Crawford School of Public Policy

CAMA

Centre for Applied Macroeconomic Analysis

Did Marginal Propensities to Consume Change with the Housing Boom and Bust?

CAMA Working Paper 32/2023
July 2023

Yunho Cho
Jinan University

James Morley
University of Sydney
Centre for Applied Macroeconomic Analysis, ANU

Aarti Singh
University of Sydney
Centre for Applied Macroeconomic Analysis, ANU

Abstract

We extend a widely-used semi-structural model to identify and estimate dynamic consumption elasticities with respect to transitory income shocks. Applying our model to household survey data, we find a structural break in marginal propensities to consume following the end of the housing market boom, with the average across households increasing significantly. Our results suggest important heterogeneity by different household balance sheet characteristics and that the increase in the average was driven by higher short-run consumption elasticities for homeowners with low liquid wealth. The change in consumption behavior appears to be related to tighter borrowing constraints more than a shift in wealth distributions.

Keywords

marginal propensity to consume, Great Recession, consumption insurance, liquid wealth, house prices

JEL Classification

E21, C13, C33, D12, D14

Address for correspondence:

(E) cama.admin@anu.edu.au

ISSN 2206-0332

Did marginal propensities to consume change with the housing boom and bust?*

Yunho Cho† James Morley‡ Aarti Singh§

July 25, 2023

Abstract

We extend a widely-used semi-structural model to identify and estimate dynamic consumption elasticities with respect to transitory income shocks. Applying our model to household survey data, we find a structural break in marginal propensities to consume following the end of the housing market boom, with the average across households increasing significantly. Our results suggest important heterogeneity by different household balance sheet characteristics and that the increase in the average was driven by higher short-run consumption elasticities for homeowners with low liquid wealth. The change in consumption behavior appears to be related to tighter borrowing constraints more than a shift in wealth distributions.

Keywords: Marginal propensity to consume; Great Recession; consumption insurance; liquid wealth; house prices.
JEL codes: E21; C13; C33; D12; D14.

*We thank Alex Ballantyne, Chris Edmond, Miguel Faria-e-Castro, Chris Gibbs, James Graham, James Heckman, Virgiliu Midrigan, Robert Moffitt, Pablo Ottonello, Bruce Preston, Satoshi Tanaka, Lawerence Uren, Gianluca Violante, Eric Young, Yu Zheng, and conference and seminar participants at AMES (Xiamen), ASSA Virtual Meeting, EEA-ESEM (Manchester), Frontiers in Econometrics Workshop (Sydney), HKUST-Jinan Joint Conference on Macroeconomics (Guangzhou), IAAE (Rotterdam), Jinan IESR Quantitative Macro Workshop, SED Annual Meeting (St. Louis), Sydney MRG Workshop, the Bank of Japan, the St. Louis Fed, the Institute for Employment Research, Keio University, Kyoto University, Shanghai University of Finance and Economics, University of Melbourne, University of Pittsburgh, and the Virtual Australian Macroeconomics Seminar for helpful comments. This research was supported by the Australian Research Council grant DE130100806. The usual disclaimers apply.

†Institute for Economic and Social Research, Jinan University; yunho.cho@outlook.com

‡School of Economics, University of Sydney; Centre for Applied Macroeconomic Analysis, ANU; james.morley@sydney.edu.au

§Corresponding author: School of Economics, University of Sydney; Centre for Applied Macroeconomic Analysis, ANU; aarti.singh@sydney.edu.au

1 Introduction

Heterogeneity in the marginal propensity to consume (MPC) out of transitory income is important for macroeconomic policy. For example, Demyanyk, Loutskina, and Murphy (2019) argue that fiscal stimulus during the Great Recession could have been more effective had it been targeted to geographical areas with higher levels of household debt because households in those areas might have had higher MPCs. The idea that MPCs could be related to household balance sheets is motivated by consumption theories with precautionary savings due to the presence of either occasionally-binding borrowing constraints or concave marginal utility in the presence of income uncertainty and incomplete markets. Specifically, households with low levels of wealth should have relatively high MPCs; see, for example, Carroll and Kimball (1996), Carroll (1997), and Carroll (2004). At the same time, Kaplan and Violante (2014) argue that higher returns on illiquid assets induce a tradeoff between consumption smoothing and higher lifetime consumption such that even wealthy households will find it optimal to hold relatively few liquid assets, potentially making them also sensitive to transitory changes in income. Given that housing represents a large, illiquid component of household wealth often associated with mortgage debt and building on the literature on why consumption fell during the Great Recession (see, for example, Dynan, 2012, Mian, Rao, and Sufi, 2013, Huo and Ríos-Rull, 2016, Baker, 2018, Garriga and Hedlund, 2020, Jones, Midrigan, and Philippon, 2020, and Kaplan, Mitman, and Violante, 2020a,b), our main research question is whether and how, in addition to directly affecting the level of consumption, the housing market boom and bust in the mid 2000s might have also affected MPCs and altered patterns of heterogeneity related to household balance sheets.

To investigate how MPCs might have changed with the housing boom and bust, we estimate a semi-structural model of household consumption and income using biennial data from the Panel Survey of Income Dynamics (PSID) for 1998-2016. Semi-structural models allow the use of statistical methods to infer responses to idiosyncratic permanent or transitory income shocks without the econometrician directly observing these shocks, but only assuming a structure for the underlying income and consumption processes.[1] Importantly, we extend the widely-used Blundell, Pistaferri, and Preston (2008) (BPP hereafter) semi-structural model to identify and estimate dynamic consumption elasticities with respect to transitory income shocks. This modification of the BPP model addresses a concern raised by Commault (2022) with the original BPP model if consumption does not actually follow a random walk and directly provides "intertemporal" MPCs in the sense of Auclert, Rognlie, and Straub (2018). It is also consistent with non-zero transitory consumption responses that we find in simulated data from the calibrated Kaplan and Violante (2010) structural life-cycle model with incomplete markets and borrowing constraints. Furthermore, our estimates of MPCs based on short-run elasticities are conceptually closer to what is

[1]Unlike econometricians, households might directly observe the permanent and transitory income shocks, as supported by the findings in Druedahl and Jørgensen (2020).

captured in natural experiments such as short-term consumption responses to tax rebates (Parker, Souleles, Johnson, and McClelland, 2013), lottery winnings (Fagereng, Holm, and Natvik, 2021), and mortgage modification programs (Ganong and Noel, 2020) given that these experiments can capture transitory consumption responses, while the original BPP model assumes only permanent responses and, therefore, estimates averages of short-run and long-run responses.

We obtain reasonably precise estimates even for relatively small samples of different household groups from before to after the housing boom and bust (i.e. "1998-2006" versus "2007-2016") by applying the quasi maximum likelihood estimation (QMLE) approach for semi-structural models of household data developed in Chatterjee, Morley, and Singh (2021). Although the semi-structural approach has been used extensively in the literature, it is almost always based on GMM or related moments-based estimators; see, for example, Kaplan, Violante, and Weidner (2014), Auclert (2019), and Crawley (2020). However, as shown in Chatterjee et al. (2021), QMLE is more accurate than GMM for the same model given highly non-Normal shocks and especially in smaller samples with many missing observations such as we are considering in our analysis that involves biennial waves of data with every second year missing. Furthermore, in contrast to Commault's (2022) limited-information moments-based approach, our full-information QMLE approach identifies and estimates both short-run and long-run consumption elasticities even with biennial data and allows us to consider formal statistical tests for heterogeneity across household groups and for structural breaks in model parameters. Notably, we also find that likelihood-based inference for our model mitigates the large downward bias in estimating consumption insurance with respect to permanent income risk that Kaplan and Violante (2010) highlight afflicts the BPP moments-based estimator when considering simulated data from their life-cycle model.

A key empirical finding when applying our extended semi-structural model to the PSID data is that estimated short-run elasticities with respect to transitory income shocks are larger than long-run elasticities when considering all households in our sample and for all groups of households that we consider based on different balance sheet characteristics. This supports the idea of "intertemporal" MPCs proposed in Auclert et al. (2018) and justifies our extended model specification beyond BPP to include a transitory consumption response parameter. In terms of explaining heterogeneity in implied MPCs across households, our estimates suggest that the level of liquid wealth for a homeowner is more important than homeownership status or the liquidity-related "hand-to-mouth" status emphasized by Kaplan, Violante, and Weidner (2014), although we note the opposite is true for heterogeneity in consumption insurance against permanent income risk.

Our main empirical finding is that the average MPC across all households in the sample increased significantly following the end of the housing boom. The increase appears to persist well after the Great Recession ended and our results for household groups suggest that it was driven by a doubling of the estimated transitory consumption response parameter for homeowners with low (i.e. below-median) liquid wealth. Tests for a structural break in the transitory consumption response parameter and the implied MPC are significant when considering all households, homeowners, and homeowners with low liquid wealth, while they are not significant for other groups or stratifications of households or for permanent consumption responses of any group. The finding in terms of a large change in the transitory consumption response parameter for low liquid wealth homeowners provides further strong validation of our extension of the BPP model to identify and estimate dynamic elasticities with respect to transitory income shocks and suggests that, consistent with two-asset consumption theories with housing as the primary illiquid asset such as in Boar, Gorea, and Midrigan (2020), liquidity-constrained homeowners are particularly sensitive to transitory income shocks, with correspondingly higher MPCs.[2] Notably, as we show in our analysis, the change in MPCs for low liquid wealth homeowners does not appear to be due to a change in wealth distributions. Instead, as the housing market went bust, it appears that homeowners faced tighter credit conditions in terms of mortgage loans including refinancing and then a persistent decline in home equity loans, making them less able to use their housing wealth to insure against bad income realizations, a widespread practice for U.S. households documented in Hurst and Stafford (2004), with the use of home-equity borrowing being particularly prevalent in the years leading up to the Great Recession according to Mian and Sufi (2011).

An implication of higher MPCs following the end of the housing boom, especially for homeowners with low levels of liquid wealth, is correspondingly larger consumption elasticities with respect to house prices according to the rule-of-thumb formula in Berger, Guerrieri, Lorenzoni, and Vavra (2018). Even taking into account different median levels of consumption, these implied elasticities suggest a larger role of the deterioration in housing wealth for liquidity-constrained homeowners than deleveraging in driving down the level of consumption during the Great Recession, consistent with Kaplan et al. (2020a,b). This result supports the idea that stabilization policies designed to address liquidity constraints of homeowners are more effective than debt relief programs. Thus, our analysis of survey data using a semi-structural model reinforces the findings in Ganong and Noel (2020) using a natural experiment that mortgage modification programs with restructuring of monthly payments should stimulate consumption more than adjusting the principal on mortgages.

The rest of this paper is organized as follows: Section 2 presents the model. Section 3 describes the data. Section 4 reports our empirical results. Section 5 concludes.

[2] Boar et al. (2020) argue that liquidity-constrained households are more prevalent than "hand-to-mouth" households. In particular, they define "hand-to-mouth" households as those for whom the borrowing constraint on liquid assets (i.e. the risk-free asset) binds. By contrast, homeowners for whom a constraint on the minimum mortgage payment binds are defined as "liquidity constrained". Their model, which is calibrated to the U.S. economy in 2001, suggests that 26% of homeowners and 37% of households are hand-to-mouth, while over 80% of homeowners (corresponding to more than 50% of households) are liquidity constrained.

2 Model

In this section, we present a theoretically-motivated extension of BPP's semi-structural model that decomposes idiosyncratic log income (y) and consumption (c) for household i into permanent and transitory components at time t, where the components are "unobserved" in the sense that we do not have separate data directly on them. We also discuss justification of various specification issues and our estimation approach, including within the context of simulated data from a calibrated structural life-cycle model.

First, following BPP, we assume annual income follows an unobserved components process with a random walk trend and an MA(1) transitory component:

$$y_{it} = \tau_{it} + \epsilon_{it} + \theta\epsilon_{it-1}, \qquad \epsilon_{it} \sim i.i.d.(0, \sigma^2_{\epsilon t}), \tag{1}$$

$$\tau_{it} = \tau_{it-1} + \eta_{it}, \qquad \eta_{it} \sim i.i.d.(0, \sigma^2_{\eta t}), \tag{2}$$

where, given household-specific initial condition $\tau_{i0} = \bar{\tau}_{i0}$, the stochastic trend for income, τ_{it}, follows a random walk driven by idiosyncratic permanent income shocks, η_{it}, such as promotion or major health diagnoses that affect the ability to work, and the transitory component of income depends on idiosyncratic transitory income shocks, ϵ_{it}, such as a temporary bonus, according to moving-average process with parameter θ. It is sometimes argued that "permanent" income for households cannot literally follow a random walk given finite lives and might instead be modeled as a stationary AR(1) "persistent" component. The random walk assumption in the BPP model should thus be taken as a parsimonious way to capture highly-persistent income shocks. Estimates of other parameters are reasonably robust to this assumption or the alternative of a stationary autoregressive process as long as the underlying shock only dies out only very slowly over time. Also, more complicated dynamics for the transitory component, such as a higher-order moving-average process, could be allowed for as long as they are sufficiently different than a highly-persistent trend process. However, sample autocorrelations for two-year idiosyncratic income growth in the household survey data that we consider in our empirical analysis do not support more serial correlation than MA(1) dynamics in annual transitory income.

Second, as highlighted in Commault (2022), consumption will, in general, be a function of current and past income shocks in a standard life-cycle setting given a consumption decision rule that depends on current shocks and current assets. Specifically, following Arellano, Blundell, and Bonhomme (2017), a decision rule $c_{it} = f(\tau_{it}, \epsilon_{it}, W_{it})$ implies a consumption function $c_{it} = g(\tau_{it}, \ldots, \tau_{i1}, \epsilon_{it}, \ldots, \epsilon_{i1}, W_{i1})$ given assets evolving according to $W_{it} = h(W_{it-1}, \tau_{it-1}, \epsilon_{it-1})$, where W_{it} denotes household wealth at time t. Thus, extending BPP in the simplest possible way to accommodate dynamic consumption elasticities with respect to transitory income shocks, we assume the following unobserved components process for consumption:

$$c_{it} = \gamma_\eta \tau_{it} + \kappa_{it} + \tilde{\gamma}_\epsilon \epsilon_{it} + v_{it}, \qquad v_{it} \sim i.i.d.(0, \sigma^2_{vt}), \tag{3}$$

$$\kappa_{it} = \kappa_{it-1} + \bar{\gamma}_\epsilon \epsilon_{it} + u_{it}, \qquad u_{it} \sim i.i.d.(0, \sigma^2_{ut}), \tag{4}$$

where consumption depends on permanent income with elasticity γ_η, an additional stochastic trend to consumption, κ_{it}, which, given household-specific initial condition $\kappa_{i0} = \bar{\kappa}_{i0}$, is driven by permanent effects (i.e. annuity values) of transitory income shocks according to the long-run elasticity $\bar{\gamma}_\epsilon$ and idiosyncratic permanent consumption shocks, u_{it}, such as could result from heterogeneous responses to wealth shocks, and a transitory component driven by transitory income shocks according to the elasticity $\tilde{\gamma}_\epsilon$ and idiosyncratic transitory consumption shocks, v_{it}, such as surprise household expenditures unrelated to income, idiosyncratic responses to aggregate shocks, or possibly random measurement error in reported consumption, as interpreted in BPP. We highlight that the inclusion of the $\tilde{\gamma}_\epsilon \epsilon_{it}$ term in the consumption equation is the only modification from the original BPP model specification and is what helps identify dynamic consumption elasticities, a central focus of our empirical analysis. We also note that we could have considered a more general distributed lag structure $\sum_{i=0}^{q} \tilde{\gamma}_{\epsilon i} \epsilon_{t-i}$ in the consumption equation to capture persistent, but still transitory effects of transitory income shocks. Indeed, we find such a structure is relevant for borrowing-constrained households in simulated data from a calibrated life-cycle model, but we find no evidence of significant distributed lags in the household survey data used in our empirical analysis.

The key parameters from our model are the γ's, which capture the responses of consumption to income shocks. While these parameters are assumed to be constant over time in the semi-structural model, we test for a structural break in their values from before to after the housing boom and bust, i.e. the null hypothesis $H_0 : \gamma_{\text{pre}} = \gamma_{\text{post}}$ is that a consumption response parameter does not change its value between the 1998-2006 and 2007-2016 subsamples. Meanwhile, following BPP, we assume that the various idiosyncratic shocks are not correlated with each other, over time, or across households, although we allow for changes in their variances from before to after the housing boom and bust in order to any avoid possible spurious evidence of time-varying consumption response parameters that could result from a failure to account for relevant heteroskedasticity.[3] When estimating the model for a particular group of households, parameters are assumed to be the same across households within the group. However, as discussed in Commault (2022), the consumption response parameters can be interpreted as averages for each group, thus heterogeneity due to a possible distribution of preferences is implicitly allowed for within groups, in addition to being explicitly allowed for when estimating the model for different

[3] Interestingly, we find little difference in estimated shock volatilities between the 1998-2006 and 2007-2016 subsamples, especially in terms of the permanent and transitory income risks. Full sets of estimates, including for shock volatilities, are reported in the appendix, but we do not focus on the shock volatilities when reporting our results in Section 4 given their apparent stability over the full 1998-2016 sample period.

groups. See Gelman (2021) and Aguiar, Bils, and Boar (2020) on the possible role of preferences in explaining heterogeneity in consumption responses. We also conduct heterogeneity tests for differences in averages across groups, i.e. the null hypothesis $H_0 : \gamma_g = \gamma, \forall g$ is that the parameter for each group g is the same as the parameter for all groups within a given stratification of households.[4]

Given idiosyncratic income and consumption data in logs, the sum of the consumption response parameters that load on ϵ_{it}, which we denote as $\gamma_\epsilon \equiv \bar{\gamma}_\epsilon + \tilde{\gamma}_\epsilon$, is the short-run elasticity of consumption with respect to transitory income shocks, i.e. $\gamma_\epsilon = \frac{\partial c_{it}}{\partial \epsilon_{it}}$, while $\bar{\gamma}_\epsilon = \lim_{h\to\infty} \frac{\partial c_{it+h}}{\partial \epsilon_{it}}$ is the long-run elasticity with respect to transitory income shocks and $\gamma_\eta = \frac{\partial c_{it}}{\partial \eta_{it}}$ is the (assumed constant) elasticity with respect to permanent income shocks, where $1 - \gamma_\eta$ would correspond to what Kaplan and Violante (2010) refer to as "consumption insurance" with respect to permanent income risk. We highlight that our assumption of dynamic consumption elasticities with respect to transitory income shocks is consistent with non-zero transitory consumption responses that we find in simulated data from the calibrated Kaplan and Violante (2010) structural life-cycle model with incomplete markets and a zero borrowing constraint.[5] These non-zero transitory responses directly imply that our extended semi-structural model provides a better reduced-form for a structural life-cycle model with optimizing households subject to borrowing constraints than the original BPP specification.

To estimate parameters for the semi-structural model, we cast its unobserved components representation presented above into state-space form and employ QMLE as in Chatterjee et al. (2021) (full details of this estimation approach are provided in the appendix). In our analysis, we face smaller sample sizes to identify parameters when grouping households by different balance sheet characteristics and allowing for structural breaks. By using QMLE, we are addressing concerns raised in Altonji and Segal (1996) about small-sample biases related to estimation of weighting matrices for GMM. In particular, Chatterjee et al. (2021) show that GMM estimates for the BPP

[4]To conduct heterogeneity tests, we jointly estimate the model allowing for different parameters depending on the classification of a household and then test parameter equality across groups. Given the assumed independence of shocks across households, the joint estimation produces the same estimates as when we estimate one group at a time. It also produces almost identical test results as assuming estimates are independent across groups, with a small dependence given the transition of some households between groups. This is in contrast to the structural break tests for which it is more important to take into account the covariance between estimators for parameters before and after the break when constructing test statistics.

[5]In particular, it is straightforward to show for our model that $\tilde{\gamma}_\epsilon \neq 0$ corresponds to $cov(\Delta c_{it}, \epsilon_{it-1}) \neq 0$. When considering simulated data from the calibrated Kaplan and Violante (2010) model with a risk-free asset and a zero borrowing constraint, we find that $cov(\Delta c_{it}, \epsilon_{it-1}) < 0$ for younger households who are more likely to hit the borrowing constraint given an assumption of no initial wealth at age 25, while it is equal to zero for older households. Correspondingly, for the 50,000 working-age (ages 26-59) households in the simulated data, we estimate $\tilde{\gamma}_\epsilon$ to be 0.06, while it is 0.13 for the younger households (ages 26-45) and 0.00 for the older households (ages 46-59), noting that these estimates are extremely precise given the very large sample size for the simulated data. Focusing on low asset (bottom quartile) households, the estimate for $\tilde{\gamma}_\epsilon$ is particularly high at 0.35, consistent with the intuition in Kaplan and Violante (2010) that households near the borrowing constraint will immediately drop their consumption given a negative transitory income shock in order to avoid the large utility loss of hitting the constraint in the future, but then they will be expected to reverse this drop in the next period in order to bring consumption back towards its level prior to the shock.

model are not robust to alternative weighting schemes, while QMLE provides more accurate and precise estimates for highly non-Normal skewed and fat-tailed data like idiosyncratic income and consumption growth from the PSID. Part of the better performance of QMLE is due to a more efficient treatment of missing observations by using the Kalman filter and modeling the data in log levels rather than growth rates, implying observations are included in estimation even when consecutive observations in levels needed to form growth rates are missing. However, it is important to note that, by placing diffuse priors on household-specific initial conditions $\bar{\tau}_{i0}$ and $\bar{\kappa}_{i0}$ when calculating the quasi likelihood using the Kalman filter, estimation in levels would be completely equivalent to estimation in growth rates in the absence of missing data and, therefore, implicitly allows for household-specific fixed effects. To see this, note that our model implies the following for the growth rates of income and consumption:

$$\Delta y_{it} = \eta_{it} + \epsilon_{it} + (\theta - 1)\epsilon_{it-1} - \theta\epsilon_{it-2}, \tag{5}$$

$$\Delta c_{it} = \gamma_\eta \eta_{it} + \gamma_\epsilon \epsilon_{it} - \tilde{\gamma}_\epsilon \epsilon_{it-1} + u_{it} + v_{it} - v_{it-1}, \tag{6}$$

which exactly corresponds to the BPP model specification in growth rates when $\tilde{\gamma}_\epsilon = 0$.

By fully specifying our semi-structural model, it is straightforward to test the restricted BPP specification and to separately estimate both the short-run and long-run elasticities, in contrast to the limited-information moments-based approach taken in Commault (2022), which given annual data only identifies a passthrough coefficient that is equivalent to the short-run elasticity γ_ϵ, not the transitory consumption response parameter $\tilde{\gamma}_\epsilon$ or long-run elasticity $\bar{\gamma}_\epsilon$, separately, and given biennial data only identifies a "biennial" passthrough coefficient that depends on both the short-run elasticity γ_ϵ and long-run elasticity $\bar{\gamma}_\epsilon$, as well as the MA parameter θ, although it is equal to the short-run elasticity in the limiting case that $\theta = 0$. Note that we provide a full comparison to the results in Commault (2022) in Section 4.3. Also, we emphasize that our QMLE approach allows us to easily consider formal statistical tests for other restrictions on parameters, such as homogeneity across groups or stability over time, based on Wald statistics using the estimated parameter variance-covariance matrix calculated with the Huber-White sandwich formula.

Notably, full-information likelihood-based inference appears not to suffer from the same large downward bias in estimating consumption insurance with respect to permanent income risk that Kaplan and Violante (2010) highlight afflicts the BPP moments-based estimator when considering simulated data from their calibrated structural model. In particular, given simulated data in the zero-borrowing-constraint setting for their model, we find accurate estimates for consumption insurance of 10% for younger households (ages 26-45) and 47% for older households (ages 46-59), where the true average values for the two age groups are 10% and 48%, respectively. There still seems to be some downward bias when combining all households in estimation as the estimate is 20% for all households, while the true average value is 26%. However, this bias must reflect a some nonlinearity when pooling households with very different true values, as the weighted average of our estimates for younger and older households is 25%, close to the true average.[6] This finding suggests there is a benefit to looking at estimates for more homogeneous groups, which further supports using QMLE given that Chatterjee et al. (2021) show it is more precise than GMM in smaller samples. Meanwhile, estimates based on QMLE for consumption insurance with respect to transitory income risk (i.e. $1 - \gamma_\epsilon$) are also accurate for the simulated data, although it is generally necessary to include our new $\tilde{\gamma}_\epsilon \epsilon_{it}$ term and sometimes even distributed lags of transitory effects of transitory income shocks for the most borrowing-constrained households in order to capture higher-order serial correlation in consumption growth for such households. For example, when including one distributed lag, the estimated consumption insurance with respect to transitory income for all households in the simulated data is 82%, which is very close to the true average value of 83%.

