Marginal propensities to consume before and after the Great Recession *

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Abstract

We extend a semi-structural model of household income and consumption to allow for dynamic consumption elasticities with respect to transitory income shocks. Likelihood-based inference for our model accurately estimates consumption insurance against income shocks in simulated data from a life-cycle model with borrowing constraints and captures non-zero transitory consumption responses for constrained households. Applying our model to data from a representative sample of U.S. households, we find that short-run elasticities with respect to transitory income shocks are substantially larger than long-run elasticities. We also find a structural break in the transitory sensitivity of consumption from before to after the Great Recession, implying an increase in the estimated marginal propensity to consume out of transitory income for all households by more than 40%. There is considerable heterogeneity in estimates across households grouped by various balance sheet characteristics, with the significant increase in transitory sensitivity of consumption for all households driven by homeowners with lower levels of liquid wealth. Our estimates also imply large consumption elasticities with respect to house prices, supporting 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.

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

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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 if it had been targeted to geographical areas with higher levels of household debt on the basis that households in those areas might have 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 higher MPCs; see, for example, Carroll and Kimball (1996), Carroll (1997), and Carroll (2019). However, Kaplan and Violante (2014) argue that higher returns on illiquid assets induce a tradeoff between consumption smoothing and higher lifetime consumption such that even wealthier households will find it optimal to hold relatively few liquid assets and could also be sensitive to transitory changes in income, with this sensitivity related to different types of wealth in terms of liquidity. Given that housing is the largest component of household wealth and is an illiquid asset typically financed by debt contracts, our main research question, then, is whether the boom and bust in the U.S. housing market around the Great Recession increased MPCs and altered patterns of heterogeneity related to household balance sheets.[1]

To investigate how MPCs have changed with the Great Recession, we estimate a semi-structural model of household consumption and income using data from the Panel Survey of Income Dynamics (PSID) for 1998-2016. We extend the Blundell, Pistaferri, and Preston (2008) (BPP hereafter) model to allow for dynamic consumption elasticities with respect to transitory income shocks, addressing a concern recently raised by Commault (2020) with estimation of the original BPP model if consumption does not follow a random walk. This modification is consistent with non-zero transitory consumption responses that we find in simulated data from the calibrated Kaplan and Violante (2010) life-cycle model with incomplete markets and borrowing constraints. It also provides MPCs that are conceptually closer

[1]There is a large literature on why consumption fell during the Great Recession, including the role of the deterioration in housing wealth; 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). On the empirical side, Mian et al. (2013) argue that the fall in consumption was largely driven by exposure to housing leverage. However, Kaplan et al. (2020a,b) argue that the it was due to a negative housing wealth effect.

to what is captured in natural experiments such as short-term consumption responses to tax rebates.[2] We obtain precise estimates even for the smaller samples of particular household groups before and after the Great Recession ("1998-2006" and "2007-2016") by applying the quasi maximum likelihood estimation (QMLE) approach for semi-structural models developed in Chatterjee, Morley, and Singh (2021).[3] 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 consider in our analysis. In addition, the QMLE approach allows us to easily consider formal Wald tests for a structural break in different model parameters from before to after the Great Recession. Notably, we find that likelihood-based inference for our model also avoids 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 calibrated life-cycle model.

Our first main finding is that short-run elasticities with respect to transitory income shocks are substantially larger than long-run elasticities for all households and all groupings of households that we consider based on their balance sheet characteristics. In terms of heterogeneity in implied MPCs, 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 that homeownership status and housing wealth appear more important for heterogeneity in consumption insurance against permanent income risk.[4] Our second main finding is that the estimated average MPC for all households in our sample increased by more than 40% from before to after the Great Recession, with the increase appearing to be persistent and driven by a doubling of the estimated

[2]In addition to tax rebates (Parker, Souleles, Johnson, and McClelland, 2013), natural experiments related to lottery winnings (Fagereng, Holm, and Natvik, 2020) and mortgage modification programs (Ganong and Noel, 2020) have also been used to identify exogenous income changes and their impact on consumption. These experiments can capture transitory consumption responses, while the original BPP model assumes only permanent responses.

[3]As popularized by BPP, 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. Unlike econometricians, households are assumed to directly observe the shocks, as supported by the findings in Druedahl and Jørgensen (2020). This approach has been used extensively, although often based on GMM and related moments-based estimators rather than the more precise QMLE approach taken in our analysis; see, for example, Kaplan, Violante, and Weidner (2014) and Auclert (2019).

