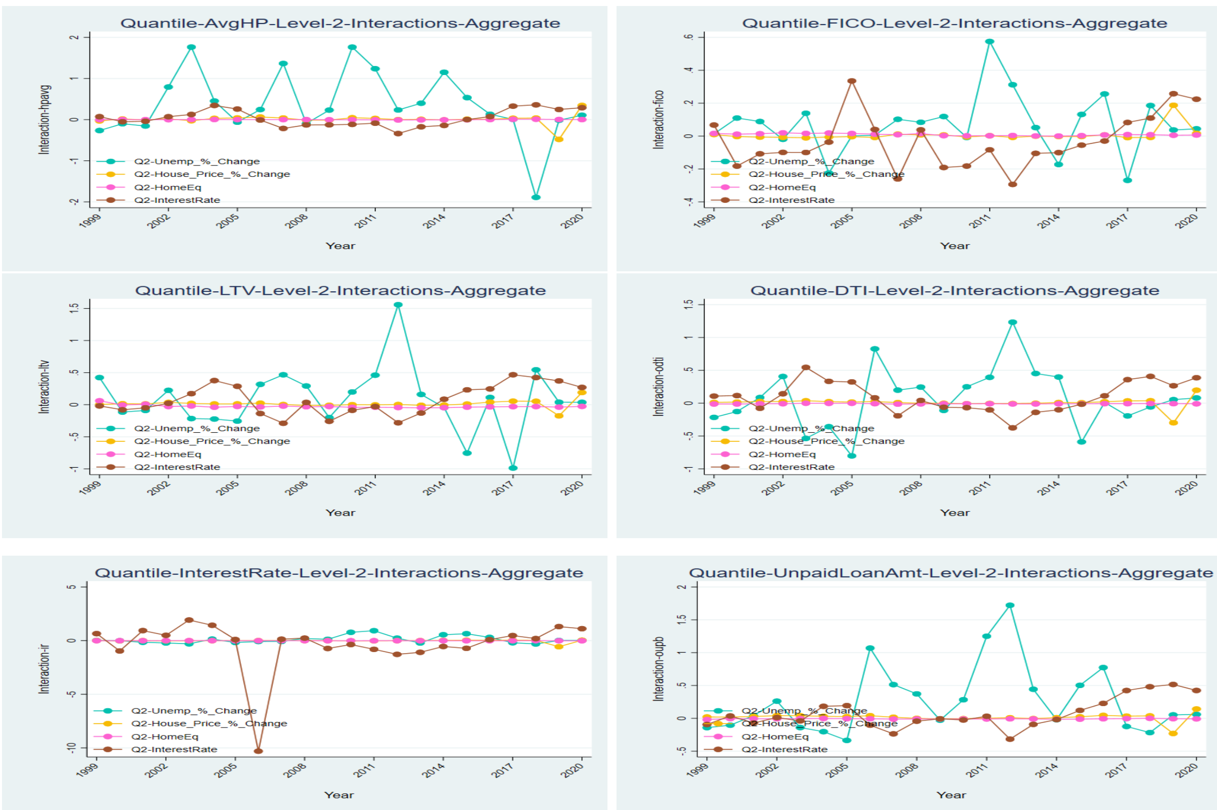


Figure C.20: 5 quantiles: Interaction Effects for quantile 3

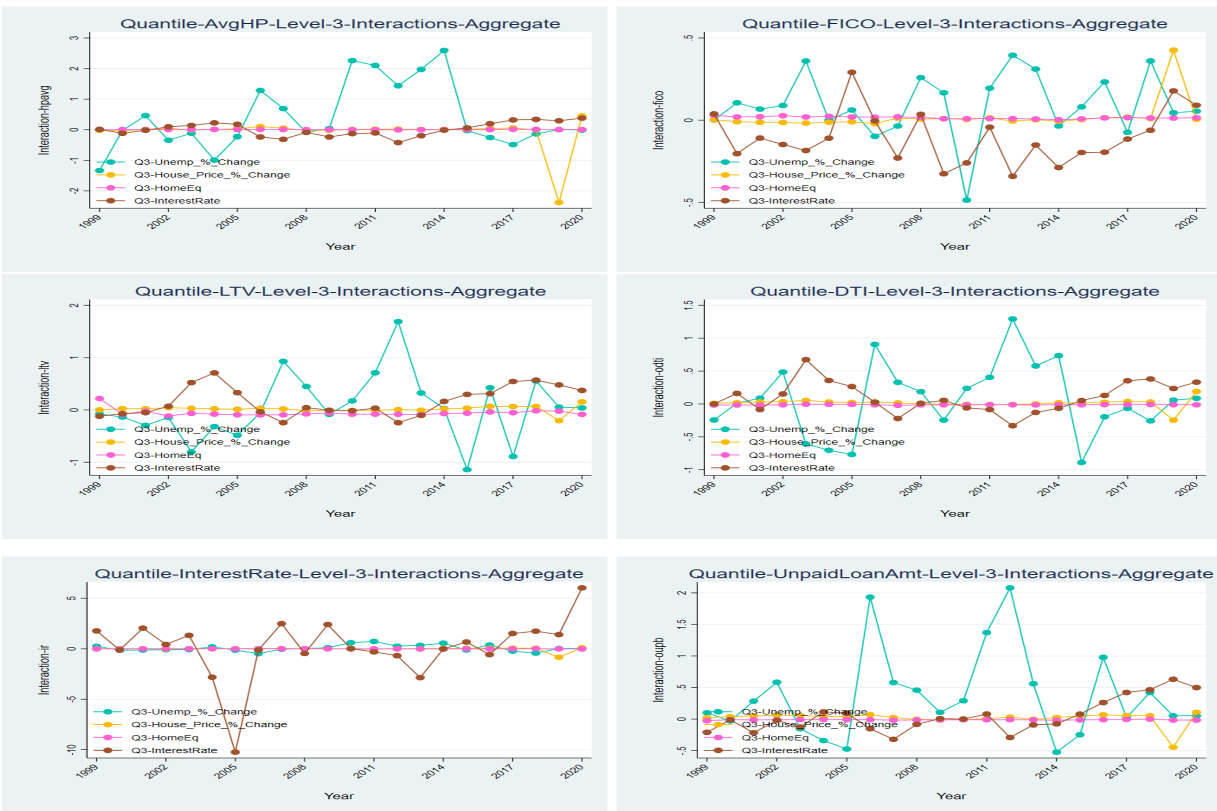


Figure C.21: 5 quantiles: Interaction Effects for quantile 4