Finally, it should be noted that our assumption of constant γ's inherently implies symmetric and proportional responses to different shocks, while it is clearly possible that responses depend on the sign or size of shocks. Arellano et al. (2017) investigate nonlinearities in the relationship between income and consumption using a nonparametric approach with quantile regressions and find some size and sign effects for the persistence of income shocks and asymmetries in consumption responses. Adapting our QMLE approach to capture such nonlinearities is technically feasible, but practically challenging given the need to extend beyond the basic Kalman filter. In preliminary analysis, we considered formal tests of our linear specification by checking if the consumption responses were significantly different depending on the mean, variance, or skewness of idiosyncratic income growth in a particular wave and found no evidence for such effects, although this could possibly be due to low power for the tests given relatively small effective sample sizes. For some household groups, we did find significant differences for the transitory consumption response parameters depending on the sign of idiosyncratic income growth for each household, but the average of the sign-dependent estimates were very close to what we find and report with our linear specification. Thus, we take our estimates as reflecting average effects across different types of shocks, including positive versus negative, and leave further examination of possible nonlinearities to future research.

3 Data

In this section, we describe the data used in our empirical analysis. Except where otherwise noted, the data are from the PSID, which is a longitudinal survey of a representative sample of approximately 5,000 U.S. households, with information on a variety of economic and social

[6] By way of comparison, Table 1 in Kaplan and Violante (2010) reports an estimate of consumption insurance based on the BPP approach of 7% for simulated data from their model with a true average value of 23% for households in the 27-57 age group they consider, while their Figure 3 often reports negative and downward biased estimates for younger households for which we find no bias with our estimate of average consumption insurance with respect to permanent income risk for simulated data from their model.

indicators, including those related to income, expenditures, wealth, and demographic attributes. Between 1968-1996, the survey interviewed both the original families and their split-off annually, but did so only biennially since 1997. Starting in 1999, the survey began collecting information on household expenditure covering 70% of consumption categories in the Consumer Expenditure Survey. Therefore, to obtain consistent measures of income and consumption for each household, we look at the ten waves of data from 1999 to 2017, which correspond to observations for a 1998-2016 sample period due to the retrospective nature of the survey. To address a variety of data-reporting issues, we closely follow the initial sample selection in Kaplan et al. (2014), the full details for which are provided in the appendix.

Our measure of income is the annual flow of after-tax disposable income for each household, where household income tax is calculated using the NBER's TAXSIM program. Total household income consists of labor income, transfers, social security, and head and spouse's investment income such as income from housing leases, interest, dividend payments, trusts, and alimony. We consider total income, as in BPP, but our estimates of the transitory consumption response parameters are highly robust to excluding asset income. Income is deflated into real terms (1999 dollars) using the Consumer Price Index (CPI) obtained from the Bureau of Labor Statistics

Our measure of consumption is also an annual flow and includes three broad categories: food, other nondurables (excluding food), and housing. Food consumption includes food at home, delivery, and eaten out. Other nondurables includes gasoline, health insurance, health services, public transport, utilities, education, and childcare. While we include the actual reported rent for households living in rental housing, we impute rent for homeowners. Following some of the related literature, e.g. Blundell, Pistaferri, and Saporta-Eksten (2016), we consider the user-cost of owner-occupied housing, which takes into account interest payments on mortgages, depreciation, and expectation of house price appreciation when imputing rent. Based on the user-cost estimates of Poterba and Sinai (2010), the annual imputed rent in our analysis is 6% of the self-reported house value from the PSID. Given possible issues with this approach to measuring imputed rent, we also confirm that our results are qualitatively robust to excluding housing from our measure of consumption. Each component of consumption is deflated using the corresponding sub-index of the CPI.

Following BPP, we isolate idiosyncratic income and consumption for each household in our sample by controlling for year and cohort (year-of-birth) effects, education, race, family size, number of children, presence of an outside dependent, presence of income recipients other than husband and wife, region, residence in a large city, and employment status, allowing for potentially time-varying effects of education, race, region, and employment status by interacting with time dummies. Specifically, we regress logs of household income and consumption on the various controls:

$$\ln Y_{it} = \beta' X_{it} + y_{it}, \tag{7}$$

$$\ln C_{it} = \alpha' X_{it} + c_{it}, \tag{8}$$

where Y_{it} and C_{it} denote our measures of income and consumption, X_{it} is a vector of control variables, and y_{it} and c_{it} correspond to the residual measures of idiosyncratic log income and consumption used in the estimation of our semi-structural model.

The PSID also provides information on household wealth in every wave. Following Kaplan et al. (2014), we classify wealth into two categories: liquid wealth and illiquid wealth. Liquid wealth is liquid assets less liquid debt, where liquid assets include cash, stocks, and bonds and liquid debt includes credit card debt, student loans, medical bills, legal bills, and other personal loans before 2011 and only credit card debt from 2011.[7] Illiquid wealth consists of housing wealth (house value minus first and second mortgages), pensions, and non-primary real estate, where pensions and non-primary real estate are reported as net values in the data. Total wealth is defined as the sum of liquid wealth (minus non-credit card debt given the measure of liquid wealth after 2011) and illiquid wealth. A related aspect of the balance sheet that we consider is household leverage, which is measured as the ratio of house value to total wealth, as in Mian, Rao, and Sufi (2013). All wealth variables are deflated using the CPI.

To consider groups of households based on homeownership status, we classify households as being either renters or homeowners. Table 1 reports balance sheet values and demographic characteristics based on homeownership status. Renters are relatively young, poor, and likely to be liquidity constrained. Homeowners are older, wealthier, and more likely to be married. Following Kaplan et al. (2014), we also group households based on hand-to-mouth (HtM) status into poor hand-to-mouth (PHtM), wealthy hand-to-mouth (WHtM), and non-hand-to-mouth (NHtM) categories.[8] Summary statistics for the HtM groups are also reported in Table 1 and suggest PHtM households have a similar profile to renters (only 7% of PHtM households own a house), while WHtM households have a similar profile to homeowners (93% of WHtM households own a house).

Noting that housing constitutes 66% of the value of illiquid assets in our sample, we further stratify homeowners into subgroups based on liquid wealth, housing wealth, and leverage. Ta-

[7] Before 2011, the PSID did not report the individual components of liquid debt, but instead reported an aggregated measure of debt including credit card debt, student loans, medical bills, legal bills, and other personal loans. However, since 2011, each individual component of liquid debt is separately reported. We follow Kaplan et al. (2014) to account for changes in reporting norms in the PSID. Note that the median real liquid wealth was \$1,724 before 2011 and \$2,137 from 2011.

[8] Specifically, households are classified as HtM if their liquid wealth is positive and less than half of their bi-weekly income or their liquid wealth is negative and less than the difference between half of their bi-weekly income and a credit limit that is equivalent to the monthly income. If a household has a positive (zero or negative) amount of illiquid wealth, then it is classified as wealthy (poor) HtM. As reported in the first row of Table 1, the share of HtM households sums to 37% of our sample, which is in line with the share reported in other studies that use the PSID; see, for example, Aguiar et al. (2020).

Table 1: Summary statistics for household groups by homeownership and HtM status

	All (1)	Renters (2)	Homeowners (3)	PHtM (4)	WHtM (5)	NHtM (6)
Share (% of total population)	–	31.1	68.9	16.1	20.8	63.1
Income	48,870	29,470	61,266	24,689	46,616	59,642
Consumption	22,439	16,942	26,049	15,511	22,345	25,131
Balance sheet variables						
Liquid wealth	2,000	0	4,987	0	-7,086	20,138
Illiquid wealth	37,432	0	73,457	0	38,180	83,867
Housing wealth	25,000	0	52,005	0	29,833	54,224
Total wealth	49,979	0	95,614	-2,685	26,472	144,493
Debt	41,483	1,119	94,000	3,729	76,128	52,046
Leverage	1.11	–	1.11	–	2.32	0.91
Demographic characteristics						
Age	43	36	45	37	43	46
Frac. college-educated	0.65	0.59	0.70	0.47	0.60	0.73
Frac. married	0.67	0.37	0.81	0.38	0.72	0.74
Frac. homeowners	0.69	0	1	0.07	0.93	0.79
Frac. employed	0.87	0.83	0.91	0.77	0.86	0.89
Frac. in Midwest	0.27	0.23	0.29	0.23	0.30	0.28
Frac. in South	0.32	0.31	0.32	0.34	0.37	0.30
Frac. in West	0.23	0.29	0.21	0.28	0.19	0.23

Notes: Summary statistics related to balance sheet variables and demographic characteristics are reported for all households in the sample and groups based on homeownership and HtM status, where 'PHtM' refers to poor hand-to-mouth, 'WHtM' to wealthy hand-to-mouth, and 'NHtM' to non-hand-to-mouth. Income, consumption, balance sheet variables, and age are median values over the full sample period of 1998-2016 for each group after applying the two-consecutive-period restriction. All dollar measures are real with the base year of 1999.

ble 2 reports balance sheet values and demographic characteristics for the different subgroups of homeowners. A homeowner is classified in the "low" ("high") category for a particular balance sheet variable if their balance sheet value is below or equal to (above) the median value across all homeowners in a given year.[9] The low liquid wealth and low housing wealth homeowners are relatively poor and likely to be liquidity constrained given that they have very low or negative liquid wealth. However, their median levels of liquid wealth are higher than that of WHtM households in Table 1. Homeowners stratified by housing wealth have the most geographic dispersion with low housing wealth homeowners relatively more prevalent in the Midwest and the South and less prevalent in the West and the Northeast (the remaining left-out category in the tables). Meanwhile, high leverage homeowners have sizeable liquid wealth and are more likely to be employed, but are highly indebted overall.

To address issues with transitions over time between categories, we follow Cloyne, Ferreira, and Surico (2020) by only including households in a particular group at a given point of time

[9] We have considered other stratifications of homeowners than based on real levels, including the various balance sheet measures as percentages of income. However, the differences in estimates across the subgroups were less pronounced in the other cases.

Table 2: Summary statistics for homeowner subgroups

	Low LW (1)	High LW (2)	Low HW (3)	High HW (4)	High Lev. (5)	Low Lev. (6)
Income	48,423	73,080	50,330	71,869	57,741	65,167
Consumption	22,142	29,607	20,770	32,088	25,103	26,885
Balance sheet variables						
Liquid wealth	-900	59,691	473	30,694	1,406	59,891
Illiquid wealth	37,816	172,123	27,455	198,458	48,404	215,458
Housing wealth	30,887	100,690	21,372	128,717	40,653	108,681
Total wealth	31,577	314,617	29,043	278,280	51,489	389,221
Debt	79,657	78,250	83,394	70,000	102,079	28,362
Leverage	2.21	0.67	2.26	0.82	2.50	0.52
Demographic characteristics						
Age	43	49	41	51	42	52
Frac. college-educated	0.58	0.79	0.61	0.77	0.67	0.72
Frac. married	0.76	0.84	0.76	0.84	0.79	0.81
Frac. employed	0.88	0.89	0.90	0.87	0.93	0.84
Frac. in Midwest	0.30	0.29	0.36	0.24	0.28	0.29
Frac. in South	0.35	0.29	0.37	0.27	0.33	0.30
Frac. in West	0.20	0.23	0.15	0.27	0.20	0.24

Notes: Summary statistics related to balance sheet variables and demographic characteristics are reported for homeowners stratified into subgroups based on liquid wealth (LW), housing wealth (HW), and leverage (Lev.), where 'Low' and 'High' refer to homeowners below or above median for a particular balance sheet variable. Income, consumption, balance sheet variables, and age are median values over the full sample period of 1998-2016 for each group after applying the two-consecutive-period restriction. All dollar measures are real with the base year of 1999.

when estimating parameters for that group if they are classified in the category for at least two consecutive waves including the current one. Furthermore, to reduce compositional changes for groups in our time-varying estimation, we include households in a group when estimating parameters for the 2007-2016 subsample period only if, in addition to satisfying the two consecutive waves minimum, they were classified in the same category at some point during the 1998-2006 subsample period. At the same time, in order to better match age profiles across subsamples and keep sample sizes large enough to estimate parameters with a certain degree of precision, our sample selection includes households in a group when estimating parameters in the first subsample period even if they do not appear in that group in the second subsample period. This inclusive approach to sample selection is especially important for renters, PHtM, and WHtM households, given substantial proportions of households only classified in these categories prior to 2007 compared to those for both subsample periods. However, we confirm that our results are qualitatively robust to only considering households in a group who were classified in a category both prior to 2007 and afterwards, with similar but less precise estimates prior to 2007 for this alternative sample selection. More details of the group classification and related robustness results are provided in the appendix.

4 Empirical results

In this section, we first consider consumption elasticities, implied consumption insurance and MPCs, and heterogeneity across households groups over the full sample period from 1998 to 2016. Then, to address a possible structural break following the end of the housing boom, we investigate whether consumption responses changed over the subsample periods of 1998-2006 and 2007-2016 and why they might have changed. Next, we compare our results to the existing literature on MPCs. Finally, we explore implications of our results for why consumption fell during the Great Recession.

4.1 Full-sample estimates

Table 3 reports estimates of consumption response parameters and heterogeneity tests for the full sample period of 1998-2016 (results for all model parameters are provided in the appendix). Because the PSID data is only available biennially for this sample period, we cannot separately identify the conditional variance of transitory income shocks, σ_ϵ^2 from the moving-average parameter for transitory income, θ, as biennial observations can only identify the overall unconditional variance of transitory income, $(1+\theta^2)\sigma_\epsilon^2$. Thus, for our benchmark analysis, we set $\theta = 0$ for identification, noting that this places a lower-bound on our estimates of $\bar{\gamma}_\epsilon$ and $\tilde{\gamma}_\epsilon$. Specifically, for a given unconditional variance of transitory income and non-zero values of θ, the estimated σ_ϵ^2 would decrease as the absolute value of θ increases, implying correspondingly larger estimates of $\bar{\gamma}_\epsilon$ and $\tilde{\gamma}_\epsilon$ to capture equivalent movements in observed biennial consumption growth. We consider the quantitative implications of non-zero values of θ in Section 4.3 when we compare our results to others in the literature.

We also note that, in addition to allowing for heteroskedasticity from before to after the housing boom and bust, our group-level estimation implicitly allows for different shock variances across groups. Meanwhile, when households are combined into larger groups, elasticity estimates are generally similar to weighted averages of estimates for subgroups, suggesting that the assumption of the same variances within a larger group does not distort elasticity estimates even if shock volatility estimates differ across subgroups when estimated separately. For notable discrepancies in elasticity estimates, such as, for example, with the lower and comparatively imprecise estimates of γ_η in Table 3 for both subgroups of homeowners based on liquid wealth than for all homeowners, it appears to be due to the sample selection in terms of the two-consecutive-wave rule for inclusion in a group and, therefore, within-group heterogeneity, rather than heterogeneity in shock variances. In particular, the relevant shock volatility estimates are very similar across these subgroups and to the estimates for all homeowners.

Table 3: Full-sample consumption response estimates and heterogeneity tests

	All	Renter	Homeowner	PHtM	WHtM	NHtM
γ_η	0.38 (0.03)	0.49 (0.00)	0.32 (0.03)	0.46 (0.02)	0.47 (0.09)	0.34 (0.04)
$\bar{\gamma}_\epsilon$	0.03 (0.01)	0.01 (0.01)	0.03 (0.03)	0.00 (0.00)	0.03 (0.01)	0.03 (0.01)
$\tilde{\gamma}_\epsilon$	0.11 (0.01)	0.12 (0.02)	0.11 (0.02)	0.12 (0.03)	0.13 (0.03)	0.10 (0.02)
γ_ϵ	0.14 (0.02)	0.13 (0.03)	0.14 (0.02)	0.12 (0.03)	0.16 (0.03)	0.13 (0.02)
$E[C_{it}/Y_{it}]$	0.58 (0.00)	0.70 (0.01)	0.52 (0.00)	0.78 (0.02)	0.59 (0.02)	0.51 (0.00)
MPC	0.08 (0.01)	0.09 (0.02)	0.07 (0.01)	0.10 (0.03)	0.10 (0.02)	0.07 (0.01)
$\text{Wald}_{H_0:\gamma_{\eta,g}=\gamma_\eta,\forall g}$		28.6 (0.00)			17.3 (0.00)	
$\text{Wald}_{H_0:\text{MPC}_g=\text{MPC},\forall g}$		1.35 (0.25)			2.50 (0.29)	
No. of households	5,047	2,047	3,633	1,060	1,285	3,659

	Low LW	High LW	Low HW	High HW	High Lev.	Low Lev.
γ_η	0.30 (0.08)	0.27 (0.05)	0.39 (0.05)	0.27 (0.05)	0.34 (0.08)	0.22 (0.05)
$\bar{\gamma}_\epsilon$	0.02 (0.01)	0.03 (0.01)	0.02 (0.01)	0.02 (0.01)	0.03 (0.02)	0.01 (0.01)
$\tilde{\gamma}_\epsilon$	0.17 (0.03)	0.08 (0.02)	0.13 (0.03)	0.10 (0.02)	0.14 (0.03)	0.12 (0.03)
γ_ϵ	0.19 (0.03)	0.11 (0.02)	0.15 (0.03)	0.12 (0.02)	0.16 (0.03)	0.14 (0.03)
$E[C_{it}/Y_{it}]$	0.56 (0.01)	0.48 (0.00)	0.49 (0.00)	0.55 (0.01)	0.51 (0.00)	0.52 (0.00)
MPC	0.11 (0.02)	0.05 (0.01)	0.07 (0.02)	0.07 (0.01)	0.08 (0.02)	0.07 (0.01)
$\text{Wald}_{H_0:\gamma_{\eta,g}=\gamma_\eta,\forall g}$	0.14 (0.70)		2.87 (0.09)		0.98 (0.32)	
$\text{Wald}_{H_0:\text{MPC}_g=\text{MPC},\forall g}$	7.32 (0.01)		0.12 (0.73)		0.39 (0.53)	
No. of households	2,198	1,949	2,266	1,910	2,011	1,793

Notes: Point estimates with standard errors in parentheses for the full sample period of 1998-2016 are reported based on QMLE unless otherwise noted below. γ_η is the elasticity of consumption with respect to permanent income shocks, $\bar{\gamma}_\epsilon$ is the long-run elasticity of consumption with respect to transitory income shocks, $\tilde{\gamma}_\epsilon$ is the transitory consumption response parameter for transitory income shocks, γ_ϵ is the short-run elasticity with respect to transitory income shocks, $E[C_{it}/Y_{it}]$ is the mean consumption-income ratio (sample average with standard error based on least squares), and MPC is $\gamma_\epsilon \times E[C_{it}/Y_{it}]$. Heterogeneity tests based on Wald statistics with p-values in parentheses for $\chi^2(q-1)$ distributions are reported for the null hypothesis of homogeneity across stratified groups, where q is the number of groups within a given stratification. Wald statistics and standard errors for MPCs based on QMLE take mean consumption-income ratios as known given highly precise estimates. The upper panel reports inferences for all households in the sample and groups based on homeownership and HtM status, where 'PHtM' refers to poor hand-to-mouth, 'WHtM' to wealthy hand-to-mouth, and 'NHtM' to non-hand-to-mouth, while the lower panel reports inferences for homeowners stratified into subgroups based on liquid wealth (LW), housing wealth (HW), and leverage (Lev.), where 'Low' and 'High' refer to homeowners below or above median for a particular balance sheet variable.

Heterogeneity in consumption responses to permanent income shocks

Before looking at consumption responses to transitory income shocks and implied MPCs, we start by considering consumption responses to permanent income shocks, which were the focus of analysis using the semi-structural model in BPP. As reported in Table 3, the estimate of the elasticity of consumption with respect to permanent income shocks, γ_η, is 0.38, with a standard error of 0.03, for all households in our sample, which implies that, on average, U.S. households have consumption insurance against permanent income risk of 62%. This finding is comparable to the estimated γ_η of 0.45, with a standard error of 0.04, for all households and corresponding average consumption insurance of 55% in Chatterjee et al. (2021) for the BPP model specification and data, which is a panel of annual observations for disposable income from the PSID and imputed nondurable consumption over an earlier sample period of 1978-1992.

We note there are many possible sources of this apparent deviation from the permanent income hypothesis under which consumption is predicted to respond one-for-one to changes in permanent income. As discussed in Jappelli and Pistaferri (2010), reasons include partial self-insurance via wealth, as well as informal insurance via family networks and social insurance via governments and other organizations. BPP also note that estimates of γ_η could be biased downwards if households have advanced information about the permanent income shock or the shock is not as persistent as assumed with the random walk assumption for permanent income. Meanwhile, possible reasons why our estimate of consumption insurance is considerably higher than the comparable estimate of 36% reported in BPP include the imprecision of BPP's GMM estimate and its sensitivity to weighting scheme highlighted by Chatterjee et al. (2021), as well as a downward bias in the BPP estimate compared to its true theoretical value found by Kaplan and Violante (2010), which, as noted in Section 2, does not seem as severe when conducting likelihood-based inference with our extended semi-structural model on simulated data from their life-cycle model.

As might be expected, homeowners, NHtM, high liquid wealth, high housing wealth, and low leverage households all appear better able to absorb permanent income risk than their counterparts. Given data limitations for the earlier sample period, Chatterjee et al. (2021) do not consider the same household groups based on household balance sheet characteristics as considered here, but they do find that older (ages 48-65) and college-educated households have higher consumption insurance than their counterparts, with similar point estimates (standard errors) for γ_η of 0.25 (0.06) and 0.29 (0.04), respectively, to what we find for high liquid wealth, high housing wealth, and low leverage homeowners in Table 3, all of which subgroups are older and more likely to be college-educated than their counterparts according to Table 2. Interestingly, however, we found much less evidence of heterogeneity in consumption insurance when stratifying households in our sample by age or education, although this may be due to less precise estimates given only biennial observations for a different sample period than the BPP data, differences in sample selection with BPP considering only continuously-married households, and our extended model specification compared to BPP and Chatterjee et al. (2021).

To illustrate the link between heterogeneity in consumption insurance and household balance sheets, Figure 1 plots the estimated consumption insurance for each household group against their median total wealth and housing wealth. What is clear from this figure is that, while households generally do not have full consumption insurance against permanent income risk, wealthier households have a greater ability to absorb permanent income risk than poorer households. In particular, the implied correlations in Figure 1 are significant at a 5% level. From Table 3, HtM status also appears to be important, although we find that liquid wealth is less important than

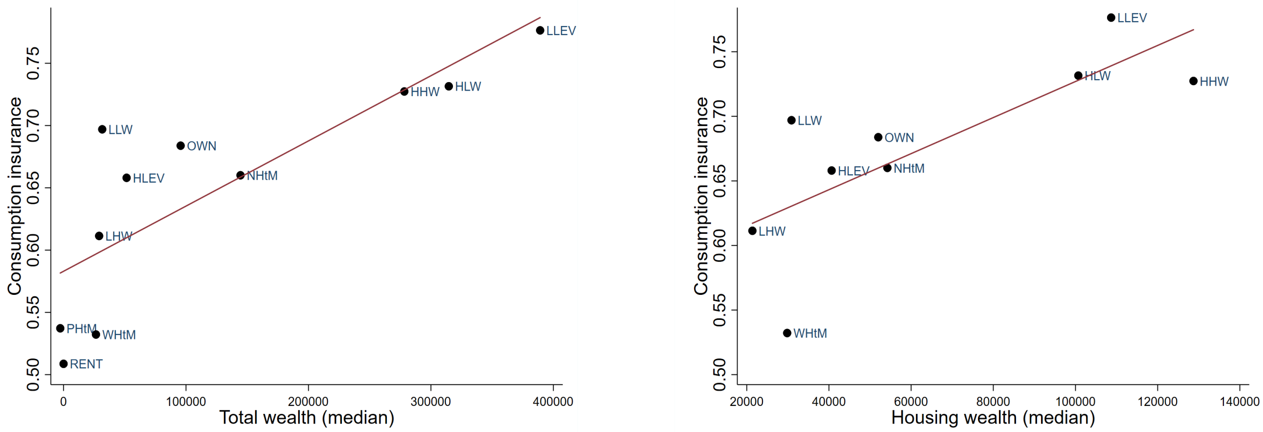


Figure 1: Consumption insurance vs. wealth

Notes: Consumption insurance against idiosyncratic permanent income risk is plotted against total wealth (left panel) and housing wealth (right panel) for different household groups. Each point corresponds to the estimated consumption insurance with respect to permanent income risk on the y-axis and the corresponding median balance sheet value on the x-axis for groups based on homeownership status (RENT/OWN), HtM status (PHtM/WHtM/NHtM), and homeowners further stratified into subgroups based on liquid wealth (LLW/HLW), housing wealth (LHW/HHW), and leverage (LLEV/HLEV), where the first 'L' or 'H' refers to households below or above median for a particular balance sheet variable. The estimates and balance sheet values are for the full sample period of 1998-2016.

housing wealth or homeownership status. Specifically, the statistical significance of differences in consumption insurance is confirmed for renters versus homeowners and by HtM status by the Wald tests for heterogeneity of γ_η, while the heterogeneity tests are not significant at least at conventional levels when stratifying homeowners by liquid wealth, housing wealth, or leverage.[10]

Heterogeneity in consumption responses to transitory income shocks

Next, we turn to our main focus on consumption responses to transitory income shocks and implied MPCs. As reported in Table 3, the long-run elasticity of consumption with respect to transitory income shocks, $\bar{\gamma}_\epsilon$, is estimated to be 0.03, with a standard error of 0.01, for all households. In line with what might be expected given the age distributions of the various household groups (in particular, substantial remaining life expectancies when receiving a transitory income shock), the estimate of $\bar{\gamma}_\epsilon$ is small for every household group and is often statistically insignificant. Thus, given that $\gamma_\epsilon \equiv \bar{\gamma}_\epsilon + \tilde{\gamma}_\epsilon$, any meaningful heterogeneity in the short-run elasticity of consumption with respect to transitory income shocks, γ_ϵ, must be driven by differences in our new transitory consumption response parameter $\tilde{\gamma}_\epsilon$ compared to the original BPP model specification. Notably, the estimates of $\tilde{\gamma}_\epsilon$ are clearly statistically significant for all households and for all groupings of households. Thus, we can uniformly reject the implicit restriction in the original BPP model speci-

[10] We note that the Wald statistics are identical to squared t statistics for testing the equality of two estimated parameters and they have the same p-values as a two-tailed t test given an asymptotic standard normal distribution under the null hypothesis of parameter equality. The only exception is the HtM case that involves two restrictions when testing the equality of three estimated parameters across the subgroups and, therefore, requires construction of a Wald statistic rather than consideration of a single t statistic. Hence, to be general, we report all of the tests in terms of Wald statistics.

fication that $\tilde{\gamma}_\epsilon = 0$ and these results provide strong support for our extended model specification that identifies and estimates dynamic consumption elasticities with respect to transitory income shocks.