[4]Preferences may also play a role in explaining heterogeneity; see Gelman (2020) and Aguiar, Bils, and Boar (2020). This source of heterogeneity is implicitly allowed for in our approach given that our consumption elasticity estimates can be interpreted as average elasticities for each group under consideration; see Commault (2020).

transitory sensitivity of consumption for homeowners with lower (i.e. below-median) liquid wealth. The Wald tests for a structural break in the transitory sensitivity of consumption are significant for all households, homeowners, and homeowners with lower liquid wealth, while they are not significant for other groups or stratifications of households or for permanent consumption responses of any group. These results support our extension of the BPP model to include dynamic elasticities with respect to transitory income shocks and suggest 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.[5] In particular, as the housing market went bust, homeowners lost access to home equity lines of credit and other sources of liquidity given the fall in the value of their collateral and were, therefore, less able to use housing wealth to insure against bad income realizations, a widespread practice for U.S. households documented in Hurst and Stafford (2004).

A key implication of higher MPCs with the Great Recession, especially for homeowners with lower levels of liquid wealth, is larger consumption elasticities with respect to house prices based on the rule-of-thumb formula in Berger, Guerrieri, Lorenzoni, and Vavra (2018). These implied elasticities support 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, consistent with the arguments in Kaplan, Mitman, and Violante (2020a,b). Furthermore, our results suggest that stabilization policies designed to address liquidity constraints of homeowners would be more effective than debt relief programs during and in the aftermath of recessions associated with large declines in house prices. Thus, our analysis using a semi-structural model confirms 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.

[5] 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 our extended semi-structural model based on BPP that decomposes idiosyncratic log income (y) and consumption (c) for a household i into permanent and transitory components at time t. The model is extended from BPP to accommodate dynamic consumption elasticities with respect to transitory income shocks and has the following unobserved components representation:

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

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

where, as detailed below, the terms on the right hand side of these equations are permanent and transitory components of income and consumption and the $\tilde{\gamma}_\epsilon \epsilon_{it}$ term in the consumption equation in particular is the only addition to the original BPP model specification. Given household-specific initial conditions τ_{i0} and κ_{i0}, the permanent components are assumed to evolve as random walks:[6]

$$\tau_{it} = \tau_{it-1} + \eta_{it} \qquad \eta_{it} \sim i.i.d.(0, \sigma^2_{\eta,t}) \tag{3}$$

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

For each household, the common stochastic trend for income and consumption (i.e. "permanent income"), τ_{it}, is driven by idiosyncratic permanent income shocks, η_{it}, such as promotion or major health diagnoses that affect the ability to work. Each household is also subject to idiosyncratic transitory income shocks, ϵ_{it}, with temporary dynamic effects on income according to an MA(1) process with parameter θ. Consumption has an additional stochastic trend, κ_{it}, that is driven by idiosyncratic permanent consumption shocks, u_{it}, such as could result from heterogeneous responses to wealth shocks. Idiosyncratic transitory consumption shocks, v_{it}, are also allowed for in order to capture surprise household expenditures unrelated to income, idiosyncratic responses to aggregate shocks, or possibly random measurement error in reported consumption. Following BPP, we assume that these idiosyncratic shocks are not correlated with each other, over time, or across households, but we allow

[6] It is sometimes argued that these components cannot literally follow random walks given finite lives and should instead be modeled as stationary AR(1) processes and referred to as "persistent" components. The random walk assumption in the BPP model should thus be taken as a parsimonious way to capture highly-persistent processes. Estimates of other parameters should be relatively robust to this assumption or the alternative of stationary AR(1) processes as long as some shocks to income and consumption die out only very slowly over time.

for changes in their variances from before to after the Great Recession in order to avoid any spurious evidence of time-varying consumption response parameters due to a failure to account for relevant heteroskedasticity.[7] When estimating the model for any particular group of households, parameters are assumed to be the same within the group. However, as discussed in Commault (2020), 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 by separate estimation across groups.