Figure C.22: 5 quantiles: Interaction Effects for quantile 5

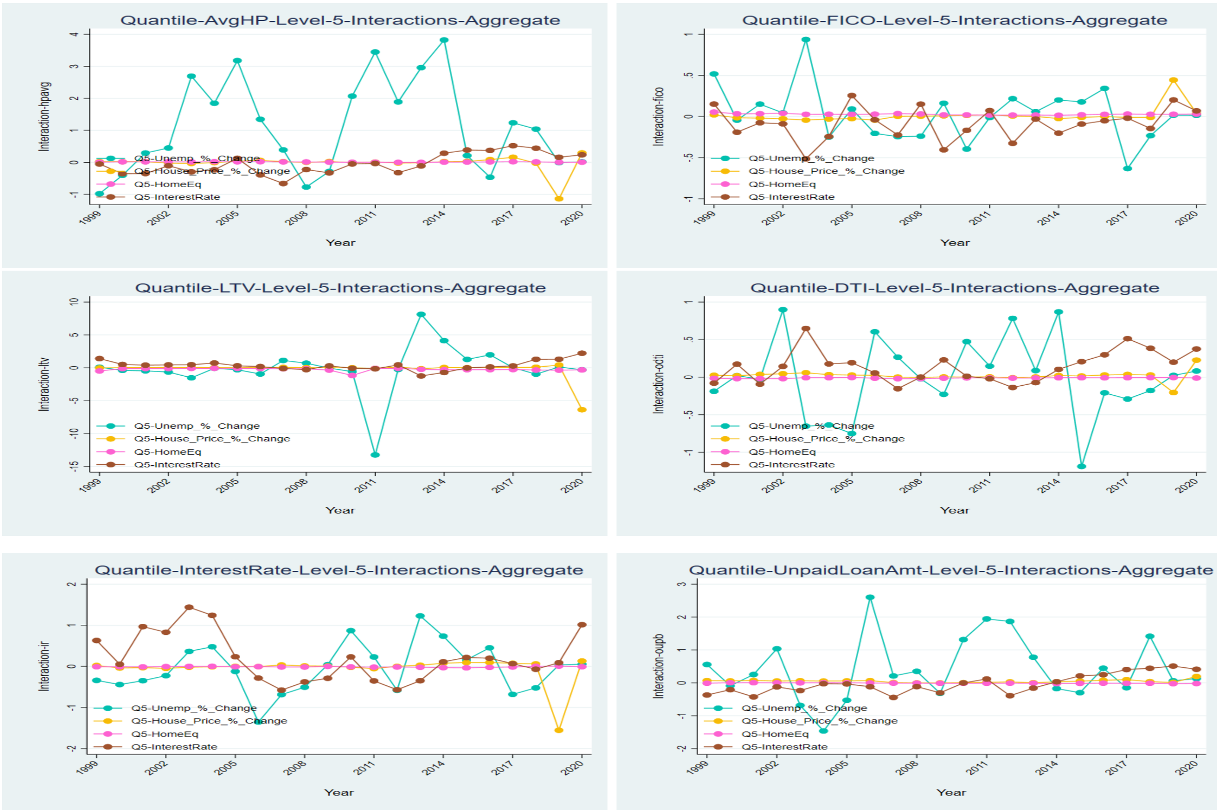


Figure C.23: Coefficient values with region dummies