Examining the cross-sectional patterns of heterogeneity in the transitory consumption response parameter in more detail, we find that homeowners with low liquid wealth, low housing wealth, and high leverage have larger estimates for transitory consumption response parameters than their respective counterparts. Among all of these subgroups, homeowners with low liquid wealth have the largest estimate of $\tilde{\gamma}_\epsilon$ at 0.17, with a standard error of 0.03. Of these households, only 42% are WHtM (see the appendix for a tabulation matrix of overlaps across groups). Although they are similar to the WHtM in many respects, the median value of their liquid assets is $-\$900$ vs. $-\$7,086$ for WHtM households; see Tables 1 and 2. We also note that removing WHtM households from this subgroup actually further increases the estimate of $\tilde{\gamma}_\epsilon$ to 0.25, with a standard error of 0.05. These results strongly suggest that, even when not necessarily defined as HtM, these homeowners are liquidity constrained. Consistent with related literature that distinguishes households based on their HtM status, for example Kaplan et al. (2014) and Aguiar, Bils, and Boar (2020), we also find that HtM households, both PHtM and WHtM, have larger estimates for transitory consumption response parameters than NHtM households, although the differences are much smaller than when stratifying homeowners by liquid wealth.[11]

The short-run elasticity γ_ϵ is sometimes directly referred to as the "MPC", e.g. Jappelli and Pistaferri (2010) and Kaplan et al. (2014), but we reserve that label for 'dollar-for-dollar' consumption responses to transitory income shocks often reported in natural experiments. These dollar-for-dollar MPCs are given by the short-run elasticity multiplied by the consumption-income ratio in levels (rather than residual logs).[12] Specifically, for each group, we calculate the implied $\text{MPC} \equiv \gamma_\epsilon \times E[C_{it}/Y_{it}]$, which provides a lower-bound estimate of the average across households in a particular group if there is a positive relationship between the elasticity and the consumption-income ratio across households within a group, as noted in Commault (2022) and also discussed in more detail in the appendix, which reports indirect evidence of such a positive relationship, but the implied downward bias from it is small, at most on the order 0.01-0.02. To estimate $E[C_{it}/$

[11] Even though we find liquid wealth of homeowners is the key characteristic behind heterogeneity in the transitory consumption response, we do not want to downplay the potential role of HtM status in explaining consumption behavior. In particular, we find somewhat more heterogeneity along the HtM dimension when we consider a sample selection that does not exclude transient households, i.e. households with a status for less than two consecutive waves. The results for this alternative sample selection suggest that WHtM households have notably larger transitory consumption response parameters compared PHtM and NHtM households, with estimates (standard errors) for $\tilde{\gamma}_\epsilon$ of 0.18 (0.04), 0.13 (0.03), and 0.10 (0.03), respectively. Meanwhile, as shown in the appendix, estimates are robust to considering the alternative classification, following Zeldes (1989), of households as being "hand-to-mouth" based on whether their real net wealth is less than the head of household's two-month labor earnings.

[12] Technically, we are referring to the "contemporaneous" MPC, while Auclert et al. (2018) consider "intertemporal" MPCs. To estimate an MPC at a longer horizon, we would use the long-run elasticity. Given that our estimated long-run elasticities are all small and often insignificant, the implied longer-horizon MPCs would be much smaller than the contemporaneous MPCs. As noted in Section 2, we could have also considered distributed lags in the consumption equation of our model, which would allow for more complicated patterns of intertemporal MPCs. But, again, these distributed lags were not significant for the household survey data.

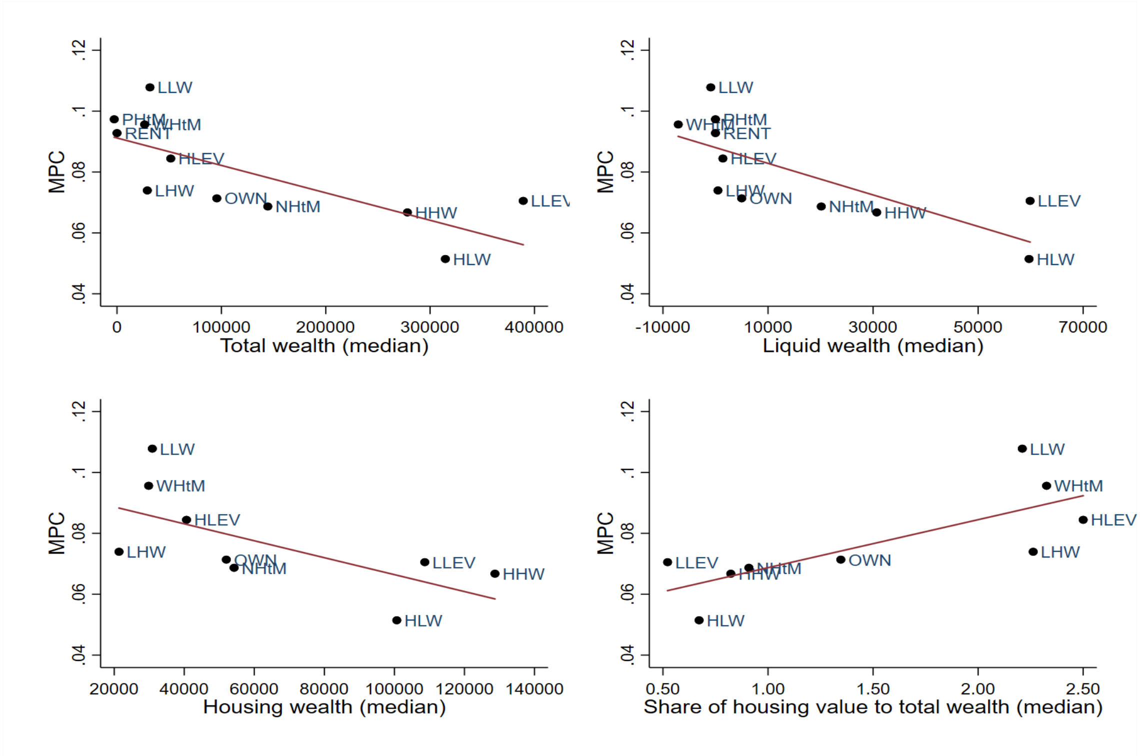


Figure 2: MPCs vs. wealth and leverage

Notes: The marginal propensity to consume out of idiosyncratic transitory income shocks is plotted against total wealth (left panel) and housing wealth (right panel) for different household groups. Each point corresponds to the estimated MPC based on the mean consumption-income ratio times the the short-run elasticity of consumption with respect to transitory income shocks on the y-axis and the corresponding median balance sheet value on the x-axis for groups based on homeownership status (RENT/OWN), HtM status (PHtM/WHtM/NHtM), and homeowners further stratified into subgroups based on liquid wealth (LLW/HLW), housing wealth (LHW/HHW), and leverage (LLEV/HLEV), where the first 'L' or 'H' refers to households below or above median for a particular balance sheet variable. The estimates and balance sheet values are for the full sample period of 1998-2016.

Y_{it}], we use the sample average with standard errors based on least squares. Because these estimates are extremely precise, we can treat the mean consumption-income ratio as known when calculating standard errors or conducting Wald tests for the MPCs. In principle, different ratios for different household groups could play a role in MPC heterogeneity even given similar short-run elasticities. However, we find that, in practice, most of the heterogeneity is related to differences in the transitory consumption response parameters, as is clear from the estimates of mean consumption-income ratios and the implied MPCs reported in Table 3.

Figure 2 plots the implied MPC for each household group against key balance sheet measures of median total wealth, liquid wealth, housing wealth, and leverage. The MPCs for the different groups of households provide some evidence of heterogeneity related to these balance sheet characteristics, with a significant difference in estimates based on liquid wealth confirmed by the Wald test for heterogeneity of MPCs reported in Table 3. The apparent negative relationship between the MPCs and total wealth, liquid wealth, and housing wealth (top panels and bottom left panel) is consistent with what would be predicted by either one or two-asset incomplete markets models, e.g. Carroll (1997) and Kaplan and Violante (2014).[13] There is also an apparent positive relationship between the MPCs and household leverage (bottom right panel), implying that highly-indebted homeowners tend to respond more to transitory income shocks. As in Figure 1, the implied correlations in Figure 2 are all significant at a 5% level, except for housing wealth, which is significant at a 10% level.

4.2 Time-varying estimates

Given a link between heterogeneity in consumption responses and household balance sheet characteristics, a natural question is whether the consumption responses changed over time with the end of the housing boom just prior to the Great Recession. Perhaps, then, what is surprising is that we find the time-varying estimates of the permanent consumption response parameters $\bar{\gamma}_\epsilon$ and γ_η suggest no economically or statistically significant changes for any group. Thus, the relatively precise full-sample estimates of $\bar{\gamma}_\epsilon$ and γ_η in Table 3, which again suggest permanent responses to transitory shocks are small and heterogeneity in consumption insurance is more related to homeownership or HtM status than wealth or leverage, remain relevant to understanding consumption behavior even after the housing bust. We only a find a statistically significant change in the new parameter in our semi-structural model, i.e. the transitory consumption response parameter $\tilde{\gamma}_\epsilon$, and not even for every group, although it is significant when considering all households together.

Table 4 reports the time-varying transitory consumption response estimates and structural break tests (again, results for all model parameters are provided in the appendix). The structural break tests for the transitory consumption response parameter, i.e. $H_0 : \tilde{\gamma}_{\epsilon,\text{pre}} = \tilde{\gamma}_{\epsilon,\text{post}}$ where the pre-break period is 1998-2006 and the post-break period is 2007-2016, are significant for all households and homeowners at the conventional 5% level and for low liquid wealth homeowners at the 1% level. The fact that the structural break tests are not significant for the other groups of households suggests the change in the transitory consumption response for low liquid wealth homeowners drives the significant change in the transitory consumption response parameter for homeowners and all households, although it should be noted that the estimated transitory consumption response parameter increased for all groups, even though the increase is not always statistically significant. The stronger link of the change in the transitory consumption response to liquid wealth than other balance sheet variables also suggests that our findings are not being driven by underlying demographic characteristics that are more related to the other balance sheet

[13]The negative correlation between MPCs and liquid wealth is also consistent with a number of other empirical studies, including Zeldes (1989), Johnson, Parker, and Souleles (2006), Parker et al. (2013), Baker and Yannelis (2017), Fagereng et al. (2021), and Ganong, Jones, Noel, Greig, Farrell, and Wheat (2020). The link appears to be stronger than in the case of consumption insurance, suggesting households are more willing incur transaction costs in accessing illiquid funds to smooth their consumption in the face of a permanent shock than a transitory shock. A difference in sensitivity to permanent and transitory shocks based on household liquidity is further motivated by the finding in Guvenen, Ozkan, and Song (2014) that permanent income shocks occur less frequently than transitory income shocks and so households are more willing to pay fixed transaction costs to offset them given a low probability of being quickly reversed compared to transitory shocks that are expected to dissipate over time.

Table 4: Time-varying transitory consumption response estimates and structural break tests

	All	Renters	Homeowners	PHtM	WHtM	NHtM
$\tilde{\gamma}_{\epsilon,\text{1998-2006}}$	0.09 (0.02)	0.10 (0.03)	0.08 (0.02)	0.07 (0.05)	0.09 (0.04)	0.09 (0.02)
$\tilde{\gamma}_{\epsilon,\text{2007-2016}}$	0.14 (0.02)	0.12 (0.04)	0.14 (0.02)	0.08 (0.07)	0.13 (0.05)	0.12 (0.03)
$E[C_{it}/Y_{it}]_{\text{1998-2006}}$	0.56 (0.01)	0.67 (0.00)	0.52 (0.00)	0.78 (0.00)	0.61 (0.00)	0.50 (0.00)
$E[C_{it}/Y_{it}]_{\text{2007-2016}}$	0.59 (0.00)	0.68 (0.00)	0.51 (0.00)	0.76 (0.00)	0.57 (0.00)	0.50 (0.00)
$\text{MPC}_{\text{1998-2006}}$	0.07 (0.01)	0.08 (0.02)	0.06 (0.01)	0.05 (0.04)	0.08 (0.03)	0.06 (0.01)
$\text{MPC}_{\text{2007-2016}}$	0.10 (0.01)	0.10 (0.03)	0.09 (0.01)	0.05 (0.05)	0.10 (0.03)	0.08 (0.01)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$	4.53 (0.03)	0.31 (0.58)	5.09 (0.02)	0.01 (0.93)	0.40 (0.53)	0.92 (0.34)
$\text{Wald}_{H_0:\text{MPC}_{\text{pre}}=\text{MPC}_{\text{post}}}$	6.09 (0.01)	0.32 (0.57)	4.81 (0.03)	0.01 (0.94)	0.24 (0.62)	0.95 (0.33)
No. of households	3,977	1,278	2,930	612	890	2,566
	Low LW	**High LW**	**Low HW**	**High HW**	**High Lev.**	**Low Lev.**
$\tilde{\gamma}_{\epsilon,\text{1998-2006}}$	0.13 (0.03)	0.08 (0.03)	0.12 (0.03)	0.08 (0.02)	0.12 (0.03)	0.10 (0.03)
$\tilde{\gamma}_{\epsilon,\text{2007-2016}}$	0.26 (0.04)	0.12 (0.04)	0.13 (0.05)	0.12 (0.03)	0.17 (0.04)	0.12 (0.04)
$E[C_{it}/Y_{it}]_{\text{1998-2006}}$	0.56 (0.00)	0.47 (0.00)	0.48 (0.00)	0.56 (0.00)	0.52 (0.00)	0.50 (0.00)
$E[C_{it}/Y_{it}]_{\text{2007-2016}}$	0.55 (0.00)	0.48 (0.00)	0.49 (0.00)	0.54 (0.00)	0.50 (0.00)	0.52 (0.00)
$\text{MPC}_{\text{1998-2006}}$	0.08 (0.02)	0.05 (0.01)	0.07 (0.02)	0.05 (0.01)	0.08 (0.02)	0.05 (0.01)
$\text{MPC}_{\text{2007-2016}}$	0.15 (0.02)	0.07 (0.02)	0.08 (0.02)	0.07 (0.02)	0.11 (0.02)	0.07 (0.02)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$	9.33 (0.00)	1.13 (0.29)	0.06 (0.81)	1.28 (0.26)	1.51 (0.22)	0.48 (0.49)
$\text{Wald}_{H_0:\text{MPC}_{\text{pre}}=\text{MPC}_{\text{post}}}$	8.54 (0.00)	1.15 (0.28)	0.08 (0.78)	1.05 (0.31)	1.12 (0.29)	0.69 (0.41)
No. of households	1,631	1,429	1,663	1,440	1,462	1,334

Notes: Point estimates with standard errors in parentheses for a pre-break sample period of 1998-2006 and a post-break sample period of 2007-2016 are reported based on QMLE unless otherwise noted below. $\tilde{\gamma}_\epsilon$ is the transitory consumption response parameter for transitory income shocks, $E[C_{it}/Y_{it}]$ is the mean consumption-income ratio (sample average with standard error based on least squares), and MPC is $\gamma_\epsilon \times E[C_{it}/Y_{it}]$, where γ_ϵ is the short-run elasticity with respect to transitory income shocks. Structural break tests based on Wald statistics with p-values in parentheses for a $\chi^2(1)$ distribution are reported for the null hypothesis of no structural break. Wald statistics and standard errors for MPCs based on QMLE take mean consumption-income ratios as known given highly precise estimates. The upper panel reports inferences for all households in the sample and groups based on homeownership and HtM status, where 'PHtM' refers to poor hand-to-mouth, 'WHtM' to wealthy hand-to-mouth, and 'NHtM' to non-hand-to-mouth, while the lower panel reports inferences for homeowners stratified into subgroups based on liquid wealth (LW), housing wealth (HW), and leverage (Lev.), where 'Low' and 'High' refer to homeowners below or above median for a particular balance sheet variable.

variables, such as geographic location with housing wealth or employment status with leverage, as evident in Table 2.

Then, as also reported in Table 4, increased transitory consumption response parameters given reasonably stable consumption-income ratios translate into higher implied MPCs in the 2007-2016 subsample period. The estimated average MPC for all households increased from 0.07 to 0.10, with standard errors of 0.01 in both cases, given an increase in the estimate of $\tilde{\gamma}_\epsilon$ from 0.09 to 0.14, with standard errors of 0.02 in both cases, while the estimated MPC for low liquid wealth homeowners almost doubled from 0.08 to 0.15, with standard errors of 0.02 in both cases, given an increase in the estimate of $\tilde{\gamma}_\epsilon$ from 0.13 to 0.26, with standard errors of 0.03 and 0.04, respectively.

These changes are also statistically significant according to structural break tests for MPCs, i.e. we can reject the null that $H_0 : \text{MPC}_{\text{pre}} = \text{MPC}_{\text{post}}$.

It should be noted that the finding of an increase in MPCs following the end of the housing boom is only evident given the inclusion of the transitory consumption response parameter $\tilde{\gamma}_\epsilon$ in our semi-structural model. In particular, not only is the full-sample estimate of the MPC for all households smaller at 0.05 instead of 0.08 if we were to consider the original BPP specification that assumes a constant elasticity with respect to transitory income shocks, but the time-varying MPC estimates are also equal to 0.05 in both subsample periods. Thus, we highlight that it is only by allowing for dynamic consumption elasticities that we are able to detect a change in MPCs from before to after the housing boom and bust.

Why did MPCs increase following the end of the housing boom?

Our findings of higher MPCs, especially for low liquidity homeowners, are immediately suggestive of the deterioration in housing wealth combined with liquidity constraints making consumption more sensitive to transitory income shocks following the housing bust. A question, though, is how much these results actually reflect a movement along household consumption functions due a change in wealth distributions versus being driven by a shift in consumption functions for other reasons (see Kaplan and Violante, 2022). We argue that the change in MPCs does not actually appear to be related to a change in wealth distributions, but rather is due to a tighter borrowing constraints given less credit availability for low liquidity homeowners. Meanwhile, the shift in consumption functions does not appear to be due to other reasons such as changes in interest rates, risk/uncertainty, or patience.

To help investigate the possible role of a change in wealth distributions in explaining the structural break in the estimated MPC for low liquid wealth homeowners in particular, Figure 3 reports the real liquid and total wealth distributions for these homeowners in three subsample periods of 1998-2006, 2007-2012, and 2013-2016. Comparing the 1998-2006 and 2007-2012 distributions, we can see that both liquid and total wealth deteriorated initially after the housing bust. The deterioration was across the whole distribution of households in the low liquid wealth category. Then, as house prices recovered, total wealth in the 2013-2016 subsample period mostly returned to similar levels as in the earlier 1998-2006. Indeed, the recovery is essentially complete for all but the top two deciles. At the same time liquid wealth more than recovered for all but the top two deciles, meaning liquid wealth levels were quite similar in the overall 2007-2016 subsample period as in the earlier 1998-2006 subsample period. Thus, if the change in MPCs reflects a movement along consumption functions with respect to liquid or total wealth, we would expect that shift to produce substantially higher MPCs around 2007-2012 than in 2013-2106. Also, assuming MPCs among low liquid wealth homeowners are higher for lower levels of liquid wealth, the distributional shifts with more of a recovery of total and especially liquid wealth at the bottom end of the distribution should have led to a drop in MPCs within the 2007-2016 subsample period.

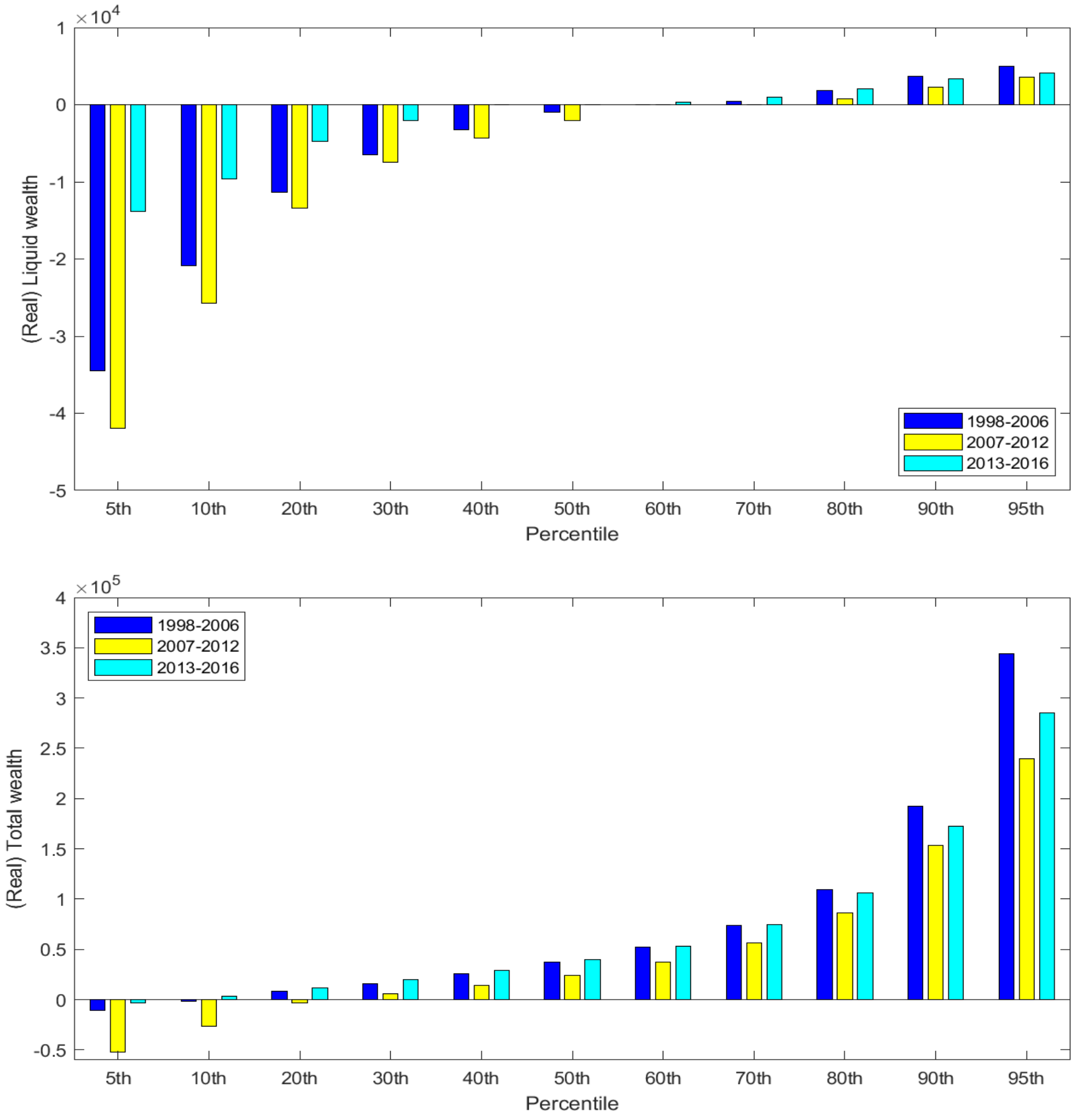


Figure 3: Wealth distributions for low liquid wealth homeowners in three subsample periods

Notes: Median values of real liquid and total wealth are reported for deciles of low liquid wealth homeowners for subsample periods of 1998-2006 (blue bars), 2007-2011 (yellow bars), and 2013-2016 (teal bars). The top panel displays the distributions for liquid wealth, while the bottom panel displays the distributions for total wealth.