The key parameters in our model are the γ's, which capture the responses of consumption to income shocks. Unlike shock variances, these parameters are assumed to be constant over time, although we test for a structural break in their values from before to after the Great Recession in Section 4.2.[8] Following BPP, the parameters $\bar{\gamma}_\epsilon$ and γ_η capture the impacts of transitory and permanent income shocks on permanent consumption, while we add $\tilde{\gamma}_\epsilon$ to the BPP model in order to capture the impact of transitory income shocks on transitory consumption.[9] 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

[7] Interestingly, we find little difference in estimated shock volatilities from before to after the Great Recession, especially in terms of the permanent and transitory income risks. Full sets of estimates, including for shock volatilties, 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 considered in our empirical analysis.

[8] Constant γ's also imply symmetric and proportional responses to different shocks, while it is clearly possible that responses depend on the sign or size of shocks. Arellano, Blundell, and Bonhomme (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 a 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 Wald tests of our linear specification by checking if the consumption responses are different depending on the mean, variance, or skewness of residual income growth in a particular wave and found no evidence of significant differences, although this could be due to the possibility of low power for the tests given small effective sample sizes. For some household groups, we did find significant differences for the transitory sensitivity of consumption depending on the sign of residual 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 and leave a deeper examination of possible nonlinearities to future research.

[9] It is possible to consider a more general distributed lag structure $\sum_{i=0}^{q} \tilde{\gamma}_{\epsilon i} \epsilon_{t-i}$ to capture persistent, but still transitory effects of transitory income shocks. We find such a structure is relevant for borrowing-constrained households in simulated data from a calibrated life-cycle model, but no evidence for significant lags in the actual data.

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) life-cycle model with incomplete markets and a zero borrowing constraint.[10] These non-zero transitory responses directly imply that our extended semi-structural model provides a better reduced-form for a structural model with optimizing households subject to borrowing constraints than the original BPP specification.

To estimate parameters for the semi-structural model, we cast the unobserved components representation of the model into state-space form and employ QMLE following 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 balance sheet characteristics and allowing for structural breaks. By using QMLE, we are able to address 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 estimates for the BPP model are not robust to alternative weighting schemes for GMM, 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 there is not another consecutive observation in levels to form a growth rate. However, it is crucial to note that, by placing diffuse priors on household-specific initial conditions τ_{i0} and κ_{i0} when calculating the quasi likelihood using the Kalman filter, estimation in levels would be completely equivalent to

[10] 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, we estimate $\tilde{\gamma}_\epsilon$ to be 0.06 for all 50,000 working-age (ages 26-59) households, 0.13 for younger households (ages 26-45), and 0.00 for older households (ages 46-59), noting that the estimates are extremely precise given the very large sample size. 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 are expected to reverse this drop in the next period in order to bring consumption back towards its level prior to the shock.

estimation in growth rates in the absence of missing values and, therefore, implicitly allows for household fixed effects. In addition, the QMLE approach lets us easily consider Wald tests for restrictions on parameters based on the estimated parameter variance-covariance matrix calculated using the Huber-White sandwich formula. We calculate Wald statistics to test the stability of the consumption response parameters from before to after the Great Recession.

Notably, 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 model. In particular, given simulated data in the zero-borrowing-constraint setting, we find accurate estimates for consumption insurance of 0.10 for younger households (ages 26-45) and 0.47 for older households (ages 46-59), where the true average values for the two age groups are 0.10 and 0.48, respectively. There still seems to be some downward bias when combining all households in estimation as the estimate is 0.20 for all households, while the true average value is 0.26. However, this bias must reflect a some nonlinearity when combining households with very different true values as the weighted average of our estimates for younger and older households is 0.25. Furthermore the bias is clearly much less pronounced than for a moments-based estimator. Specifically, Table 1 in Kaplan and Violante (2010) reports an estimate based on the BPP approach of 0.07 given a true average value of 0.23 for households in the 26-57 age group, while their Figure 3 often reports negative and downward biased estimates for households in the 26-45 age range over which we find no bias with our estimate of average consumption insurance with respect to permanent income risk. Meanwhile, estimates for consumption insurance with respect to transitory income risk (i.e., $1 - \gamma_\epsilon$) are also accurate, 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.