Notably, however, we find no support for additional structural changes in our model parameters other than with the housing bust, including no evidence of a decline in MPCs within the 2007-2016 subsample period in particular. To examine the possibility of any such additional structural change, we conduct three robustness checks, the full results for which are provided in the appendix. First, we test for structural breaks within the 1998-2006 and 2007-2016 subsample periods for all households. We cannot reject that parameters remain constant between 1998-2001 and 2002-2006 and between 2007-2012 and 2013-2016, with all parameter estimates quite similar before and after the additional breaks. The p-values for additional structural breaks in MPCs within the 1998-2006 and 2007-2016 subsample periods are 0.91 and 0.46, respectively. Meanwhile, the estimated MPC actually increases somewhat from 2007-2012 to 2013-2016, although the increase is not statistically significant. Second, we consider time-varying estimates for different groups of households where we restrict the post-break subsample period to 2007-2012. If the change in consumption responses had been more transitory due to large fluctuations in wealth distributions around the Great Recession, we would expect larger estimated changes in parameters given the shorter second subsample period. However, the results, including for the structural break tests with the housing boom and bust, are generally quite similar to those reported in Table 4. Third, we consider the possibility of more frequent changes in model parameters for all households by allowing for a change in parameters after every two waves. Again, we find the same pattern of changes in the transitory consumption response parameters as in Table 4, although the parameter estimates are not precise even given the focus only on results for all households that reflect the most cross-sectional data with which to identify parameters. The estimates clearly support a persistent change in transitory consumption responses from before to after the housing boom and bust rather than just a temporary change during the Great Recession, with the estimate of $\tilde{\gamma}_\epsilon$ for the 2013-2016 subsample period of 0.15, with a standard error of 0.05, being even a bit higher than the 2009-2012 subsample period estimate of 0.13, with a standard error of 0.03.

Another reason why consumption responses could have changed sometime around the Great Recession is that real interest rates have been unusually low in latter part of our 1998-2016 sample period; see, for example, Holston, Laubach, and Williams (2017). The motivating theoretical optimization problem for households with CRRA utility considered in BPP suggests that the long-run elasticity $\bar{\gamma}_\epsilon$ is positively related to the interest rate, effectively corresponding to the annuity value of a transitory income shock under the permanent income hypothesis. Thus, we might have expected this parameter to decrease over the sample period. Evidently, then, given the lack of evidence for a change in $\bar{\gamma}_\epsilon$, the aggregate and idiosyncratic effects of changes in interest rates on consumption have been captured by time dummies in first-stage regression for household consumption and the idiosyncratic consumption shocks, respectively. Therefore, a change in interest rates does not appear to be a source of our estimated changes in MPCs.

Similarly, risk/uncertainty might have played a role in the change in MPCs. Bloom (2014) documents the countercyclicality of uncertainty at both macroeconomic and microeconomic levels, with higher uncertainty reducing households' willingness to spend. We note that the effects on consumption of changes in aggregate uncertainty should be controlled for with the first-stage regression for household consumption and heterogeneity in responses possibly captured by idiosyncratic consumption shocks. Furthermore, despite the obvious increase in macroeconomic uncertainty with the Great Recession, we find what might be surprisingly stable idiosyncratic shock variances from before to after the housing market boom and bust, as well as within the 2007-2016 subsample period (see the appendix for full estimates). This result is also consistent with findings in Chopra (2022) of very similar volatilities for both wages and earnings when comparing between recessions and expansions using PSID data from 1977-2016. He also finds the estimated variance of transitory income shocks using a moments-based estimator is actually smaller in recessions than expansions, although they are not significantly different. Thus, changes in idiosyncratic risk/uncertainty does not seem to be a driver of the change in estimated MPCs, at least not the large change that occurred with the housing market boom and bust.

Another possible explanation for a change in MPCs is a change in the patience of households. However, it is notable that the long-run elasticities with respect to transitory income shocks did not change when the short-run elasticities increased. So it is not a matter of households bringing forward spending to the short run with an offsetting decrease in the long run, as one might expect if households became less patient. Also, it is not clear why low liquid wealth homeowners in particular would become more impatient when other households do not show a significant change in their behavior.

Our interpretation of the time-varying estimates is that consumption behavior during the housing boom was more unusual than in the bust because of the ubiquity of home equity lines of credit in the early 2000s, with the change in MPCs following the housing bust corresponding more to a "return to normal" of consumption functions for low liquid wealth households due to tighter borrowing constraints given less credit availability. This is consistent with the idea that homeowners were able to easily access additional liquidity from their housing wealth through cash-out refinancing or home equity lines of credit during the housing boom, in line with the empirical evidence in Hurst and Stafford (2004) that households used their housing wealth to insure against bad income realizations, but it became much more costly for them to do so during the housing bust as credit conditions worsened. This reduced access to credit made it more difficult for low liquid wealth homeowners to borrow to smooth consumption in the event of transitory shocks to their income; see also Gross, Notowidigdo, and Wang (2020), who find an increase of about 30% in the MPC out of liquidity between 2007 and 2009 using U.S. credit card transaction data, a similar magnitude to the increase in the average MPC that we find with the PSID data. Furthermore, even with a recovery of house prices by the end of our sample period, it is not clear that credit conditions have returned to what they were at the height of the housing boom. Pistaferri (2016) reports data that suggest home equity cash-out refinancing activity was unusually high in the early to mid 2000s, but fell to and remained at the same low levels following the Great Recession as it was in the 1990s. Plots of data for home equity loans confirming this pattern are reported in the appendix, as are plots based on Butta, Laufer, and Ringo (2017) and Butta and Canner (2013) for mortgage applications and approvals, including for refinancing, which started declining following the end of the housing boom and approvals in particular have remained around the same lower level throughout the 2007-2016 subsample period. Thus, tighter credit constraints for homeowners in particular provides a plausible explanation for increase in MPCs, although we acknowledge that establishing a causal relationship would require further investigation likely with other data than the PSID and we leave it for future research.[14]

In terms of testing the idea of a return to normal after the housing boom, we find an estimate of $\tilde{\gamma}_\epsilon$ of 0.09, with a standard error of 0.02, for all households in the earlier BPP sample from 1978-1992, although the data are not directly comparable for a variety of reasons. This compares to estimates for our sample from the PSID when considering only continuously-married households and excluding (imputed) rent to be more comparable to the BPP sample of 0.03, with a standard error of 0.02, in the 1998-2006 subsample period and 0.16, with a standard error of 0.04, in the 2007-2016 subsample period. So, arguably, the larger transitory sensitivity of consumption after the housing bust is more of a return to normal than a break from the past. Also, supporting the role of home equity lines influencing MPCs is a lack of significant change in transitory consumption responses or MPCs for PHtM households in Table 4, who are liquidity constrained, but are mostly renters according to Table 1 and generally would have not had access home equity lines of credit even during the housing boom.

Additional robustness checks

We conduct a number of additional robustness checks for the time-varying estimates, with the full results provided in the appendix. First, as noted when describing the data, we consider the effects of excluding (imputed) rent from the measure of household consumption and find the results are qualitatively robust, with the main difference being somewhat larger estimated short-run elasticities, although the implied MPCs are similar to our benchmark results given the comparatively lower consumption-income ratios for this alternative measure of consumption. Second, given substantial overlaps between low liquid wealth homeowners, high leverage homeowners, and WHtM households (again, see the appendix for a tabulation matrix of overlaps across groups in the time-varying sample), we isolate the roles of particular aspects of household balance sheets by excluding overlapping households from the subgroups. Sample sizes become smaller and standard errors larger, which in turn impacts the power of the Wald tests for a structural break. However, what we are interested in is whether the changes in the transitory consumption response in the post-break period is in the same direction after removing the overlapping households. We find that excluding WHtM households from the low liquid wealth subgroup alters the estimated post-break transitory consumption response parameter $\tilde{\gamma}_{\epsilon,2007\text{-}2016}$ from 0.26 to an even larger 0.39, with standard errors of 0.04 and 0.10, respectively, and the Wald statistic for the structural

[14]The timing of the structural break generally aligns with our explanation as credit conditions generally deteriorated in the United States by the end of 2007. See, for example, net percentage of domestic banks tightening standards for credit card loans, net percentage of domestic banks reporting increased willingness to make consumer installment loans, and, more comprehensively, the Chicago Fed National Financial Conditions Credit Subindex, although the home equity lines of credit series reported in the appendix actually peaked at the beginning of 2009. When we considered alternative timing for the structural break to have a change in parameters starting in 2005 or 2009, we found the Wald statistics for a change in the transitory consumption response parameter $\tilde{\gamma}_\epsilon$ for all households was insignificant, with values of 2.94 and 1.44, respectively, compared to 4.53 for the change in parameters starting in 2007, as reported in Table 4.

break test still significant at the 1% level in this case. Excluding high leverage homeowners leads to a similar estimate as before of 0.25, with a standard error of 0.10. By contrast, excluding low liquid wealth homeowners from high leverage subgroup alters the estimated post-break transitory consumption response parameter $\tilde{\gamma}_{\epsilon,2007\text{-}2016}$ from 0.17 to a considerably smaller 0.07, with standard errors of 0.04 and 0.08, respectively. This suggests that liquid wealth is more relevant than HtM status or leverage when considering changes in consumption responses to transitory income shocks following the end of the housing boom.[15] Third, to further corroborate our results, we also consider estimation using an alternative sample selection of only households who appear in a particular group in both subsample periods. For most of the household groups, the main conclusions drawn based on the estimates in Table 4 remain unchanged with no obvious indication of a direction of bias in our benchmark estimates versus the alternative estimates. Again, low liquid wealth homeowners stand out and their transitory consumption response parameter increased significantly, statistically and economically, from before to after the housing boom and bust.[16]

4.3 Comparison to other results

In comparing our estimates to other results in the literature, it is important to reiterate that the time period t in our model corresponds to one year given that income and consumption are annual flows in the PSID, while, as explained in Section 3, waves of data are only available biennially for the 1998-2016 sample period that we consider in our empirical analysis. Thus, we treat the alternating years with no data as missing observations to be handled by the Kalman filter just like any other missing observations from an unbalanced panel. Indeed, one of the contributions of our analysis is to show how to consider PSID data from 1998-2016 that includes richer information on expenditures and wealth than the earlier annual PSID data considered in BPP (wealth information was only available in three waves of 1984, 1989, and 1994 before 1999 and did not include details about retirement savings), but still be able to precisely estimate the same elasticity parameters as BPP (and more by allowing for dynamic elasticities with respect to transitory income shocks) even though observations for every second year are missing.

It should be emphasized that our approach is different from simply working with wave growth rates over a two-year horizon. Commault (2022) points out that studies using moments-based es-

[15] We also estimate our model for subgroups based on debt-to-asset ratios for homeowners. The estimated transitory consumption response parameters for homeowners with above-median debt-to-asset ratios in the pre- and post-break periods are 0.14 and 0.13, with standard errors of 0.03 and 0.05, respectively, suggesting this leverage-related balance sheet characteristic is not relevant for explaining the structural break in the average transitory consumption response parameter for all households.

[16] We have also considered estimation using all households before and after the structural break, not just those classified in groups based on our benchmark sample selection. This selection is reasonable in this case when considering all households as PSID keeps the composition of households for their panel as representative as possible and we are obviously not concerned about controlling for transitions in and out of the 'all households' category. For this selection, the Wald statistic for a change in the average MPC is 5.66 (versus 6.09 under our benchmark sample selection), which is still significant at the 5% level.

timates with biennial wave growth rates are actually estimating what she refers to as the "biennial passthrough" coefficient:

$$\phi_2^\epsilon \equiv \frac{cov(c_{it} - c_{it-2}, \epsilon_{it} + \theta\epsilon_{it-1})}{var(\epsilon_{it} + \theta\epsilon_{it-1})}. \tag{9}$$

In terms of our extended BPP model, the implied growth rates across two-year waves are given as follows:

$$y_{it} - y_{it-2} = \eta_{it} + \eta_{it-1} + \epsilon_{it} + \theta\epsilon_{it-1} - \epsilon_{it-2} - \theta\epsilon_{it-3}, \tag{10}$$

$$c_{it} - c_{it-2} = \gamma_\eta(\eta_{it} + \eta_{it-1}) + \gamma_\epsilon\epsilon_{it} + \bar{\gamma}_\epsilon\epsilon_{it-1} - \tilde{\gamma}_\epsilon\epsilon_{it-2} + u_{it} + u_{it-1} + v_{it} - v_{it-2}. \tag{11}$$

Thus, it is straightforward to solve for the biennial passthrough coefficient as a function of the model parameters:

$$\phi_2^\epsilon = \frac{\gamma_\epsilon + \theta\bar{\gamma}_\epsilon}{1 + \theta^2}. \tag{12}$$

Then, it is easy to see that, as long as $\theta \neq 0$, the biennial passthrough coefficient will be different from an "annual passthrough" coefficient:

$$\phi^\epsilon \equiv \frac{cov(c_{it} - c_{it-1}, \epsilon_{it})}{var(\epsilon_{it})}, \tag{13}$$

for which, referring back to the expression for the consumption growth rate implied by our model in equation (6), it is straightforward to solve that it is equal to the short-run elasticity $\phi^\epsilon = \gamma_\epsilon$. Thus, put simply, ϕ_2^ϵ will only be equal to the short-run elasticity γ_ϵ if $\theta = 0$.

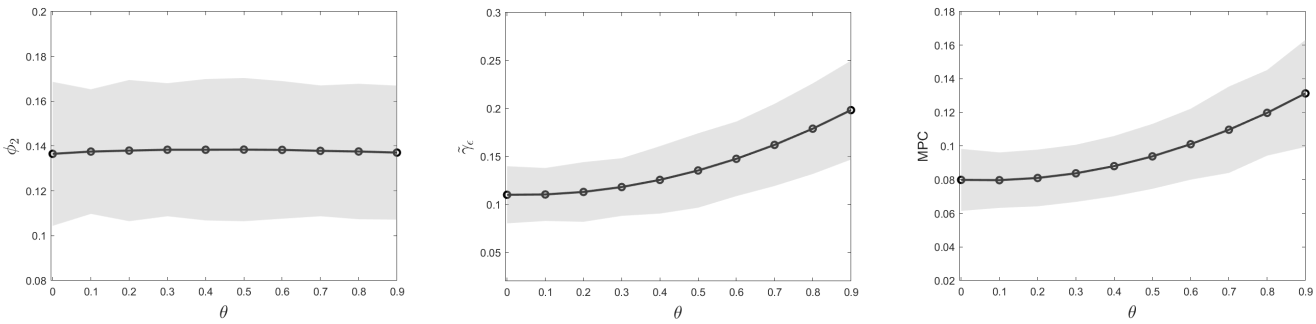
Commault (2022) shows how to get a robust moments-based estimate of the annual passthrough coefficient ϕ^ϵ even if consumption is not a random walk and $\theta \neq 0$. Specifically, she suggests using

$$\hat{\phi}^\epsilon = \frac{cov(c_{it} - c_{it-1}, y_{it+1} - y_{it+2})}{cov(y_{it} - y_{it-1}, y_{it+1} - y_{it+2})}, \tag{14}$$

which will also be robust to classical measurement error in income and shocks occurring continuously throughout a year rather than discretely at the beginning of the year, as discussed in Crawley (2020). However, this estimator is not available given only biennial wave growth rates. Therefore, she also considers a biennial passthrough estimator that she shows produces a different estimate than the annual passthrough estimator when applied to the yearly 1978-1992 PSID dataset, consistent with the presence of substantial MA dynamics in transitory income.

For a comparison to Commault's results, we estimate the biennial passthrough coefficient implied by our model for different values of the moving-average parameter θ. Figure 4 shows that the full-sample estimated biennial passthough coefficient for all households is highly robust across different values of θ from 0 to 0.9, with an estimated value of 0.14 and standard error of 0.02. This compares to the similar estimated biennial passthrough coefficient $\hat{\phi}_2^\epsilon$ of 0.13, with standard error of 0.06, reported in Table 4 of Commault (2022) for comparable data from the PSID for the same 1998-2016 sample period, confirming the greater precision of our QMLE estimates versus a moments-based approach given our substantially smaller standard error.[17]

[17] As previously mentioned, part of the efficiency gain for our estimation compared to using growth rates across



(a) ϕ_2^ϵ (b) $\tilde{\gamma}_\epsilon$ (c) MPC

Figure 4: Estimates of biennial passthrough, short-run elasticity, and MPC for different values of the moving-average parameter

Notes: ϕ_2^ϵ refers to the biennial passthrough coefficient, γ_ϵ is the short-run elasticity with respect to transitory income shocks, and θ is the MA(1) parameter. Estimates are for all households over the full sample from 1998-2016. The shaded areas depict 95% confidence intervals based on inverted t tests.

Crucially, Commault's approach only provides an estimate of biennial passthrough with biennial data, not the short-run elasticity, which can be used to calculate MPCs. It is true biennial passthrough can be used to get a lower-bound estimate of the short-run elasticity if we assume $\theta = 0$. But, as can be seen by looking at equation (12), fixing θ at another value does not separately identify the short- and long-run elasticities, γ_ϵ and $\bar{\gamma}_\epsilon$, from the biennial passthrough coefficient ϕ_2^ϵ alone. However, our parametric approach directly provides an estimate of the short-run elasticity and MPC for any given value of θ, which is useful if there is a reason to believe θ is substantially different than zero. We note that the similarity of Commault's biennial passthrough coefficient estimate to our benchmark short-run elasticity estimate under $\theta = 0$ does not tell us anything about the value of θ given that we find highly robust estimates of biennial passthrough for other values of θ.

Returning to Figure 4, we can see how estimates of the short-run elasticity and MPC change for different values of θ. Basically, the estimates are robust and similar to our benchmark case when $\theta = 0$ up to values of θ as high as 0.4, above which the estimates increase noticeably to almost double for the short-run elasticity $\tilde{\gamma}_\epsilon$ and a bit more than 50% more for the MPC. So we can quantify the lower-bound effect of setting $\theta = 0$ in our benchmark analysis, with the full-sample average MPC across all households being as high as 0.12 instead of 0.08 if transitory income shocks are extremely persistent over a two-year horizon.

We acknowledge that Commault's approach does not require as many parametric assump-

waves is that QMLE for the model in log levels retains more information because it incorporates every available observation in levels, while growth rates are only available for consecutive biennial observations in levels and so there would be more missing data in growth rates when households drop out and re-enter the survey. We find that the additional observations incorporated in our levels estimation contain useful information about the model parameters. For example, the full-sample estimated transitory consumption response parameter $\tilde{\gamma}_\epsilon$ for all households is 0.10, with a standard error of 0.02, based on QMLE for an unobserved components representation of biennial growth rates, which is very similar to, but less precise than our full-sample estimate for all households of 0.11, with a standard error of 0.01, reported in Table 3 based on estimation in levels.

tions as we make with our extended BPP model. In particular, we relax the assumption that consumption is a random walk by introducing the transitory consumption response parameter $\tilde{\gamma}_\epsilon$. However, we do this within the context of a particular parametric model, while Commault does not need to make specific assumptions about the transitory dynamics of consumption. We did consider other model specifications that also allowed for distributed lag effects of transitory income shocks on consumption. But, as noted when presenting our model in Section 2, we found no evidence to support an alternative specification for the household survey data. In particular, using annual data from the 1978-1992 BPP sample, the estimate for the first distributed lag is equal to 0.00 and not significant, while a lack of any meaningful higher-order distributed lag effects is supported by a very small second-order autocorrelation for two-year wave consumption growth in our 1998-2016 PSID sample.

Commault's approach is also more general than our model in the sense that it allows for classical measurement error in income. In principle, it is possible to include an additional noise term for income in our model in order to account for random measurement error in reported income in addition to that allowed for in consumption, although this noise term is only separately identified from transitory income shocks to the extent the latter have significant effects on consumption. Thus, we follow BPP by not including an additional noise term in our main model specification. However, we have checked whether there is empirical support for such noise and found the estimated variance is small, while other parameter estimates are very similar to those when excluding it. Specifically, when considering all households in our sample, the estimated standard deviation of the additional noise is 0.001, which is two orders of magnitude smaller than for the other shocks in the model.

As noted above, Commault's annual passthrough estimator is also robust to temporal aggregation effects, although the biennial passthrough estimator is not if the transitory income shocks have persistent effects. The issue, as detailed in Crawley (2020), is that temporal aggregation in reported data collected at discrete intervals creates a Working effect when shocks occur continuously within a time period. For his analysis, he considers the BPP model specification (i.e. $\tilde{\gamma}_\epsilon = 0$), while also assuming no moving-average dynamics in his benchmark specification in order to map observables to continuous-time diffusions. For the BPP sample with GMM estimation, he finds that assuming no persistent effects of transitory income shocks has little effect on elasticity estimates, but accounting for temporal aggregation increases the estimated elasticity with respect to transitory income from 0.05 to 0.24, with standard errors of 0.05 and 0.04, respectively. When we consider the BPP model with $\theta = 0$ for our PSID sample with QMLE, but imposing the temporal aggregation effect based on Crawley (2020) that $\partial c_{it}/\partial \epsilon_{it} = \gamma_\epsilon - (3\gamma_\eta - \gamma_\epsilon)\sigma_\eta^2/(6\sigma_\epsilon^2 - \sigma_\eta^2)$, we find the estimated elasticity increases from 0.08 to 0.13, with standard errors 0.01 in both cases. Thus, temporal aggregation could be an additional reason for some underestimation of MPCs, with the true values on the order of as much as 50% larger than when assuming discrete shocks, a similar magnitude of underestimation to what we found if transitory income shocks are very persistent over a two-year horizon. The lower-bound nature of our estimates mean that they provide a better indication of percentage changes in MPCs rather than necessarily the exact level of MPCs, at least assuming relatively stable biases from a positive correlation between short-run elasticities and consumption-income ratios, assuming no moving-average dynamics, and temporal aggregation over time.

Even acknowledging the lower-bound nature of our MPC estimates, it is clear that adjusting for the possible biases discussed above would still lead to lower estimates than typically found in natural experiments. These lower MPCs could reflect our focus on nondurable components of annual consumption, while transitory income shocks, perhaps especially one-time windfalls, might lead to intertemporal substitution of durable goods purchases within the year that would result in some of the larger estimated short-run MPCs from natural experiments, although many natural experiments also directly consider nondurables consumption. See Laibson, Maxted, and Moll (2022) on the differences between the marginal propensities to spend versus consume given durable goods and the higher values of marginal propensities to spend in natural experiment settings than implied MPCs. Another possibility is that our estimates reflect a focus on idiosyncratic income shocks in a linear setting, while responses to more aggregate or unusual shocks often considered in natural experiments may be proportionately larger. Notably, tax shocks could involve general-equilibrium effects if they have aggregate implications or different properties in terms of the ability of households to diversify against the associated income risk. It is not clear if general-equilibrium effects would necessarily dampen or amplify MPCs, but it should be more difficult to self-insure against aggregate shocks than idiosyncratic shocks, suggesting tax rebates would lead to larger MPCs than what we find for idiosyncratic income shocks.

To put our results into a quantitative dollar-based perspective, the full-sample estimated average MPC of 0.08 implies household consumption adjusts, on average, by approximately $1,200 to a one-standard-deviation transitory income shock of approximately $15,000 given mean disposable household income of $58,295 (1999 dollars). For comparison, using a hypothetical survey, Fuster, Kaplan, and Zafar (2021) find an average MPC of 0.08 or $40 for one-time windfall of $500, although they find it is higher at 0.14 or $700 for a one-time windfall of $5,000. Meanwhile, the implied response to a transitory shock does not seem particularly small in comparison to an implied response of approximately $1,500 to a one-standard-deviation permanent income shock of approximately $7,000 based on our estimates of consumption insurance and the consumption-income ratio. In dollar-for-dollar terms, the response to a one-standard-deviation transitory shock is about 40% as large as the response to a one-standard-deviation permanent shock, which is certainly much more than the proportionate annuity value response under the permanent income hypothesis for any reasonable assumption about the interest rate, again supporting our allowance for a different short-run elasticity with respect to transitory income shocks than the constant long-run elasticity assumed in BPP.

Our more granular subsample robustness analysis also allows us to compare our results to those in Ganong et al. (2020) for a similar sample period. In particular, our estimated short-run elasticity with respect to transitory income shocks γ_ϵ is 0.18, with a standard error of 0.05, for the 2013-2016 subsample period, which is smaller than, but within range of the highly precise estimate for the elasticity with respect to income of 0.23 in Ganong et al. (2020) using IV (and larger than their estimate of 0.12 using OLS) for a regression of changes in log nondurables consumption on changes in log labor income according to monthly bank account data for 20 million households from October 2012 through April 2018. In particular, their use of firm pay shocks as an instrument gives the IV estimate an interpretation as an elasticity with respect to a transitory income shock. At the same time, it should be acknowledged that their implied MPC is significantly higher at 0.22, although this appears to be due to a much higher ratio of mean consumption to mean income than reported in the PSID. Meanwhile, a recent study by Borusyak, Jaravel, and Spiess (2022) finds smaller MPCs when taking a difference-in-differences approach to estimation of the MPC based on the 2008 tax rebates. Their implied quarterly MPC for total consumption ranges from 0.08 to 0.11, which effectively implies less sensitivity to transitory income shocks than our annual MPC estimate of 0.08 unless the change in consumption from a transitory income shock is extremely persistent over a one-year horizon, in which case the estimates are very similar to ours.

4.4 Why did consumption fall during the Great Recession?

Our findings of relatively small estimated consumption responses to income shocks compared to much of the literature do beg a question as to why consumption fell so much during the Great Recession. The significant increase in the average MPC after the housing bust reported in Table 4 suggests that a greater responsiveness to transitory income shocks, especially for low liquid wealth households, is part of the story. However, a more complete answer is provided by the fact that even relatively small MPC estimates can imply sizeable consumption elasticities with respect to house prices. In particular, the decline in house prices by as much as 30% between 2007 and 2009 according to the Case-Shiller index implies a substantial negative wealth effect on the level of consumption, an effect that is amplified by the heightened responsiveness of consumption at the time.

Given a housing bust preceding the Great Recession, consumption elasticities with respect to house prices have often been employed (see, for example, Mian et al., 2013, Kaplan et al., 2020b and Berger et al., 2018) to examine quantitative effects on consumption during the Great Recession. To estimate an implied consumption elasticity with respect to house prices, which we denote as γ_{hp}, we use the rule-of-thumb approximation proposed by Berger et al. (2018):

$$\gamma_{\text{hp}} \approx \text{MPC} \times (1-\delta)\frac{P_{t-1}H_{it-1}}{C_{it}}, \tag{15}$$

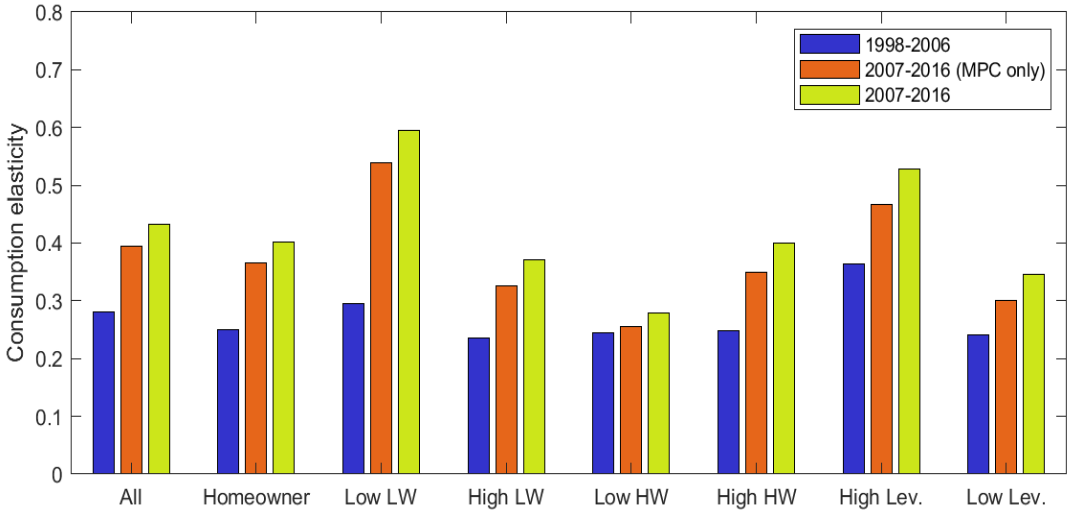


Figure 5: Implied consumption elasticities with respect to house prices

Notes: Implied consumption elasticities with respect to house prices for different household groups are reported for subsample periods of 1998-2006 (blue bars), 2007-2016 but only allowing MPCs to change while holding PH/C ratios fixed at their 1998-2006 values (orange bars), and 2007-2016 (green bars). Inferences are reported for all households, homeowners, and homeowners stratified into subgroups based on liquid wealth (LW), housing wealth (HW), and leverage (Lev.), where 'Low' and 'High' refer to homeowners below or above median for a particular balance sheet variable.

where δ is the depreciation rate for housing, set to 2% per annum following Berger et al. (2018), and the PH term is the reported house *value* (distinct from housing *wealth*, which is net of mortgage debt) in the PSID expressed in real terms using the housing sub-index of the CPI. For direct comparability with Berger et al. (2018), we use median values of the consumption-income and PH/C ratios for each household group in each subsample period to calculate the MPC and the implied elasticity with respect to house prices, respectively. The simple point of this rule-of-thumb formula is that a greater percentage increase in the MPC than a percentage decrease in PH/C ratio will imply a larger consumption elasticity with respect to house prices. Given that the increase in the estimated average MPC was more than 40% following the housing bust, we should expect the implied γ_{hp} to increase for all households even at a maximal decline in house prices of about 30%, especially given that consumption also fell during the Great Recession.

Figure 5 shows that the implied consumption elasticities with respect to house prices increased substantially after the housing bust, with the increase being largely due to changes in MPCs given similar increases when holding the PH/C ratios fixed at their 1998-2006 values. The estimate of γ_{hp} for all households is 0.28 in 1998-2006 subsample period and 0.43 in the 2007-2016 subsample period, with 95% confidence intervals in each period of [0.20, 0.36] and [0.34, 0.52], respectively. These estimates are on the high end in terms of the literature, but are in line with the estimates in the Berger et al. (2018) study from which we borrow the rule-of-thumb formula. In particular, using a sample period from 1998 to 2010 for the PSID and the BPP approach to estimate the MPC, Berger et al. (2018) find an estimate for γ_{hp} of 0.33 with a comparatively imprecise 95%

confidence interval of [0.15, 0.52]. They also find estimates above 0.5 for households with high house values.[18]

As with the MPCs, the increase in the estimate of γ_{hp} is largest and to the highest level for low liquid wealth homeowners. This finding supports a bigger role of the deterioration in housing wealth for liquidity-constrained homeowners than deleveraging in explaining the fall in consumption during the Great Recession, even given a high estimated γ_{hp} for high leverage homeowners as well. In particular, even given a somewhat lower median level of consumption for low liquid wealth homeowners than for high leverage homeowners, the low liquid wealth homeowners have a larger implied *absolute* fall in their consumption given the same percentage decrease in house prices. Specifically, ignoring homeowners who appear in both subgroups, as they have the same fall in consumption by definition, the median levels of consumption are \$21,315 and \$28,443 for the respective 732 and 543 non-overlapping households in the low liquid wealth subgroup excluding high leverage homeowners and the high leverage subgroup excluding low liquid wealth homeowners when considering those who retain their classification from before to after the housing boom and bust. The corresponding estimated consumption elasticities with respect to house prices for these non-overlapping subgroups over the 2007-2016 subsample period are 0.55 and 0.21, respectively. Thus, given a 30% decline in house prices, these estimates and median levels of consumption imply \$3,517 and \$1,792 declines in consumption for the respective median households in the two subgroups. That is, the absolute fall in consumption is estimated to be almost twice as large for non-overlapping low liquid wealth homeowners as for high leverage homeowners, with the higher representation of non-overlapping low liquid wealth homeowners reinforcing their larger implied effect on the level of aggregate consumption.

The implication that the largest negative housing wealth effects were for low liquid wealth homeowners, not high leverage homeowners, is consistent with the analysis in Kaplan et al. (2020a,b) that suggests a decline in housing wealth was more important than deleveraging households in explaining the fall in consumption during the Great Recession. In particular, the "shifted beliefs" hypothesis in Kaplan et al. (2020a) suggests that changes in expectations about future housing demand played a larger role than borrowing constraints in explaining movements in housing wealth and that the decline in housing wealth with the housing bust helped drive a decline in consumption via a wealth effect. They use a calibrated structural model with an implied average MPC out of a small windfall of cash to be 39.5% and an average elasticity of consumption to house prices of around 0.20 to generate their quantitative predictions about the wealth effects

[18] Estimates of consumption elasticities with respect to house prices vary considerably based on data and methods; see, for example, Mian et al. (2013), Aladangady (2017), Paiella and Pistaferri (2017), Kaplan et al. (2020b), Guren, McKay, Nakamura, and Steinsson (2021), and Graham and Makridis (2021). We note that the scale of our consumption elasticities may be high if the self-reported house values in the PSID are overly optimistic or the assumed 2% depreciation rate is too low. However, the qualitative differences that we find across different household groups should be informative as long as any reporting biases are similar across groups. Berger et al. (2018) also discuss a variety of theoretical reasons why their rule-of-thumb formula may not be accurate, including the presence of adjustment costs, although they show that it works well as an approximation in many settings.

of the housing bust. Their implied MPC is higher than our estimates, while their house price elasticity is lower. But our finding of an increase in MPCs following the housing bust brings our estimates closer to what they assume in the model and our higher implied aggregate house price elasticity of 0.43 in the 2007-2016 subsample period (compared to 0.28 in the 1998-2006 subsample period) actually suggests even larger wealth effects from a change in house prices than found in Kaplan et al. (2020a). Thus, our results support a wealth effect driving down consumption during the Great Recession, even if changes in wealth distributions did not appear to alter MPCs, as discussed in Section 4.2. Our higher estimated MPCs following the housing bust, especially for low liquid wealth homeowners, supports a sizeable quantitative effect of housing wealth via implications about house price consumption elasticities, in addition to the direct effect on consumption from a fall in labor income implied by the MPCs. Meanwhile, we note that heightened risk/uncertainty likely also played a role in the fall in consumption during the Great Recession, as highlighted by Bloom (2014), even if, like changes in wealth distributions, it did not necessarily alter MPCs, again as discussed in Section 4.2.

5 Conclusion

Our empirical results suggest that a decline in house prices combined with higher MPCs for liquidity-constrained homeowners led to the large fall in consumption during the Great Recession. Before the housing bust, the households with comparatively high MPCs were mainly renters and WHtM households, while homeowners with low liquid wealth or high leverage could not be distinguished from WHtM households in terms of their MPCs. However, our estimates suggest that, following the housing bust, these homeowners, particularly those with low liquid wealth, have higher MPCs than renters and WHtM households. A simple explanation for this key role of homeowner liquidity in increasing MPCs is that homeowners could access additional liquidity from their housing wealth through cash-out refinancing or home equity lines of credit during the housing boom, but it became much more difficult for them to do so or even refinance their mortgages during the housing bust and afterwards.

Our finding of a closer link of higher MPCs following the housing bust to low liquid wealth rather than high leverage supports the argument in Kaplan et al. (2020a,b) that a negative housing wealth effect more than deleveraging drove consumption down during the Great Recession. Meanwhile, the large increase in MPCs with the housing bust applied to as many as half of all homeowners (i.e. those with below median liquid wealth), with many of those households not technically classified as "hand-to-mouth" and applying even though liquid and total wealth levels for households at the lower end of the distribution shifted back to even more favourable values by the end of the 1998-2016 sample period than at the beginning. Notably, our estimates support the theoretical result of Boar et al. (2020), who model the illiquid asset as housing in a two-asset incomplete markets model and suggest that liquidity constraints bind for most homeowners, even though these homeowners would not necessarily be classified as "hand-to-mouth". In terms of policy implications, our finding of a closer association of homeowner liquidity than leverage with increased and higher MPCs supports the idea that, consistent with findings for mortgage modification in Ganong and Noel (2020), stabilization policies designed to improve liquidity such a restructuring monthly mortgage payments will be more effective than debt relief programs such as adjusting the principal on mortgages during and in the aftermath of recessions associated with large declines in house prices.

Our analysis shows that a semi-structural model applied to survey data can provide relatively precise quantitative inferences that support heterogeneity and time variation in MPCs across household groups classified by different balance sheet characteristics. Estimation of model parameters via QMLE following Chatterjee et al. (2021) allows us to consider small samples and still have enough power to reject constant parameters when there is structural change. Furthermore, likelihood-based inference appears to mitigate the large downward bias in estimating consumption insurance with respect to permanent income risk that Kaplan and Violante (2010) highlight afflicts the BPP moments-based approach when considering simulated data from their structural life-cycle model with incomplete markets and borrowing constraints. Related, we find higher estimates of consumption insurance in data from a representative sample of U.S. households than typically found in the literature.

A key innovation in our analysis beyond the original BPP model is to identify and estimate dynamic consumption elasticities with respect to transitory income shocks. This is done by adding a parameter to capture the transitory response of consumption, which addresses a concern raised in Commault (2022) with estimation of the BPP model if consumption does not actually follow a random walk and directly provides "intertemporal" MPCs in the sense of Auclert et al. (2018). We are able to estimate these dynamic elasticities precisely and separately despite considering biennial data with many missing observations, while the biennial passthrough coefficient in Commault (2022) cannot identify the short-run elasticity except in the limiting case of no moving-average dynamics in transitory income shocks. As we show, our additional transitory consumption response parameter compared to the BPP model is economically and statistically significant for all groups of households and a structural break in this parameter for all households, homeowners, and homeowners with lower levels of liquid wealth drives the statistically significant and economically relevant change in the average MPC from before to after the housing boom and bust.

We conclude by noting that future directions for research include an in-depth analysis of possible asymmetries in consumption responses and of links between unobserved income shocks and observables within our semi-structural modeling framework, building on recent related work by Ballantyne (2021) and Braxton, Herkenhoff, Rothbaum, and Schmidt (2021).

References

Aguiar, M. A., M. Bils, and C. Boar (2020). Who are the hand-to-mouth? NBER Working Paper 26643.

Aladangady, A. (2017). Housing wealth and consumption: Evidence from geographically-linked microdata. *American Economic Review 107*(11), 3415–3446.

Altonji, J. G. and L. M. Segal (1996). Small-sample bias in GMM estimation of covariance structures. *Journal of Business & Economic Statistics 14*(3), 353–366.

Arellano, M., R. Blundell, and S. Bonhomme (2017). Earnings and consumption dynamics: A nonlinear panel data framework. *Econometrica 85*(3), 693–734.

Auclert, A. (2019). Monetary policy and the redistribution channel. *American Economic Review 109*(6), 2333–2367.

Auclert, A., M. Rognlie, and L. Straub (2018). The intertemporal Keynesian cross. NBER Working Paper 25020.

Baker, S. (2018). Debt and the response to household income shocks: Validation and application of linked financial account data. *Journal of Political Economy 126*(4), 1504–1557.

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

Ballantyne, A. (2021). Household consumption: MPC asymmetry and financial frictions. Manuscript.

Berger, D., V. Guerrieri, G. Lorenzoni, and J. Vavra (2018). House prices and consumer spending. *Review of Economic Studies 85*(3), 1502–1542.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives 28*(2), 153–76.

Blundell, R., L. Pistaferri, and I. Preston (2008). Consumption inequality and partial insurance. *American Economic Review 98*(5), 1887–1921.

Blundell, R., L. Pistaferri, and I. Saporta-Eksten (2016). Consumption inequality and family labor supply. *American Economic Review 106*(2), 387–435.

Boar, C., D. Gorea, and V. Midrigan (2020). Liquidity constraints in the US housing market. NBER Working Paper 23345.

Borusyak, K., X. Jaravel, and J. Spiess (2022). Revisiting Event Study Designs: Robust and Efficient Estimation. Discussion Paper 17247, Centre for Economic Policy Research.

Braxton, J. C., K. Herkenhoff, J. Rothbaum, and L. Schmidt (2021). Changing income risk across the US skill distribution: Evidence from a generalized Kalman filter. Manuscript.

Butta, N. and G. Canner (2013). Mortgage market conditions and borrower outcomes: Evidence from the 2012 HMDA data and matched HMDA credit record data. Federal Reserve Bulletin Vol. 99, No. 4, Federal Reserve Board.

Butta, N., S. Laufer, and D. Ringo (2017). Residential mortgage lending in 2016: Evidence from the Home Mortgage Disclosure Act data. Federal Reserve Bulletin Vol. 103, No. 6, Federal Reserve Board.

Carroll, C. D. (1997). Buffer-stock saving and the life cycle/permanent income hypothesis. *Quarterly Journal of Economics 112*(1), 1–55.

Carroll, C. D. (2004). Theoretical foundations of buffer stock saving. NBER Working Paper 10867.

Carroll, C. D. and M. S. Kimball (1996). On the concavity of the consumption function. *Econometrica 64*(4), 981–992.

Chatterjee, A., J. Morley, and A. Singh (2021). Estimating household consumption insurance. *Journal of Applied Econometrics 36*(5), 628–635.

Chopra, A. (2022). Insurance cyclicality. *Available at SSRN 4168822*.

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

Commault, J. (2022). Does consumption respond to transitory shocks? reconciling natural experiments and semistructural methods. *American Economic Journal: Macroeconomics 14*(2), 96–122.

Crawley, E. (2020). In search of lost time aggregation. *Economics Letters 189*, 1089–1098.

Demyanyk, Y., E. Loutskina, and D. Murphy (2019). Fiscal stimulus and consumer debt. *Review of Economics and Statistics 101*(4), 728–741.

Druedahl, J. and Jørgensen (2020). Can consumers distinguish persistent from transitory income shocks? *The Economic Journal, 130*(632), 2410–2437.

Dynan, K. (2012). Is a household debt overhang holding back consumption? *Brookings Papers on Economic Activity 2012*(1), 299–362.

Fagereng, A., M. B. Holm, and G. J. Natvik (2021). Mpc heterogeneity and household balance sheets. *American Economic Journal: Macroeconomics 13*(4), 1–54.

Fuster, A., G. Kaplan, and B. Zafar (2021). What would you do with $500? spending responses to gains, losses, news, and loans. *The Review of Economic Studies 88*(4), 1760–1795.

Ganong, P., D. Jones, P. J. Noel, F. E. Greig, D. Farrell, and C. Wheat (2020). Wealth, race, and consumption smoothing of typical income shocks. NBER Working Paper 27552.

Ganong, P. and P. Noel (2020). Liquidity versus wealth in household debt obligations: Evidence from housing policy in the Great Recession. *American Economic Review 110*(10), 3100–3138.

Garriga, C. and A. Hedlund (2020). Mortgage debt, consumption, and illiquid housing markets in the Great Recession. *American Economic Review 110*(6), 1603–1634.

Gelman, M. (2021). What drives heterogeneity in the marginal propensity to consume? temporary shocks vs persistent characteristics. *Journal of Monetary Economics 117*, 521–542.

Graham, J. and C. A. Makridis (2021). House prices and consumption: A new instrumental variables approach. *American Economic Journal: Macroeconomics, forthcoming*.

Gross, T., M. J. Notowidigdo, and J. Wang (2020). The marginal propensity to consume over the business cycle. *American Economic Journal: Macroeconomics 12*(2), 351–384.

Guren, A. M., A. McKay, E. Nakamura, and J. Steinsson (2021). Housing wealth effects: The long view. *The Review of Economic Studies 88*(2), 669–707.

Guvenen, F., S. Ozkan, and J. Song (2014). The nature of countercyclical income risk. *Journal of Political Economy 122*(3), 621–660.

Holston, K., T. Laubach, and J. C. Williams (2017). Measuring the natural rate of interest: International trends and determinants. *Journal of International Economics 108*(Supplement 1), S59–S75.

Huo, Z. and J.-V. Ríos-Rull (2016). Financial frictions, asset prices, and the Great Recession. CEPR Discussion Paper No. DP11544.

Hurst, E. and F. Stafford (2004). Home is where the equity is: Mortgage refinancing and household consumption. *Journal of Money, Credit and Banking*, 985–1014.

Jappelli, T. and L. Pistaferri (2010). The consumption response to income changes. *Annual Review of Economics 2*(1), 479–506.

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

Jones, C., V. Midrigan, and T. Philippon (2020). Household leverage and the recession. Manuscript.

Kaplan, G., K. Mitman, and G. L. Violante (2020a). The housing boom and bust: Model meets evidence. *Journal of Political Economy 128*(9), 3285–3345.

Kaplan, G., K. Mitman, and G. L. Violante (2020b). Non-durable consumption and housing net worth in the Great Recession: Evidence from easily accessible data. *Journal of Public Economics*, 1041–1076.

Kaplan, G. and G. L. Violante (2010). How much consumption insurance beyond self-insurance? *American Economic Journal: Macroeconomics 2*(4), 53–87.

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

Kaplan, G. and G. L. Violante (2022). The marginal propensity to consume in heterogeneous agent models. *Annual Review of Economics 14*, 747–775.

Kaplan, G., G. L. Violante, and J. Weidner (2014). The wealthy hand-to-mouth. *Brookings Papers on Economic Activity 2014*(1), 77–138.

Laibson, D., P. Maxted, and B. Moll (2022). A simple mapping from mpcs to mpxs. Working Paper 29664, National Bureau of Economic Research.

Mian, A., K. Rao, and A. Sufi (2013). Household balance sheets, consumption, and the economic slump. *Quarterly Journal of Economics 128*(4), 1687–1726.

Mian, A. and A. Sufi (2011). House prices, home equity-based borrowing, and the US household leverage crisis. *American Economic Review 101*(5), 2132–2156.

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

Parker, J. A., N. S. Souleles, D. S. Johnson, and R. McClelland (2013). Consumer spending and the economic stimulus payments of 2008. *American Economic Review 103*(6), 2530–2553.

Pistaferri, L. (2016). Why has consumption remained moderate after the Great Recession? Manuscript.

Poterba, J. and T. Sinai (2010). Tax expenditures for owner-occupied housing. *American Economic Review: Papers and Proceedings 82*(2), 237–242.

Zeldes, S. P. (1989). Consumption and liquidity constraints: An empirical investigation. *Journal of Political Economy 97*(2), 305–346.

Appendix

A State-space form

In this appendix, we present the state-space form for the unobserved components representation of the modified BPP model presented in Section 2.

Letting z^x_{it} denote the accumulation of a shock process x_{it}, the observation equation for our model in levels is

$$\mathbf{y_{it}} = \mathbf{HX_{it}},$$

where

$$\mathbf{y_{it}} = \begin{bmatrix} y_{it} \\ c_{it} \end{bmatrix}, \mathbf{H} = \begin{bmatrix} 1 & \theta & 0 & 1 & 0 & 0 \\ \tilde{\gamma}_\epsilon & 0 & 1 & \gamma_\eta & \bar{\gamma}_\epsilon & 1 \end{bmatrix}, \text{ and } \mathbf{X_t} = \begin{bmatrix} \epsilon_{it} \\ \epsilon_{it-1} \\ v_{it} \\ \tau_{it} \\ z^\epsilon_{it} \\ z^u_{it} \end{bmatrix}.$$

The state equation is

$$\mathbf{X_{it}} = \mathbf{FX_{it-1}} + \mathbf{v_{it}},$$

where

$$\mathbf{F} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \mathbf{v_{it}} = \begin{bmatrix} \epsilon_{it} \\ 0 \\ v_{it} \\ \eta_{it} \\ \epsilon_{it} \\ u_{it} \end{bmatrix},$$

and the covariance matrix of $\mathbf{v}_t$, $\mathbf{Q}$, is given by

$$\mathbf{Q} = \begin{pmatrix} \sigma^2_{\epsilon t} & 0 & 0 & 0 & \sigma^2_{\epsilon t} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma^2_{vt} & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma^2_{\eta t} & 0 & 0 \\ \sigma^2_{\epsilon t} & 0 & 0 & 0 & \sigma^2_{\epsilon t} & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma^2_{ut} \end{pmatrix}.$$

Given the state-space form, the Kalman filter can then be used to calculate the quasi likelihood based on the prediction error decomposition of a multivariate Normal density and an assumption of independence of idiosyncratic income and consumption across households (i.e. the joint log likelihood is additive in household-specific log likelihoods). We adapt the Kalman filter equations to handle missing observations, which are prevalent in the PSID.

We evaluate the quasi likelihood from the second time period of the data in levels using highly diffuse priors on initial values of unobserved stochastic trends centered at $\tau_{i0|0} = y_1$, $z^\epsilon_{i0|0} = 0$, and $z^u_{i0|0} = c_1 - \gamma_\eta y_1$ (or first available values given missing observations) with variances of 100 along with $\epsilon_{i0|0} = \epsilon_{i,-1|0} = v_{i0|0} = 0$ and variances of these shocks to initialize the Kalman filter. This approach is equivalent to estimation of the model in growth rates in the absence of missing observations and, therefore, implicitly allows for household-specific fixed effects $\bar{\tau}_{i0}$ and $\bar{\kappa}_{i0}$. Standard errors for parameter estimates are calculated using the estimated parameter variance-covariance matrix using the Huber-White sandwich formula. See Chatterjee et al. (2021) for more details on estimation of the BPP model via QMLE and the Kalman filter.

B Sample selection and group classification

This appendix reports details of the sample selection and group classification summarized in Section 3.

We closely follow the sample selection in Kaplan et al. (2014). We drop low-income households who are in the SEO (Survey of Economic Opportunity). We focus on households for which there was no change of headship and the age of the head of the household is between 25 and 64. We drop households reporting zero expenditure or who had missing information on key demographics in terms of education or race. We drop households with gross income growth higher than 500% or lower than negative 80% and households with annual gross income of less than $100 U.S. dollars. We drop households either appearing for less than three waves or not for two consecutive waves. Given these adjustments, our estimation sample consists of 5,047 households with 31,830 observations. Table B–1 reports the sample adjustments and the corresponding number of observations dropped from the original PSID sample.

Table B–1: Sample selection

Description	Dropped	Remaining
Initial unbalanced sample		83,831
Intermittent headship	13,266	70,565
Income outliers	10,314	60,251
Missing observations on race, education, or state of residence	1,479	58,772
Less than 3 waves of appearance	3,289	55,483
Age restriction and SEO households	23,466	32,017
At least two consecutive waves of appearance	187	31,830

Figure B–1 reports the number of households classified in a particular group during both subsample periods (blue bars) or only one subsample period (orange or brown bars). The sum of all 3 bars gives the total number of households appearing in a particular group at some point during the full-sample analysis. The first bar of the left panel shows that 78% of all households surveyed in the first subsample period also appear in the second subsample period. Homeowners are reasonably stable in their status, with 75% of homeowners appearing as such during both periods. By contrast, renters, PHtM, and WHtM households transition out of their group more often. For example, consistent with Kaplan et al. (2014) who show that the expected duration of HtM status is 3.5 to 4.5 years, less than half of the households who appear as WHtM in the first subsample

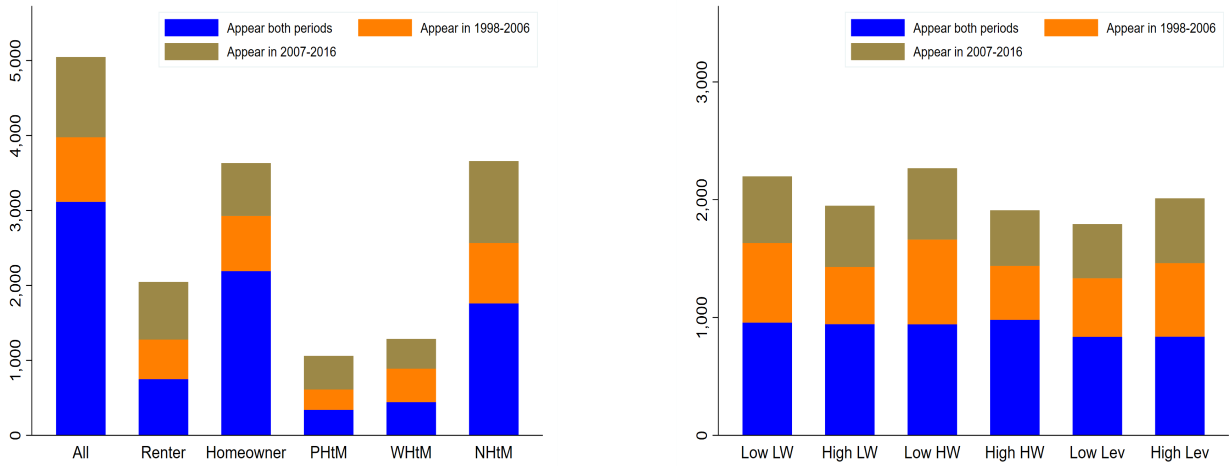


Figure B–1: Number of households in one or both subsample periods

Notes: The blue bars represent the number of households in a particular group in both periods, while the orange and brown bars show the number of households in a particular group only in one subsample period.

also appear as WHtM in the second subsample. Similarly, the results for subgroups of homeowners based on balance sheet variables presented in the right panel of Figure B–1 suggest a lot of transitions, with only just over 50% of homeowners appearing in each of the low liquid wealth, low housing wealth, and high leverage subgroups before the Great Recession also appearing in the same subgroup classification after the Great Recession.

For our analysis of time-varying MPCs, we classify households into groups based on whether they appeared in a group in the first subsample period and do not consider households who only appear in a group in the second subsample (i.e. the brown bars). For example, suppose a household was a renter before 2000 and became a homeowner from 2002 onward, this household is in the renter group in 1998 and 2000, but the homeowner group from 2002 onward. In this case, the household's residual income and consumption data for the period 1998-2000 will be used in the renter group estimation, while the household's data from 2002 onward will be used in estimating the parameters for the homeowner group. In terms of Figure B–1, this household is in the orange bar for the renter group and the blue bar for the homeowner group. This strategy is designed to reduce the effect of possible endogenous transitions from one subgroup to another between the two subsample periods considered in our analysis. For robustness, we also consider a more conservative group classification to deal with possible endogenous transitions by excluding households who were in a particular classification for only one of the two subsample periods. Specifically, we consider households in each group in the first subsample period who also remained in that same group in the second subsample period. Therefore, only the households in the blue bars in Figure B–1 are included in this robustness analysis. The results for this robustness analysis are reported in Tables D–19, D–20, and D–21.

It is worth providing some justification for our benchmark selection procedure when considering time-varying estimates. First, we note that households which appear in the first subsample but not the second subsample (i.e. the first orange bar in the left panel of Figure B–1) have not necessarily dropped out of the survey completely. Some have, but these households show no particular greater tendency to stop responding to the survey in a particular wave in the first subsample than for the PSID as a whole (the average attrition rate of the orange bar households is 13.38% versus 11.65% for the whole PSID in the 1999-2006 subsample). Instead, two other reasons for households not being included in the second subsample that are not due to dropping out of the survey are as follows: First, it is simply that some households classified in one group in the first subsample have transitioned to a different group in the second subsample. For example, a household that was a renter in the first subsample and a homeowner in the second subsample will not be included in a homeowner category in the second subsample under our selection procedure because their characteristics might be quite different than existing homeowners. Second, some households are still in the survey but have aged out of our initial selection rule of only considering household heads aged 64 years or younger to focus on responses to income risk. These households will be older than the households in the first subsample and so may have different MPCs simply due to retirement or greater age that lead to large changes in health versus income risks.

Indeed, the age issue justifies our benchmark sample selection procedure compared to the other possibilities of i) only considering households who appear in a group in both subsamples (i.e. the alternative selection used for our robustness analysis in Tables D–19, D–20, and D–21) or ii) consider all households in a group in each subsample even if they might have transitioned between groups across subsamples (i.e. the selection considered in footnote 16 in the main text). In particular, the median age for households for our benchmark sample selection in the first subsample is 43 years, while it is 42 years for the alternative sample selection that only includes households in the same group in both subsamples. This might seem like a small difference, but it reflects a higher age for those households in our benchmark selection who are not in the alternative selection (i.e. the orange bar for 'All' households in Figure B–1). The median age for these households is 49 years. A reason why it is justified to include these households in the first subsample is that the median age for households included in the second subsample under both the benchmark and alternative selection schemes (i.e. the blue bar for 'All' households in Figure B–1, which is the households who were in the same group in the first subsample) is 47 years in the second subsample. So including the households in the first subsample estimation who are no longer in a group in the second subsample provides a better matching of age profile with the households in the second subsample than excluding them. At the same time, we do not want to include households who only appear in a group in the second subsample because their characteristics are quite different than those in the first subsample. For example, the median age for these households is only 30 years, while their homeownership rate is only 43% versus 73% for the other households in the second subsample. Note that the homeownership rate for households in the first subsample under our benchmark selection or the alternative selection is 72% (while it is 71% for the households in the first subsample who are not in the second subsample).

In terms of another possible sample selection of fixing the initial group status and following the evolution of MPCs regardless of new status, we would fully expect this to lead to a change in MPCs simply because households that change status would have different MPCs if MPC heterogeneity is linked to a particular characteristic. For example, following renters when many of them become homeowners in the second subsample could well lead to a change in MPCs. But this would exactly be the case of a change being due to a change in household characteristics, not a change in consumption elasticities for households with common characteristics such as a particular homeownership status. Thus, we do not consider this sample selection.

C Effect of lower-bound approximation on MPC estimates

This appendix considers the lower-bound approximation effect on our MPC estimates due to a possible positive relationship between the short-run elasticity and the consumption-income ratio across households within a group.

Recall that our MPC estimates are based on the short-run consumption elasticity with respect to transitory income shocks multiplied by the mean consumption-income ratio, i.e. $\gamma_\epsilon \times E[C_{it}/Y_{it}]$. If we could estimate household-specific elasticities, $\gamma_{\epsilon,i}$, we would be able to directly calculate an average MPC using $E[\gamma_{\epsilon,i} \times C_{it}/Y_{it}]$. The difference between this exact average MPC and the lower-bound based on group-level estimates is $cov(\gamma_{\epsilon,i}, E[C_{it}/Y_{it}])$ given the general result that $cov(X,Y) = E[XY] - E[X]E[Y]$. Implicitly setting this covariance to zero in our MPC calculations introduces a lower-bound approximation effect on our estimates. Although we cannot directly estimate this covariance, we can quantify its likely effect by looking at group-level estimates based on deciles of household-specific average consumption-income ratios.

Noting that there are some outliers in household-specific ratios that could be due to data-reporting issues, we drop observations for which the ratio is below 0.05 or greater than 1 on the basis that these values likely reflect reporting errors (this involves dropping 2,953 observations from our total sample of 31,830 observations). Then, confirming a positive relationship that makes our MPCs correspond to lower-bound estimates, we find that there is a 66% correlation between decile-specific elasticities and average consumption-income ratios, which is highly significant according to a t statistic of 3.55. However, given small variances for the decile-specific elasticities and average ratios, the implied covariance is only 0.01, implying very little bias in our lower-bound estimates.

The decile-specific estimates might understate the true variation in household-specific elasticities, but it is notable that the variance of decile-specific elasticities is only 0.02, while the decile-specific variance of average consumption-income ratios is also only 0.02, which is the same as the sample variance of the average consumption-income ratio across households, suggesting that the decile-level granularity is sufficient to capture heterogeneity in average consumption-income ratios at least.

Even if we were to assume the household-specific variance of elasticities was as large as 0.03, which is the upper-bound of the 95% confidence interval for the decile-specific variance, and the correlation between household-specific elasticities and average consumption-income ratios were essentially perfect (i.e. equal to 1), then the implied downward bias in our estimates would still be only 0.02. Thus, for this reason at least, the effect of being a lower-bound estimate appears to be relatively small, despite an apparent significant positive relationship between short-run elasticities and consumption-income ratios.

D Full sets of estimates and robustness checks

This appendix reports the full sets of estimates for our semi-structural model and the results for a number of robustness checks discussed in Section 4 starting on the next page.

Table D–1: Full-sample estimates for all households and groups by homeownership status

		All	Renters	Homeowners
			INCOME	
σ_η	1998-2006	0.121 (0.004)	0.122 (0.098)	0.117 (0.005)
	2007-2016	0.125 (0.003)	0.136 (0.009)	0.109 (0.005)
σ_ϵ	1998-2006	0.261 (0.004)	0.307 (0.009)	0.239 (0.005)
	2007-2016	0.260 (0.004)	0.323 (0.008)	0.220 (0.005)
			CONSUMPTION	
σ_u	1998-2006	0.083 (0.008)	0.084 (0.043)	0.076 (0.007)
	2007-2016	0.102 (0.004)	0.107 (0.011)	0.095 (0.004)
σ_v	1998-2006	0.257 (0.006)	0.336 (0.020)	0.207 (0.005)
	2007-2016	0.298 (0.004)	0.358 (0.010)	0.244 (0.004)
$\bar{\gamma}_\epsilon$		0.027 (0.010)	0.011 (0.013)	0.031 (0.034)
$\tilde{\gamma}_\epsilon$		0.110 (0.014)	0.117 (0.022)	0.105 (0.016)
γ_η		0.384 (0.027)	0.491 (0.015)	0.316 (0.034)
$E[C_{it}/Y_{it}]$		0.575 (0.004)	0.700 (0.009)	0.521 (0.004)
MPC		0.080 (0.009)	0.093 (0.021)	0.071 (0.009)
$\text{Wald}_{H_0:\gamma_{\eta,g}=\gamma_\eta,\forall g}$			28.596 (0.000)	
$\text{Wald}_{H_0:\text{MPC}_g=\text{MPC},\forall g}$			1.346 (0.246)	
N		5,047	2,047	3,633

Notes: The table reports estimates of all model parameters, with standard errors in parentheses. These results are for the full-sample analysis also reported in Table 3, where the full sample period is 1998-2016. Heterogeneity tests based on Wald statistics with p-values in parentheses for $\chi^2(q-1)$ distributions are reported for the null hypothesis of homogeneity across stratified groups, where q is the number of groups within a given stratification. Wald statistics and standard errors for MPCs based on QMLE take mean consumption-income ratios as known given highly precise estimates.

Table D–2: Full-sample estimates for groups by HtM status

		PHtM	WHtM	NHtM	HtM_{nw}
			INCOME		
σ_η	1998-2006	0.121 (0.020)	0.106 (0.013)	0.109 (0.006)	0.120 (0.012)
	2007-2016	0.149 (0.016)	0.087 (0.014)	0.113 (0.005)	0.130 (0.009)
σ_ϵ	1998-2006	0.338 (0.015)	0.263 (0.011)	0.244 (0.005)	0.293 (0.010)
	2007-2016	0.331 (0.014)	0.263 (0.011)	0.236 (0.005)	0.300 (0.009)
			CONSUMPTION		
σ_u	1998-2006	0.161 (0.061)	0.074 (0.036)	0.076 (0.006)	0.062 (0.039)
	2007-2016	0.126 (0.019)	0.099 (0.015)	0.098 (0.005)	0.099 (0.011)
σ_v	1998-2006	0.352 (0.041)	0.267 (0.022)	0.218 (0.006)	0.332 (0.017)
	2007-2016	0.337 (0.015)	0.261 (0.013)	0.273 (0.006)	0.336 (0.009)
$\bar{\gamma}_\epsilon$		0.001 (0.002)	0.028 (0.013)	0.033 (0.011)	0.000 (0.000)
$\tilde{\gamma}_\epsilon$		0.117 (0.032)	0.132 (0.033)	0.010 (0.018)	0.129 (0.025)
γ_η		0.463 (0.017)	0.468 (0.092)	0.340 (0.043)	0.480 (0.012)
$E[C_{it}/Y_{it}]$		0.782 (0.020)	0.591 (0.019)	0.514 (0.003)	0.658 (0.010)
MPC		0.092 (0.027)	0.094 (0.019)	0.068 (0.009)	0.085 (0.017)
$\text{Wald}_{H_0:\gamma_{\eta,g}=\gamma_\eta,\forall g}$			17.285 (0.000)		
$\text{Wald}_{H_0:\text{MPC}_g=\text{MPC},\forall g}$			2.504 (0.286)		
N		1,060	1,285	3,659	1,886

Notes: The table reports estimates of all model parameters, with standard errors in parentheses. These results are for the full-sample analysis also reported in Table 3, where the full sample period is 1998-2016, as well as for a robustness check where, following Zeldes (1989), a household is classified as HtM_{nw} (hand-to-mouth based on net wealth) if their real net wealth is less than the head of household's two-month labor earnings. Heterogeneity tests based on Wald statistics with p-values in parentheses for $\chi^2(q-1)$ distributions are reported for the null hypothesis of homogeneity across stratified groups, where q is the number of groups within a given stratification. Wald statistics and standard errors for MPCs based on QMLE take mean consumption-income ratios as known given highly precise estimates.

Table D–3: Full-sample estimates for subgroups of homeowners

		Low LW	High LW	Low HW	High HW	High Lev.	Low Lev.
				INCOME			
σ_η	1998-2006	0.116 (0.009)	0.115 (0.008)	0.111 (0.009)	0.119 (0.008)	0.095 (0.010)	0.127 (0.010)
	2007-2016	0.096 (0.009)	0.106 (0.007)	0.107 (0.008)	0.110 (0.007)	0.091 (0.009)	0.117 (0.008)
σ_ϵ	1998-2006	0.239 (0.008)	0.239 (0.007)	0.224 (0.007)	0.246 (0.007)	0.219 (0.008)	0.254 (0.008)
	2007-2016	0.226 (0.008)	0.218 (0.007)	0.205 (0.007)	0.234 (0.007)	0.204 (0.009)	0.242 (0.008)
				CONSUMPTION			
σ_u	1998-2006	0.076 (0.014)	0.083 (0.007)	0.071 (0.008)	0.074 (0.009)	0.078 (0.007)	0.078 (0.007)
	2007-2016	0.098 (0.008)	0.093 (0.006)	0.085 (0.076)	0.093 (0.006)	0.077 (0.007)	0.097 (0.007)
σ_v	1998-2006	0.232 (0.011)	0.181 (0.006)	0.215 (0.006)	0.197 (0.012)	0.181 (0.005)	0.203 (0.006)
	2007-2016	0.252 (0.008)	0.229 (0.006)	0.263 (0.007)	0.227 (0.006)	0.224 (0.007)	0.251 (0.008)
$\bar{\gamma}_\epsilon$		0.016 (0.013)	0.025 (0.013)	0.017 (0.013)	0.018 (0.013)	0.000 (0.000)	0.012 (0.014)
$\tilde{\gamma}_\epsilon$		0.174 (0.033)	0.083 (0.024)	0.131 (0.025)	0.103 (0.020)	0.150 (0.027)	0.125 (0.026)
γ_η		0.303 (0.081)	0.268 (0.054)	0.389 (0.048)	0.273 (0.046)	0.342 (0.080)	0.223 (0.052)
$E[C_{it}/Y_{it}]$		0.559 (0.009)	0.477 (0.004)	0.491 (0.003)	0.549 (0.009)	0.511 (0.003)	0.514 (0.005)
MPC		0.108 (0.018)	0.051 (0.011)	0.073 (0.016)	0.067 (0.012)	0.084 (0.014)	0.070 (0.013)
$\text{Wald}_{H_0:\gamma_{\eta,g}=\gamma_\eta,\forall g}$		0.142 (0.707)		2.877 (0.090)		0.978 (0.323)	
$\text{Wald}_{H_0:\text{MPC}_g=\text{MPC},\forall g}$		7.320 (0.007)		0.122 (0.727)		0.394 (0.530)	
N		2,198	1,949	2,266	1,910	2,011	1,793

Notes: The table reports estimates of all model parameters, with standard errors in parentheses. These results are for the full-sample analysis also reported in Table 3, where the full sample period is 1998-2016. Heterogeneity tests based on Wald statistics with p-values in parentheses for $\chi^2(q-1)$ distributions are reported for the null hypothesis of homogeneity across stratified groups, where q is the number of groups within a given stratification. Wald statistics and standard errors for MPCs based on QMLE take mean consumption-income ratios as known given highly precise estimates.

Table D–4: Overlaps between household groups for full-sample analysis

	Renter	Homeowner	Low LW	High LW	Low HW	High HW	High Lev	Low Lev	PHtM	WHtM	NHtM
Renter	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.41	0.04	0.34
Homeowner	0.00	1.00	0.43	0.43	0.45	0.45	0.43	0.43	0.01	0.18	0.64
Low LW	0.00	1.00	1.00	0.00	0.67	0.24	0.53	0.15	0.02	0.42	0.29
High LW	0.00	1.00	0.00	1.00	0.24	0.69	0.23	0.64	0.00	0.00	1.00
Low HW	0.00	1.00	0.63	0.23	1.00	0.00	0.49	0.18	0.02	0.27	0.48
High HW	0.00	1.00	0.22	0.65	0.00	1.00	0.26	0.61	0.00	0.09	0.81
High Lev.	0.00	1.00	0.61	0.27	0.59	0.31	1.00	0.00	0.00	0.26	0.56
Low Lev.	0.00	1.00	0.17	0.72	0.21	0.73	0.00	1.00	0.00	0.07	0.85
PHtM	0.90	0.07	0.06	0.00	0.06	0.00	0.00	0.00	1.00	0.00	0.00
WHtM	0.06	0.93	0.92	0.00	0.62	0.21	0.49	0.14	0.00	1.00	0.00
NHtM	0.13	0.79	0.15	0.52	0.26	0.45	0.25	0.40	0.00	0.00	1.00

Notes: The table reports the fraction of $N \times t$ observations that overlap with other categories. These overlaps are based on the sample that was used in the analysis of consumption responses in Table 3. Each entry corresponds to the fraction of the row group that also belongs to the column group.

Table D–5: Full-sample estimates for low wealth and high leverage homeowners excluding HtM

		Low LW	Low HW	High Lev
			INCOME	
σ_η	1998-2006	0.120 (0.014)	0.095 (0.011)	0.093 (0.011)
	2007-2016	0.077 (0.013)	0.110 (0.009)	0.090 (0.011)
σ_ϵ	1998-2006	0.224 (0.012)	0.228 (0.009)	0.208 (0.009)
	2007-2016	0.213 (0.011)	0.185 (0.009)	0.194 (0.011)
			CONSUMPTION	
σ_u	1998-2006	0.081 (0.011)	0.071 (0.010)	0.081 (0.008)
	2007-2016	0.101 (0.012)	0.080 (0.011)	0.069 (0.008)
σ_v	1998-2006	0.207 (0.009)	0.206 (0.007)	0.169 (0.007)
	2007-2016	0.248 (0.012)	0.265 (0.009)	0.227 (0.008)
$\bar{\gamma}_\epsilon$		0.003 (0.031)	0.011 (0.022)	0.022 (0.012)
$\tilde{\gamma}_\epsilon$		0.250 (0.045)	0.130 (0.033)	0.121 (0.031)
γ_η		0.127 (0.092)	0.413 (0.056)	0.376 (0.068)
$E[C_{it}/Y_{it}]$		0.526 (0.005)	0.460 (0.004)	0.489 (0.003)
MPC		0.131 (0.024)	0.060 (0.015)	0.069 (0.015)
N		1,726	1,998	1,316

Notes: The table reports estimates of all model parameters, with standard errors in parentheses. These results are for a full-sample analysis of homeowners excluding hand-to-mouth households as a robustness check, where the full sample period is 1998-2016.

Table D–6: Time-varying estimates for all households and groups by homeownership status

		All	Renters	Homeowners
			INCOME	
σ_η	1998-2006	0.123 (0.004)	0.124 (0.010)	0.118 (0.005)
	2007-2016	0.120 (0.003)	0.133 (0.009)	0.104 (0.005)
σ_ϵ	1998-2006	0.261 (0.004)	0.308 (0.009)	0.238 (0.005)
	2007-2016	0.243 (0.004)	0.284 (0.010)	0.221 (0.005)
			CONSUMPTION	
σ_u	1998-2006	0.083 (0.009)	0.084 (0.041)	0.077 (0.007)
	2007-2016	0.102 (0.004)	0.104 (0.011)	0.094 (0.004)
σ_v	1998-2006	0.258 (0.006)	0.337 (0.020)	0.207 (0.005)
	2007-2016	0.283 (0.005)	0.331 (0.012)	0.236 (0.004)
$\bar{\gamma}_\epsilon$	1998-2006	0.031 (0.011)	0.019 (0.016)	0.033 (0.015)
	2007-2016	0.031 (0.011)	0.019 (0.016)	0.033 (0.015)
$\tilde{\gamma}_\epsilon$	1998-2006	0.091 (0.015)	0.097 (0.031)	0.081 (0.018)
	2007-2016	0.142 (0.021)	0.125 (0.042)	0.138 (0.024)
γ_η	1998-2006	0.359 (0.032)	0.490 (0.002)	0.307 (0.033)
	2007-2016	0.387 (0.032)	0.508 (0.004)	0.322 (0.033)
$E[C_{it}/Y_{it}]$	1998-2006	0.557 (0.007)	0.673 (0.018)	0.519 (0.008)
	2007-2016	0.591 (0.004)	0.677 (0.010)	0.514 (0.004)
MPC	1998-2006	0.068 (0.010)	0.079 (0.022)	0.059 (0.010)
	2007-2016	0.103 (0.011)	0.097 (0.027)	0.088 (0.012)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$		4.527 (0.033)	0.310 (0.578)	5.089 (0.024)
$\text{Wald}_{H_0:\text{MPC}_{\text{pre}}=\text{MPC}_{\text{post}}}$		6.093 (0.014)	0.319 (0.572)	4.814 (0.028)
N		3,977	1,278	2,930

Notes: The table reports estimates of all model parameters, with standard errors in parentheses. These results are for the time-varying analysis also reported in Table 4.

Table D–7: Time-varying estimates for groups by HtM status

		PHtM	WHtM	NHtM
			INCOME	
σ_η	1998-2006	0.123 (0.019)	0.110 (0.013)	0.112 (0.006)
	2007-2016	0.144 (0.017)	0.074 (0.015)	0.107 (0.005)
σ_ϵ	1998-2006	0.339 (0.015)	0.261 (0.011)	0.244 (0.005)
	2007-2016	0.313 (0.018)	0.272 (0.015)	0.225 (0.005)
			CONSUMPTION	
σ_u	1998-2006	0.157 (0.060)	0.072 (0.039)	0.076 (0.006)
	2007-2016	0.121 (0.020)	0.103 (0.016)	0.098 (0.005)
σ_v	1998-2006	0.352 (0.040)	0.267 (0.022)	0.219 (0.006)
	2007-2016	0.310 (0.018)	0.244 (0.016)	0.244 (0.006)
$\bar{\gamma}_\epsilon$	1998-2006	0.009 (0.025)	0.041 (0.020)	0.038 (0.014)
	2007-2016	0.010 (0.026)	0.041 (0.020)	0.038 (0.014)
$\tilde{\gamma}_\epsilon$	1998-2006	0.073 (0.057)	0.090 (0.039)	0.086 (0.021)
	2007-2016	0.081 (0.075)	0.130 (0.052)	0.117 (0.029)
γ_η	1998-2006	0.662 (0.106)	0.474 (0.034)	0.304 (0.038)
	2007-2016	0.587 (0.101)	0.497 (0.002)	0.334 (0.036)
$E[C_{it}/Y_{it}]$	1998-2006	0.780 (0.042)	0.607 (0.036)	0.495 (0.004)
	2007-2016	0.761 (0.020)	0.57 (0.01)	0.497 (0.004)
MPC	1998-2006	0.065 (0.044)	0.080 (0.031)	0.061 (0.011)
	2007-2016	0.068 (0.054)	0.098 (0.029)	0.077 (0.014)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$		0.007 (0.932)	0.398 (0.528)	0.922 (0.337)
$\text{Wald}_{H_0:\text{MPC}_{\text{pre}}=\text{MPC}_{\text{post}}}$		0.006 (0.941)	0.244 (0.621)	0.946 (0.331)
N		612	890	2,566

Notes: The table reports estimates of all model parameters, with standard errors in parentheses. These results are for the time-varying analysis also reported in Table 4.

Table D–8: Time-varying estimates for subgroups of homeowners

		Low LW	High LW	Low HW	High HW	High Lev.	Low Lev.
					INCOME		
σ_η	1998-2006	0.118 (0.008)	0.116 (0.008)	0.111 (0.009)	0.122 (0.008)	0.099 (0.009)	0.128 (0.009)
	2007-2016	0.092 (0.009)	0.102 (0.007)	0.103 (0.008)	0.108 (0.007)	0.081 (0.008)	0.110 (0.008)
σ_ϵ	1998-2006	0.238 (0.007)	0.238 (0.007)	0.225 (0.007)	0.245 (0.007)	0.218 (0.007)	0.253 (0.007)
	2007-2016	0.228 (0.008)	0.220 (0.008)	0.206 (0.007)	0.237 (0.008)	0.201 (0.010)	0.253 (0.009)
					CONSUMPTION		
σ_u	1998-2006	0.075 (0.014)	0.083 (0.007)	0.071 (0.008)	0.074 (0.009)	0.077 (0.007)	0.078 (0.007)
	2007-2016	0.093 (0.008)	0.095 (0.006)	0.084 (0.009)	0.091 (0.006)	0.077 (0.0007)	0.100 (0.007)
σ_v	1998-2006	0.233 (0.011)	0.181 (0.006)	0.214 (0.006)	0.197 (0.012)	0.182 (0.005)	0.203 (0.006)
	2007-2016	0.250 (0.008)	0.209 (0.007)	0.256 (0.008)	0.223 (0.007)	0.205 (0.007)	0.233 (0.008)
$\bar{\gamma}_\epsilon$	1998-2006	0.022 (0.016)	0.020 (0.017)	0.025 (0.018)	0.000 (0.010)	0.044 (0.017)	0.013 (0.019)
	2007-2016	0.022 (0.016)	0.020 (0.017)	0.025 (0.018)	0.000 (0.003)	0.044 (0.017)	0.013 (0.019)
$\tilde{\gamma}_\epsilon$	1998-2006	0.126 (0.032)	0.081 (0.029)	0.119 (0.034)	0.080 (0.025)	0.119 (0.017)	0.096 (0.030)
	2007-2016	0.257 (0.037)	0.124 (0.039)	0.131 (0.048)	0.119 (0.033)	0.174 (0.042)	0.122 (0.037)
γ_η	1998-2006	0.294 (0.056)	0.246 (0.052)	0.409 (0.052)	0.260 (0.043)	0.284 (0.073)	0.226 (0.052)
	2007-2016	0.327 (0.057)	0.252 (0.053)	0.397 (0.049)	0.275 (0.044)	0.306 (0.074)	0.234 (0.053)
$E[C_{it}/Y_{it}]$	1998-2006	0.564 (0.017)	0.474 (0.005)	0.485 (0.004)	0.556 (0.017)	0.517 (0.004)	0.501 (0.006)
	2007-2016	0.548 (0.007)	0.475 (0.006)	0.490 (0.006)	0.537 (0.007)	0.495 (0.006)	0.524 (0.008)
MPC	1998-2006	0.084 (0.019)	0.048 (0.013)	0.070 (0.017)	0.051 (0.014)	0.084 (0.016)	0.054 (0.014)
	2007-2016	0.153 (0.021)	0.067 (0.017)	0.077 (0.023)	0.070 (0.017)	0.108 (0.021)	0.070 (0.017)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$		9.330 (0.002)	1.132 (0.287)	0.059 (0.809)	1.279 (0.258)	1.508 (0.219)	0.476 (0.490)
$\text{Wald}_{H_0:\text{MPC}_{\text{pre}}=\text{MPC}_{\text{post}}}$		8.536 (0.003)	1.148 (0.284)	0.076 (0.783)	1.046 (0.306)	1.117 (0.291)	0.690 (0.406)
N		1,631	1,429	1,663	1,440	1,462	1,334

Notes: The table reports estimates of all model parameters, with standard errors in parentheses. These results are for the time-varying analysis also reported in Table 4.

Table D–9: Structural break tests for a break within the main subsample periods

	(98–01)(02–06)
	INCOME
$\sigma_{\eta_{98-01}}$	0.135 (0.011)
$\sigma_{\eta_{02-06}}$	0.135 (0.007)
$\sigma_{\epsilon_{98-01}}$	0.247 (0.008)
$\sigma_{\epsilon_{02-06}}$	0.251 (0.006)
	CONSUMPTION
$\sigma_{u_{98-01}}$	0.110 (0.018)
$\sigma_{u_{02-06}}$	0.095 (0.016)
$\sigma_{v_{98-01}}$	0.238 (0.010)
$\sigma_{v_{02-06}}$	0.253 (0.008)
$\bar{\gamma}_{\epsilon_{98-01}}$	0.003 (0.040)
$\bar{\gamma}_{\epsilon_{02-06}}$	0.006 (0.045)
$\tilde{\gamma}_{\epsilon_{98-01}}$	0.097 (0.039)
$\tilde{\gamma}_{\epsilon_{02-06}}$	0.094 (0.028)
$\gamma_{\eta_{98-01}}$	0.289 (0.063)
$\gamma_{\eta_{02-06}}$	0.367 (0.064)
$E[C_{i,98-01}/Y_{i,98-01}]$	0.571 (0.004)
$E[C_{i,02-06}/Y_{i,02-06}]$	0.583 (0.011)
MPC_{98-01}	0.060 (0.022)
MPC_{02-06}	0.057 (0.016)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,98-01}=\tilde{\gamma}_{\epsilon,02-06}}$	0.005 (0.944)
$\text{Wald}_{H_0:\text{MPC}_{98-01}=\text{MPC}_{02-06}}$	0.012 (0.911)
N	3977

Time varying estimates for 1998-2001 and 2002-2006

	(07–11)(12–16)
	INCOME
$\sigma_{\eta_{07-11}}$	0.129 (0.010)
$\sigma_{\eta_{12-16}}$	0.115 (0.007)
$\sigma_{\epsilon_{07-11}}$	0.253 (0.008)
$\sigma_{\epsilon_{12-16}}$	0.229 (0.005)
	CONSUMPTION
$\sigma_{u_{07-11}}$	0.093 (0.017)
$\sigma_{u_{12-16}}$	0.136 (0.009)
$\sigma_{v_{07-11}}$	0.242 (0.011)
$\sigma_{v_{12-16}}$	0.301 (0.008)
$\bar{\gamma}_{\epsilon_{07-11}}$	0.009 (0.005)
$\bar{\gamma}_{\epsilon_{12-16}}$	0.009 (0.005)
$\tilde{\gamma}_{\epsilon_{07-11}}$	0.124 (0.024)
$\tilde{\gamma}_{\epsilon_{12-16}}$	0.142 (0.040)
$\gamma_{\eta_{07-11}}$	0.448 (0.048)
$\gamma_{\eta_{12-16}}$	0.454 (0.036)
$E[C_{i,07-11}/Y_{i,07-11}]$	0.529 (0.004)
$E[C_{i,12-16}/Y_{i,12-16}]$	0.586 (0.006)
MPC_{07-11}	0.071 (0.013)
MPC_{12-16}	0.089 (0.024)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,07-11}=\tilde{\gamma}_{\epsilon,12-16}}$	0.181 (0.671)
$\text{Wald}_{H_0:\text{MPC}_{07-11}=\text{MPC}_{12-16}}$	0.557 (0.455)
N	3977

Time varying estimates for 2007-2011 and 2012-2016

Table D–10: Time-varying estimates (1998-2006) and (2007-2012) for all households and groups by homeownership status

		All	Renters	Homeowners
			INCOME	
σ_η	1998-2006	0.124 (0.004)	0.125 (0.010)	0.120 (0.005)
	2007-2012	0.128 (0.005)	0.151 (0.012)	0.111 (0.006)
σ_ϵ	1998-2006	0.259 (0.004)	0.306 (0.009)	0.236 (0.005)
	2007-2012	0.248 (0.005)	0.284 (0.013)	0.224 (0.006)
			CONSUMPTION	
σ_u	1998-2006	0.084 (0.008)	0.087 (0.041)	0.078 (0.007)
	2007-2012	0.100 (0.007)	0.105 (0.020)	0.092 (0.005)
σ_v	1998-2006	0.258 (0.006)	0.337 (0.019)	0.208 (0.005)
	2007-2012	0.254 (0.006)	0.312 (0.017)	0.205 (0.005)
$\bar{\gamma}_\epsilon$	1998-2006	0.040 (0.014)	0.030 (0.024)	0.040 (0.014)
	2007-2012	0.040 (0.014)	0.030 (0.024)	0.040 (0.014)
$\tilde{\gamma}_\epsilon$	1998-2006	0.090 (0.018)	0.091 (0.033)	0.083 (0.019)
	2007-2012	0.148 (0.024)	0.119 (0.050)	0.140 (0.028)
γ_η	1998-2006	0.340 (0.033)	0.480 (0.034)	0.282 (0.035)
	2007-2012	0.363 (0.033)	0.490 (0.015)	0.294 (0.035)
$E[C_{it}/Y_{it}]$	1998-2006	0.567 (0.007)	0.673 (0.018)	0.519 (0.008)
	2007-2012	0.531 (0.004)	0.651 (0.010)	0.490 (0.004)
MPC	1998-2006	0.072 (0.011)	0.081 (0.024)	0.064 (0.010)
	2007-2012	0.100 (0.014)	0.097 (0.032)	0.088 (0.014)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$		5.027 (0.025)	0.208 (0.648)	3.887 (0.049)
$\text{Wald}_{H_0:\text{MPC}_{\text{pre}}=\text{MPC}_{\text{post}}}$		3.864 (0.049)	0.150 (0.699)	2.821 (0.093)
N		3,977	1,278	2,930

Notes: The table reports point estimates, with standard errors in parentheses. A Wald statistic for a test of parameter stability under the null hypothesis $H_0 : \tilde{\gamma}_\epsilon$ 1998-2006 $= \tilde{\gamma}_\epsilon$ 2007-2012 is also reported, with the p-value in parentheses. These results are for a time-varying analysis using the same group classification as in Table 4, but the second subsample period ends in 2012 instead of 2016 as a robustness check.

Table D–11: Time-varying estimates (1998-2006) and (2007-2012) for groups by HtM status

		PHtM	WHtM	NHtM
			INCOME	
σ_η	1998-2006	0.125 (0.021)	0.112 (0.014)	0.113 (0.006)
	2007-2012	0.151 (0.023)	0.103 (0.018)	0.104 (0.007)
σ_ϵ	1998-2006	0.337 (0.015)	0.258 (0.011)	0.243 (0.005)
	2007-2012	0.317 (0.023)	0.265 (0.019)	0.234 (0.007)
			CONSUMPTION	
σ_u	1998-2006	0.158 (0.067)	0.070 (0.039)	0.077 (0.006)
	2007-2012	0.110 (0.041)	0.089 (0.022)	0.097 (0.007)
σ_v	1998-2006	0.354 (0.046)	0.270 (0.023)	0.220 (0.005)
	2007-2012	0.295 (0.024)	0.230 (0.016)	0.213 (0.008)
$\bar{\gamma}_\epsilon$	1998-2006	0.004 (0.084)	0.042 (0.048)	0.037 (0.016)
	2007-2012	0.014 (0.087)	0.042 (0.048)	0.037 (0.016)
$\tilde{\gamma}_\epsilon$	1998-2006	0.088 (0.053)	0.086 (0.045)	0.103 (0.024)
	2007-2012	0.170 (0.072)	0.088 (0.067)	0.127 (0.034)
γ_η	1998-2006	0.556 (0.056)	0.473 (0.019)	0.243 (0.042)
	2007-2012	0.478 (0.031)	0.492 (0.011)	0.269 (0.042)
$E[C_{it}/Y_{it}]$	1998-2006	0.780 (0.042)	0.607 (0.036)	0.495 (0.004)
	2007-2016	0.726 (0.018)	0.552 (0.013)	0.476 (0.005)
MPC	1998-2006	0.072 (0.039)	0.077 (0.025)	0.069 (0.011)
	2007-2016	0.135 (0.051)	0.072 (0.037)	0.078 (0.015)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$		0.895 (0.344)	0.001 (0.978)	0.506 (0.477)
$\text{Wald}_{H_0:\text{MPC}_{\text{pre}}=\text{MPC}_{\text{post}}}$		0.928 (0.335)	0.017 (0.897)	0.294 (0.588)
N		612	890	2,566

Notes: The table reports point estimates, with standard errors in parentheses. A Wald statistic for a test of parameter stability under the null hypothesis $H_0 : \tilde{\gamma}_\epsilon \text{ 1998-2006} = \tilde{\gamma}_\epsilon \text{ 2007-2012}$ is also reported, with the p-value in parentheses. These results are for a time-varying analysis using the same group classification as in Table 4, but the second subsample period ends in 2012 instead of 2016 as a robustness check.

Table D–12: Time-varying estimates (1998-2006) and (2007-2012) for subgroups of homeowners

		Low LW	High LW	Low HW	High HW	High Lev.	Low Lev.
					INCOME		
σ_η	1998-2006	0.121 (0.009)	0.117 (0.008)	0.113 (0.010)	0.123 (0.008)	0.101 (0.009)	0.130 (0.009)
	2007-2012	0.113 (0.010)	0.098 (0.010)	0.119 (0.011)	0.107 (0.010)	0.092 (0.011)	0.103 (0.012)
σ_ϵ	1998-2006	0.234 (0.008)	0.237 (0.006)	0.222 (0.008)	0.244 (0.007)	0.216 (0.007)	0.252 (0.008)
	2007-2012	0.217 (0.010)	0.230 (0.010)	0.200 (0.010)	0.245 (0.010)	0.201 (0.013)	0.263 (0.011)
					CONSUMPTION		
σ_u	1998-2006	0.075 (0.014)	0.084 (0.007)	0.073 (0.008)	0.075 (0.009)	0.078 (0.007)	0.078 (0.007)
	2007-2012	0.088 (0.011)	0.102 (0.006)	0.073 (0.010)	0.097 (0.007)	0.064 (0.009)	0.102 (0.007)
σ_v	1998-2006	0.233 (0.011)	0.182 (0.006)	0.214 (0.006)	0.197 (0.012)	0.182 (0.005)	0.204 (0.006)
	2007-2012	0.226 (0.009)	0.173 (0.008)	0.228 (0.008)	0.189 (0.008)	0.190 (0.008)	0.197 (0.009)
$\bar{\gamma}_\epsilon$	1998-2006	0.031 (0.015)	0.021 (0.019)	0.037 (0.019)	0.018 (0.025)	0.040 (0.018)	0.025 (0.020)
	2007-2012	0.031 (0.015)	0.022 (0.019)	0.037 (0.019)	0.018 (0.025)	0.040 (0.018)	0.025 (0.020)
$\tilde{\gamma}_\epsilon$	1998-2006	0.118 (0.033)	0.095 (0.031)	0.118 (0.033)	0.083 (0.025)	0.106 (0.026)	0.112 (0.030)
	2007-2012	0.221 (0.049)	0.133 (0.042)	0.093 (0.066)	0.114 (0.039)	0.127 (0.050)	0.115 (0.037)
γ_η	1998-2006	0.299 (0.076)	0.185 (0.061)	0.380 (0.064)	0.232 (0.046)	0.328 (0.068)	0.154 (0.052)
	2007-2012	0.333 (0.074)	0.186 (0.061)	0.367 (0.061)	0.245 (0.048)	0.358 (0.068)	0.159 (0.053)
$E[C_{it}/Y_{it}]$	1998-2006	0.564 (0.017)	0.474 (0.005)	0.485 (0.004)	0.556 (0.017)	0.517 (0.004)	0.501 (0.006)
	2007-2016	0.520 (0.007)	0.460 (0.006)	0.470 (0.006)	0.513 (0.007)	0.481 (0.006)	0.500 (0.008)
MPC	1998-2006	0.084 (0.021)	0.055 (0.014)	0.075 (0.016)	0.057 (0.014)	0.076 (0.016)	0.071 (0.016)
	2007-2016	0.131 (0.025)	0.071 (0.018)	0.061 (0.030)	0.068 (0.018)	0.080 (0.025)	0.070 (0.018)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$		3.892 (0.049)	0.854 (0.355)	0.144 (0.705)	0.646 (0.421)	0.152 (0.700)	0.006 (0.937)
$\text{Wald}_{H_0:\text{MPC}_\text{pre}=\text{MPC}_\text{post}}$		2.838 (0.092)	0.693 (0.405)	0.201 (0.653)	0.318 (0.573)	0.031 (0.860)	0.001 (0.974)
N		1,631	1,429	1,663	1,440	1,462	1,334

Notes: The table reports point estimates, with standard errors in parentheses. A Wald statistic for a test of parameter stability under the null hypothesis $H_0 : \tilde{\gamma}_\epsilon$ 1998-2006 $= \tilde{\gamma}_\epsilon$ 2007-2012 is also reported, with the p-value in parentheses. These results are for a time-varying analysis using the same group classification as in Table 4, but the second subsample period ends in 2012 instead of 2016 as a robustness check.

Table D–13: Time-varying estimates for all households allowing for a structural break every two waves

		All
		INCOME
σ_η	1998-2000	0.128 (0.013)
	2001-2004	0.131 (0.005)
	2005-2008	0.117 (0.005)
	2009-2012	0.123 (0.005)
	2013-2016	0.111 (0.008)
σ_ϵ	1998-2000	0.248 (0.008)
	2001-2004	0.262 (0.006)
	2005-2008	0.259 (0.005)
	2009-2012	0.253 (0.006)
	2013-2016	0.223 (0.008)
		CONSUMPTION
σ_u	1998-2000	0.099 (0.019)
	2001-2004	0.089 (0.010)
	2005-2008	0.061 (0.017)
	2009-2012	0.101 (0.008)
	2013-2016	0.129 (0.010)
σ_v	1998-2000	0.243 (0.009)
	2001-2004	0.253 (0.009)
	2005-2008	0.259 (0.009)
	2009-2012	0.264 (0.007)
	2013-2016	0.321 (0.010)
$\bar{\gamma}_\epsilon$	1998-2000	0.030 (0.013)
	2001-2004	0.039 (0.013)
	2005-2008	0.028 (0.013)
	2009-2012	0.027 (0.013)
	2013-2016	0.028 (0.013)
$\tilde{\gamma}_\epsilon$	1998-2000	0.093 (0.027)
	2001-2004	0.088 (0.022)
	2005-2008	0.132 (0.023)
	2009-2012	0.129 (0.028)
	2013-2016	0.147 (0.045)
γ_η	1998-2000	0.284 (0.019)
	2001-2004	0.360 (0.019)
	2005-2008	0.388 (0.019)
	2009-2012	0.389 (0.021)
	2013-2016	0.387 (0.026)
N		3,977

Notes: The table reports point estimates, with standard errors in parentheses, where we allow for a structural break every two waves.

Table D–14: Time-varying estimates excluding (imputed) rent for all households and groups by homeownership status

		All	Renters	Homeowners
			INCOME	
σ_η	1998-2006	0.123 (0.004)	0.123 (0.010)	0.119 (0.005)
	2007-2016	0.120 (0.004)	0.133 (0.009)	0.104 (0.004)
σ_ϵ	1998-2006	0.261 (0.004)	0.309 (0.009)	0.238 (0.005)
	2007-2016	0.243 (0.004)	0.284 (0.010)	0.221 (0.005)
			CONSUMPTION	
σ_u	1998-2006	0.093 (0.010)	0.096 (0.046)	0.089 (0.009)
	2007-2016	0.124 (0.004)	0.136 (0.012)	0.116 (0.005)
σ_v	1998-2006	0.329 (0.008)	0.424 (0.020)	0.290 (0.010)
	2007-2016	0.356 (0.005)	0.406 (0.012)	0.319 (0.005)
$\bar{\gamma}_\epsilon$	1998-2006	0.024 (0.013)	0.021 (0.020)	0.004 (0.068)
	2007-2016	0.024 (0.013)	0.021 (0.020)	0.004 (0.068)
$\tilde{\gamma}_\epsilon$	1998-2006	0.128 (0.018)	0.156 (0.033)	0.112 (0.026)
	2007-2016	0.171 (0.025)	0.132 (0.049)	0.180 (0.033)
γ_η	1998-2006	0.300 (0.026)	0.451 (0.049)	0.239 (0.042)
	2007-2016	0.342 (0.026)	0.513 (0.007)	0.271 (0.043)
$E[C_{it}/Y_{it}]$	1998-2006	0.327 (0.007)	0.453 (0.017)	0.344 (0.007)
	2007-2016	0.387 (0.003)	0.458 (0.008)	0.352 (0.003)
MPC	1998-2006	0.056 (0.007)	0.080 (0.017)	0.040 (0.009)
	2007-2016	0.075 (0.010)	0.070 (0.022)	0.064 (0.011)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$		2.576 (0.108)	0.166 (0.683)	3.913 (0.048)
$\text{Wald}_{H_0:\text{MPC}_\text{pre}=\text{MPC}_\text{post}}$		3.380 (0.066)	0.142 (0.706)	4.352 (0.037)
N		3,977	1,278	2,930

Notes: The table reports point estimates, with standard errors in parentheses. A Wald statistic for a test of parameter stability under the null hypothesis $H_0 : \tilde{\gamma}_\epsilon$ 1998-2006 $= \tilde{\gamma}_\epsilon$ 2007-2016 is also reported, with the p-value in parentheses. These results are for a time-varying analysis using the same group classification as in Table 4, however consumption for each household does not include rent or imputed rent as a robustness check.

Table D–15: Time-varying estimates excluding (imputed) rent for groups by HtM status

		PHtM	WHtM	NHtM
			INCOME	
σ_η	1998-2006	0.121 (0.021)	0.110 (0.014)	0.112 (0.006)
	2007-2016	0.145 (0.018)	0.076 (0.016)	0.107 (0.004)
σ_ϵ	1998-2006	0.340 (0.015)	0.261 (0.011)	0.244 (0.005)
	2007-2016	0.312 (0.018)	0.271 (0.015)	0.225 (0.005)
			CONSUMPTION	
σ_u	1998-2006	0.222 (0.069)	0.083 (0.045)	0.086 (0.007)
	2007-2016	0.144 (0.024)	0.114 (0.020)	0.122 (0.006)
σ_v	1998-2006	0.403 (0.036)	0.367 (0.042)	0.282 (0.005)
	2007-2016	0.415 (0.023)	0.322 (0.018)	0.320 (0.007)
$\bar{\gamma}_\epsilon$	1998-2006	0.008 (0.034)	0.032 (0.016)	0.018 (0.015)
	2007-2016	0.008 (0.034)	0.032 (0.016)	0.018 (0.015)
$\tilde{\gamma}_\epsilon$	1998-2006	0.140 (0.060)	0.122 (0.048)	0.117 (0.025)
	2007-2016	0.016 (0.081)	0.149 (0.072)	0.157 (0.036)
γ_η	1998-2006	0.639 (0.157)	0.411 (0.125)	0.239 (0.043)
	2007-2016	0.652 (0.149)	0.414 (0.108)	0.273 (0.042)
$E[C_{it}/Y_{it}]$	1998-2006	0.537 (0.041)	0.440 (0.036)	0.314 (0.003)
	2007-2016	0.519 (0.016)	0.423 (0.012)	0.326 (0.004)
MPC	1998-2006	0.082 (0.032)	0.067 (0.022)	0.043 (0.008)
	2007-2016	0.015 (0.041)	0.076 (0.030)	0.057 (0.011)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$		1.541 (0.215)	0.117 (0.732)	1.180 (0.277)
$\text{Wald}_{H_0:\text{MPC}_\text{pre}=\text{MPC}_\text{post}}$		1.634 (0.201)	0.069 (0.793)	1.535 (0.215)
N		612	890	2,566

Notes: The table reports point estimates, with standard errors in parentheses. A Wald statistic for a test of parameter stability under the null hypothesis $H_0 : \tilde{\gamma}_\epsilon\ _{\text{1998-2006}} = \tilde{\gamma}_\epsilon\ _{\text{2007-2016}}$ is also reported, with the p-value in parentheses. These results are for a time-varying analysis using the same group classification as in Table 4, however consumption for each household does not include rent or imputed rent as a robustness check.

Table D–16: Time-varying estimates excluding imputed rent for subgroups of homeowners

		Low LW	High LW	Low HW	High HW	High Lev.	Low Lev.
				INCOME			
σ_η	1998-2006	0.118 (0.008)	0.116 (0.008)	0.112 (0.009)	0.122 (0.008)	0.099 (0.009)	0.129 (0.009)
	2007-2012	0.092 (0.009)	0.102 (0.007)	0.102 (0.008)	0.108 (0.007)	0.081 (0.009)	0.110 (0.008)
σ_ϵ	1998-2006	0.237 (0.007)	0.238 (0.007)	0.224 (0.007)	0.245 (0.007)	0.218 (0.007)	0.253 (0.008)
	2007-2012	0.228 (0.008)	0.221 (0.008)	0.207 (0.008)	0.237 (0.008)	0.201 (0.098)	0.253 (0.009)
				CONSUMPTION			
σ_u	1998-2006	0.081 (0.017)	0.095 (0.009)	0.083 (0.010)	0.092 (0.016)	0.090 (0.010)	0.097 (0.018)
	2007-2012	0.112 (0.010)	0.122 (0.007)	0.101 (0.009)	0.122 (0.008)	0.089 (0.010)	0.132 (0.009)
σ_v	1998-2006	0.316 (0.021)	0.265 (0.007)	0.275 (0.007)	0.303 (0.021)	0.259 (0.007)	0.295 (0.025)
	2007-2012	0.319 (0.010)	0.303 (0.009)	0.321 (0.009)	0.326 (0.010)	0.287 (0.009)	0.318 (0.011)
$\bar{\gamma}_\epsilon$	1998-2006	0.007 (0.014)	0.001 (0.010)	0.017 (0.043)	0.000 (0.000)	0.030 (0.019)	0.002 (0.046)
	2007-2012	0.008 (0.014)	0.001 (0.010)	0.017 (0.043)	0.000 (0.000)	0.030 (0.019)	0.003 (0.048)
$\tilde{\gamma}_\epsilon$	1998-2006	0.156 (0.034)	0.100 (0.035)	0.139 (0.038)	0.104 (0.033)	0.154 (0.035)	0.110 (0.043)
	2007-2012	0.300 (0.049)	0.171 (0.047)	0.171 (0.058)	0.142 (0.041)	0.207 (0.055)	0.165 (0.047)
γ_η	1998-2006	0.269 (0.088)	0.132 (0.065)	0.348 (0.069)	0.184 (0.057)	0.179 (0.081)	0.166 (0.051)
	2007-2012	0.305 (0.087)	0.160 (0.065)	0.342 (0.066)	0.216 (0.059)	0.239 (0.082)	0.183 (0.051)
$E[C_{it}/Y_{it}]$	1998-2006	0.403 (0.017)	0.285 (0.004)	0.361 (0.004)	0.328 (0.016)	0.335 (0.003)	0.320 (0.005)
	2007-2016	0.403 (0.006)	0.293 (0.004)	0.377 (0.006)	0.327 (0.005)	0.332 (0.005)	0.342 (0.006)
MPC	1998-2006	0.066 (0.017)	0.029 (0.010)	0.056 (0.014)	0.032 (0.011)	0.062 (0.013)	0.036 (0.011)
	2007-2016	0.124 (0.019)	0.050 (0.013)	0.071 (0.021)	0.044 (0.013)	0.078 (0.018)	0.057 (0.014)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$		6.857 (0.009)	2.092 (0.148)	0.288 (0.591)	0.680 (0.410)	0.834 (0.361)	1.324 (0.250)
$\text{Wald}_{H_0:\text{MPC}_{\text{pre}}=\text{MPC}_{\text{post}}}$		6.887 (0.009)	2.308 (0.129)	0.434 (0.510)	0.668 (0.414)	0.767 (0.381)	1.773 (0.182)
N		1,631	1,429	1,663	1,440	1,462	1,334

The table reports point estimates, with standard errors in parentheses. A Wald statistic for a test of parameter stability under the null hypothesis $H_0 : \tilde{\gamma}_\epsilon$ 1998-2006 $= \tilde{\gamma}_\epsilon$ 2007-2016 is also reported, with the p-value in parentheses. These results are for a time-varying analysis using the same group classification as in Table 4, however consumption for each household does not include rent or imputed rent as a robustness check.

Table D–17: Overlaps between household groups for time-varying analysis

	Renter	Homeowner	Low LW	High LW	Low HW	High HW	High Lev	Low Lev	PHtM	WHtM	NHtM
Renter	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.41	0.04	0.34
Homeowner	0.00	1.00	0.40	0.40	0.41	0.43	0.34	0.36	0.00	0.15	0.61
Low LW	0.00	1.00	1.00	0.00	0.64	0.21	0.52	0.13	0.01	0.38	0.25
High LW	0.00	1.00	0.00	1.00	0.19	0.70	0.19	0.65	0.00	0.00	1.00
Low HW	0.00	1.00	0.62	0.18	1.00	0.00	0.45	0.17	0.01	0.25	0.43
High HW	0.00	1.00	0.19	0.65	0.00	1.00	0.23	0.60	0.00	0.07	0.81
High Lev.	0.00	1.00	0.60	0.22	0.59	0.30	1.00	0.00	0.00	0.23	0.51
Low Lev.	0.00	1.00	0.17	0.72	0.19	0.52	0.00	1.00	0.00	0.05	0.85
PHtM	0.93	0.02	0.02	0.00	0.02	0.00	0.00	0.00	1.00	0.00	0.00
WHtM	0.05	0.93	0.92	0.00	0.62	0.17	0.48	0.10	0.00	1.00	0.00
NHtM	0.12	0.81	0.13	0.53	0.23	0.46	0.23	0.41	0.00	0.00	1.00

Notes: The table reports the fraction of $N \times t$ observations that overlap with other categories. These overlaps are based on the sample that was used in the analysis of time-varying consumption responses in Table 4. Each entry corresponds to the fraction of the row group that also belongs to the column group.

Table D–18: Time-varying estimates for miscellaneous subgroups of homeowners

		Low LW w/o WHtM	Low LW w/o High Lev	High Lev. w/o Low LW	High DtA	Low DtA
				INCOME		
σ_η	1998-2006	0.117 (0.014)	0.150 (0.016)	0.099 (0.017)	0.111 (0.009)	0.124 (0.008)
	2007-2016	0.093 (0.015)	0.107 (0.020)	0.079 (0.017)	0.105 (0.008)	0.109 (0.008)
σ_ϵ	1998-2006	0.229 (0.011)	0.260 (0.015)	0.193 (0.015)	0.212 (0.008)	0.250 (0.007)
	2007-2016	0.186 (0.017)	0.230 (0.024)	0.200 (0.027)	0.190 (0.008)	0.248 (0.008)
				CONSUMPTION		
σ_u	1998-2006	0.091 (0.013)	0.105 (0.024)	0.091 (0.010)	0.084 (0.007)	0.080 (0.007)
	2007-2016	0.081 (0.016)	0.107 (0.016)	0.064 (0.013)	0.089 (0.007)	0.099 (0.007)
σ_v	1998-2006	0.205 (0.010)	0.256 (0.016)	0.140 (0.01.)	0.192 (0.005)	0.203 (0.006)
	2007-2016	0.238 (0.017)	0.286 (0.018)	0.203 (0.013)	0.217 (0.007)	0.238 (0.008)
$\bar{\gamma}_\epsilon$	1998-2006	0.003 (0.074)	0.023 (0.022)	0.014 (0.037)	0.025 (0.021)	0.000 (0.000)
	2007-2016	0.003 (0.074)	0.023 (0.022)	0.014 (0.037)	0.025 (0.021)	0.000 (0.000)
$\tilde{\gamma}_\epsilon$	1998-2006	0.139 (0.054)	0.141 (0.072)	0.126 (0.071)	0.144 (0.032)	0.107 (0.024)
	2007-2016	0.393 (0.092)	0.254 (0.101)	0.067 (0.084)	0.135 (0.052)	0.149 (0.031)
γ_η	1998-2006	0.221 (0.107)	0.222 (0.130)	0.387 (0.137)	0.290 (0.056)	0.235 (0.047)
	2007-2016	0.295 (0.112)	0.226 (0.134)	0.374 (0.136)	0.316 (0.056)	0.250 (0.048)
$E[C_{it}/Y_{it}]$	1998-2006	0.531 (0.006)	0.600 (0.039)	0.481 (0.006)	0.494 (0.004)	0.529 (0.006)
	2007-2016	0.528 (0.009)	0.576 (0.012)	0.463 (0.008)	0.483 (0.005)	0.542 (0.007)
MPC	1998-2006	0.075 (0.030)	0.098 (0.045)	0.067 (0.036)	0.084 (0.016)	0.054 (0.014)
	2007-2016	0.209 (0.047)	0.160 (0.054)	0.037 (0.036)	0.077 (0.025)	0.078 (0.017)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$		6.941 (0.008)	1.219 (0.270)	0.360 (0.550)	0.038 (0.844)	1.485 (0.223)
$\text{Wald}_{H_0:\text{MPC}_{\text{pre}}=\text{MPC}_{\text{post}}}$		6.900 (0.009)	1.044 (0.307)	0.412 (0.521)	0.077 (0.782)	1.701 (0.192)
N		753	560	391	1,658	1,454

Notes: The table reports point estimates, with standard errors in parentheses. A Wald statistic for a test of parameter stability under the null hypothesis $H_0 : \tilde{\gamma}_\epsilon$ 1998-2006 $= \tilde{\gamma}_\epsilon$ 2007-2016 is also reported, with the p-value in parentheses. These results are for a time-varying analysis using different subgroup classification of homeowners than in Table 4 as a robustness check. Columns 3-4 report estimates for low liquid wealth (LW) homeowners (homeowners whose liquid wealth is below the median liquid wealth value across all homeowners in a given year) removing overlapping homeowners with high leverage and WHtM households, respectively. Column 5 reports the estimates for high leverage homeowners removing overlapping low liquid wealth homeowners. The last two columns report estimates for high and low debt-to-asset (DtA) subgroups where the DtA ratio is defined as total debt (mortgages + credit card debt + non-credit card debt) divided by total asset (checks and savings + house + pension).

Table D–19: Time-varying estimates for all household and groups by homeownership status using an alternative sample selection

		All	Renters	Homeowners
			INCOME	
σ_η	1998-2006	0.120 (0.004)	0.121 (0.011)	0.115 (0.005)
	2007-2016	0.121 (0.004)	0.130 (0.009)	0.106 (0.004)
σ_ϵ	1998-2006	0.257 (0.004)	0.327 (0.011)	0.229 (0.005)
	2007-2016	0.243 (0.004)	0.284 (0.010)	0.221 (0.005)
			CONSUMPTION	
σ_u	1998-2006	0.082 (0.008)	0.059 (0.043)	0.077 (0.007)
	2007-2016	0.103 (0.004)	0.108 (0.011)	0.094 (0.004)
σ_v	1998-2006	0.252 (0.006)	0.333 (0.022)	0.204 (0.006)
	2007-2016	0.283 (0.005)	0.331 (0.012)	0.235 (0.004)
$\bar{\gamma}_\epsilon$	1998-2006	0.033 (0.013)	0.036 (0.024)	0.034 (0.014)
	2007-2016	0.033 (0.012)	0.035 (0.024)	0.034 (0.015)
$\tilde{\gamma}_\epsilon$	1998-2006	0.099 (0.018)	0.119 (0.037)	0.089 (0.022)
	2007-2016	0.143 (0.023)	0.131 (0.042)	0.137 (0.025)
γ_η	1998-2006	0.351 (0.026)	0.448 (0.038)	0.304 (0.035)
	2007-2016	0.379 (0.025)	0.472 (0.028)	0.319 (0.035)
$E[C_{it}/Y_{it}]$	1998-2006	0.552 (0.008)	0.703 (0.029)	0.508 (0.010)
	2007-2016	0.559 (0.004)	0.677 (0.010)	0.514 (0.004)
MPC	1998-2006	0.073 (0.011)	0.108 (0.027)	0.063 (0.012)
	2007-2016	0.099 (0.012)	0.112 (0.028)	0.088 (0.022)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$		3.087 (0.079)	0.049 (0.823)	3.125 (0.077)
$\text{Wald}_{H_0:\text{MPC}_{\text{pre}}=\text{MPC}_{\text{post}}}$		3.342 (0.068)	0.010 (0.920)	3.343 (0.068)
N		3,117	749	2,190

Notes: The table reports point estimates, with standard errors in parentheses. A Wald statistic for a test of parameter stability under the null hypothesis $H_0 : \tilde{\gamma}_\epsilon$ 1998-2006 $= \tilde{\gamma}_\epsilon$ 2007-2016 is also reported, with the p-value in parentheses. These results are for a time-varying analysis using an alternative sample selection described in Appendix B as a robustness check.

Table D–20: Time-varying estimates for groups by HtM status using an alternative sample selection

		PHtM	WHtM	NHtM
			INCOME	
σ_η	1998-2006	0.124 (0.024)	0.107 (0.015)	0.110 (0.006)
	2007-2016	0.141 (0.017)	0.079 (0.015)	0.109 (0.005)
σ_ϵ	1998-2006	0.352 (0.019)	0.248 (0.015)	0.236 (0.006)
	2007-2016	0.313 (0.017)	0.272 (0.015)	0.225 (0.005)
			CONSUMPTION	
σ_u	1998-2006	0.031 (0.095)	0.056 (0.047)	0.079 (0.006)
	2007-2016	0.127 (0.017)	0.100 (0.017)	0.100 (0.005)
σ_v	1998-2006	0.370 (0.029)	0.291 (0.038)	0.206 (0.057)
	2007-2016	0.309 (0.018)	0.244 (0.016)	0.244 (0.006)
$\bar{\gamma}_\epsilon$	1998-2006	0.014 (0.030)	0.044 (0.026)	0.044 (0.017)
	2007-2016	0.018 (0.032)	0.044 (0.026)	0.044 (0.017)
$\tilde{\gamma}_\epsilon$	1998-2006	0.115 (0.073)	0.084 (0.064)	0.079 (0.025)
	2007-2016	0.086 (0.074)	0.121 (0.055)	0.116 (0.031)
γ_η	1998-2006	0.609 (0.061)	0.464 (0.025)	0.298 (0.045)
	2007-2016	0.546 (0.050)	0.490 (0.017)	0.326 (0.043)
$E[C_{it}/Y_{it}]$	1998-2006	0.755 (0.018)	0.658 (0.078)	0.475 (0.003)
	2007-2016	0.761 (0.020)	0.573 (0.013)	0.497 (0.004)
MPC	1998-2006	0.098 (0.050)	0.084 (0.046)	0.059 (0.012)
	2007-2016	0.078 (0.052)	0.095 (0.029)	0.079 (0.015)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$		0.086 (0.770)	0.190 (0.663)	1.142 (0.285)
$\text{Wald}_{H_0:\text{MPC}_{\text{pre}}=\text{MPC}_{\text{post}}}$		0.072 (0.790)	0.037 (0.848)	1.540 (0.215)
N		340	442	1,761

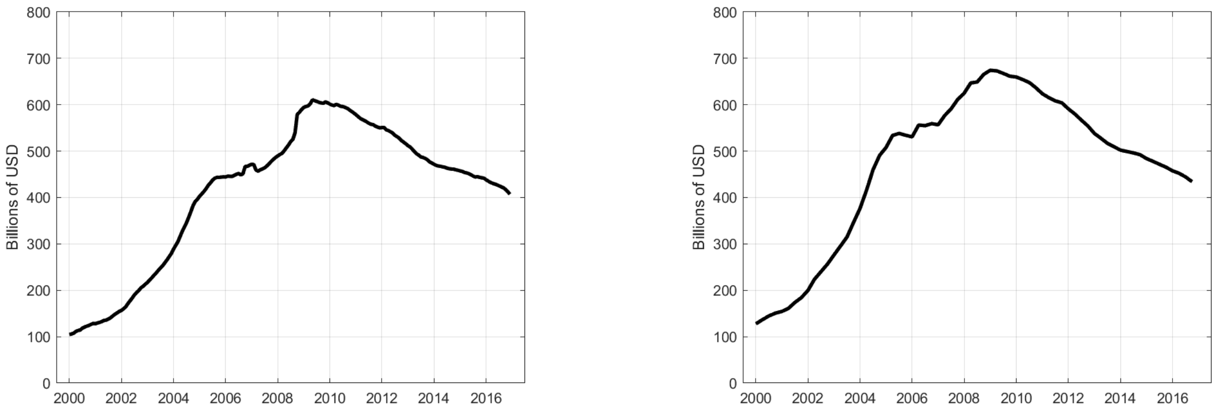
Notes: The table reports point estimates, with standard errors in parentheses. A Wald statistic for a test of parameter stability under the null hypothesis $H_0 : \tilde{\gamma}_\epsilon$ 1998-2006 $= \tilde{\gamma}_\epsilon$ 2007-2016 is also reported, with the p-value in parentheses. These results are for a time-varying analysis using an alternative sample selection described in Appendix B as a robustness check.

Table D–21: Time-varying estimates for subgroups of homeowners using an alternative sample selection

		Low LW	High LW	Low HW	High HW	High Lev.	Low Lev.
					INCOME		
σ_η	1998-2006	0.113 (0.008)	0.118 (0.008)	0.103 (0.010)	0.120 (0.008)	0.095 (0.009)	0.130 (0.010)
	2007-2016	0.095 (0.009)	0.104 (0.007)	0.104 (0.008)	0.110 (0.007)	0.085 (0.008)	0.110 (0.008)
σ_ϵ	1998-2006	0.227 (0.008)	0.226 (0.008)	0.219 (0.009)	0.234 (0.008)	0.201 (0.008)	0.249 (0.009)
	2007-2016	0.228 (0.008)	0.220 (0.008)	0.206 (0.008)	0.237 (0.008)	0.200 (0.010)	0.253 (0.009)
					CONSUMPTION		
σ_u	1998-2006	0.070 (0.014)	0.082 (0.007)	0.068 (0.009)	0.075 (0.010)	0.074 (0.007)	0.078 (0.008)
	2007-2016	0.093 (0.008)	0.096 (0.006)	0.084 (0.008)	0.092 (0.006)	0.078 (0.007)	0.100 (0.007)
σ_v	1998-2006	0.233 (0.017)	0.178 (0.006)	0.213 (0.007)	0.194 (0.016)	0.175 (0.006)	0.203 (0.007)
	2007-2016	0.250 (0.008)	0.209 (0.007)	0.256 (0.008)	0.222 (0.007)	0.204 (0.007)	0.233 (0.008)
$\bar{\gamma}_\epsilon$	1998-2006	0.023 (0.025)	0.031 (0.025)	0.035 (0.025)	0.012 (0.017)	0.055 (0.022)	0.008 (0.021)
	2007-2016	0.023 (0.026)	0.031 (0.024)	0.035 (0.025)	0.012 (0.017)	0.055 (0.022)	0.008 (0.021)
$\tilde{\gamma}_\epsilon$	1998-2006	0.124 (0.040)	0.097 (0.036)	0.104 (0.034)	0.100 (0.028)	0.133 (0.037)	0.117 (0.034)
	2007-2016	0.246 (0.040)	0.121 (0.040)	0.122 (0.053)	0.120 (0.034)	0.161 (0.045)	0.125 (0.036)
γ_η	1998-2006	0.326 (0.071)	0.218 (0.057)	0.411 (0.085)	0.247 (0.045)	0.293 (0.059)	0.217 (0.053)
	2007-2016	0.356 (0.072)	0.227 (0.056)	0.400 (0.079)	0.263 (0.045)	0.313 (0.070)	0.227 (0.053)
$E[C_{it}/Y_{it}]$	1998-2006	0.575 (0.028)	0.455 (0.004)	0.484 (0.005)	0.544 (0.022)	0.507 (0.005)	0.490 (0.006)
	2007-2016	0.548 (0.007)	0.475 (0.006)	0.490 (0.006)	0.537 (0.007)	0.495 (0.006)	0.524 (0.008)
MPC	1998-2006	0.085 (0.025)	0.058 (0.015)	0.067 (0.020)	0.061 (0.016)	0.096 (0.020)	0.061 (0.017)
	2007-2016	0.148 (0.021)	0.072 (0.017)	0.077 (0.025)	0.071 (0.017)	0.107 (0.022)	0.070 (0.018)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$		6.223 (0.013)	0.345 (0.556)	0.114 (0.735)	0.305 (0.581)	0.323 (0.570)	0.044 (0.833)
$\text{Wald}_{H_0:\text{MPC}_\text{pre}=\text{MPC}_\text{post}}$		5.237 (0.022)	0.533 (0.465)	0.139 (0.709)	0.261 (0.609)	0.222 (0.638)	0.180 (0.671)
N		958	944	942	981	839	837

Notes: The table reports point estimates, with standard errors in parentheses. A Wald statistic for a test of parameter stability under the null hypothesis $H_0 : \tilde{\gamma}_\epsilon$ 1998-2006 $= \tilde{\gamma}_\epsilon$ 2007-2016 is also reported, with the p-value in parentheses. These results are for a time-varying analysis using an alternative sample selection described in Appendix B as a robustness check.

E Additional figures



(a) Home equity loans (b) Home equity lines of credit

Figure E–1: Home equity loans and line of credit

Source: Board of Governors of the Federal Reserve System and Federal Deposit Insurance Corporation. Both series retrieved from FRED, Federal Reserve Bank of St. Louis.

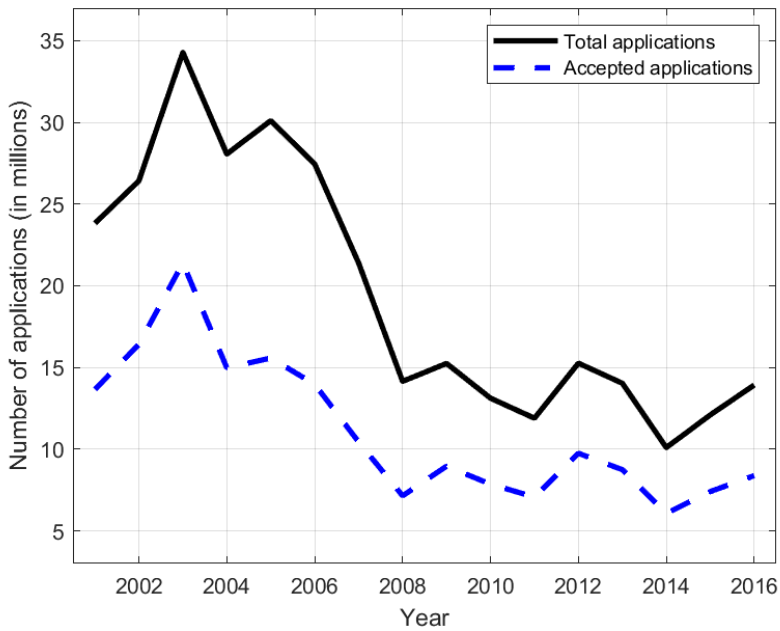


Figure E–2: Residential mortgage lending

Notes: The figure plots the number of residential mortgage lending applications, including lending for home purchases, refinances, and home improvements. The data for these series were collected from Table 1 in Butta et al. (2017) and Table 3 in Butta and Canner (2013). The black solid line shows the number of total applications and the blue dashed line shows the number of accepted applications. The original series is from Home Mortgage Disclosure Act (HMDA) data which can be obtained from https://www.consumerfinance.gov/data-research/hmda/.