In thinking about our application to the actual data, it is important to note that the time period t in our model denotes a year given that the income and consumption data we use correspond to annual flows. However, as explained in more detail in Section 3, waves of data are only available biennially in the PSID 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 other missing observations from an unbalanced panel. It should be highlighted that this approach is potentially different from working with wave growth rates implied by the model. In particular, the implied growth rates across two-year waves are given as follows:

$$y_{it} - y_{it-2} = \eta_{it} + \eta_{it-1} + \epsilon_{it} + \theta\epsilon_{it-1} - \epsilon_{it-2} - \theta\epsilon_{it-3} \tag{5}$$

$$c_{it} - c_{it-2} = \gamma_\eta(\eta_{it} + \eta_{it-1}) + \gamma_\epsilon\epsilon_{it} + \bar{\gamma}_\epsilon\epsilon_{it-1} + \tilde{\gamma}_\epsilon\epsilon_{it-2} + u_{it} + u_{it-1} + v_{it} - v_{it-2} \tag{6}$$

Based on a moments-based approach to estimation, the short-run elasticity, γ_ϵ, could be identified for this model given what Commault (2020) refers to as the "biennial passthrough" coefficient, $\hat{\phi}_2^\epsilon = \frac{cov(c_{it}-c_{it-2}, y_{it}-y_{it+2})}{cov(y_{it}-y_{it-2}, y_{it}-y_{it+2}))}$, as long as there are no moving-average dynamics, i.e. $\theta = 0$. However, if there are moving-average dynamics, it would be an "annual passthrough" coefficient, $\hat{\phi}^\epsilon = \frac{cov(c_{it}-c_{it-1}, y_{it+1}-y_{it+2})}{cov(y_{it}-y_{it-1}, y_{it+1}-y_{it+2})}$, that would identify γ_ϵ, but $\hat{\phi}^\epsilon$ cannot be calculated given only biennial observations of the levels data. By contrast, our QMLE approach directly estimates γ_ϵ even when only biennial observations are available, although estimation requires an assumption about the value of the moving-average parameter θ, which is not econometrically identified given only biennial observations. Specifically, biennial observations identify only the unconditional variance of transitory income, $(1+\theta^2)\sigma_\epsilon^2$, rather than the conditional variance, σ_ϵ^2. So for 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 the same movements in biennial consumption growth.

For identification given only biennial observations, we set the moving-average parameter $\theta = 0$, which places a lower-bound on the estimated consumption responses to transitory income shocks. However, we find the estimates are the same to three decimals if instead we were to assume moving-average dynamics similar to what BPP found using annually-available observations of household income from the PSID for an earlier sample period in their analysis. Specifically, BPP find an estimate of θ around 0.1 (implying $\theta^2 \approx 0.01$), so the changes in the estimates of σ_ϵ^2, $\bar{\gamma}_\epsilon$, and $\tilde{\gamma}_\epsilon$ for such a value instead of $\theta = 0$ are negligible and we do not consider this identification assumption to be a reason why estimated MPCs are lower than often found in natural experiments.[11] We also note that Commault (2020) reports a biennial passthrough coefficient $\hat{\phi}_2^\epsilon$ of 0.13 (with a standard error of 0.06) in her Table 4 when considering comparable data from the PSID for the same 1998-2016 sample period

[11]The data from the BPP sample also suggest no distributed lag transitory effect of transitory income shocks on consumption, with the estimate for the first distributed lag equal to 0.00 (and not significant). A lack of higher-order distributed lag effects is further supported by a very small second-order autocorrelation for two-year wave consumption growth in our PSID sample.

for which we find a short-run elasticity γ_ϵ estimate reported in Section 4 of 0.14 (with a standard error of 0.02), supporting the idea that the moving-average dynamics are minimal given that $\hat{\phi}_2^\epsilon$ would identify γ_ϵ if the moving-average parameter $\theta = 0$ and also confirming the greater precision of our QMLE estimates versus a moments-based approach.

As noted above, part of the efficiency gain for our estimation compared to working with growth rates across 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 will have 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, although we again emphasize that our estimation implicitly allows for household fixed effects, even though it is conducted in levels, by placing diffuse priors on household-specific initial conditions τ_{i0} and κ_{i0}. To see how levels and growth rate estimates are related, but levels estimation is more precise due to fewer missing observations, note that the transitory consumption response parameter $\tilde{\gamma}_\epsilon$ is estimated to be 0.10 (with a standard error of 0.02) for all households in our sample over the full 1998-2016 sample period based on QMLE for an unobserved components representation of biennial growth rates, which is very similar to, but less precise than, the corresponding estimate reported in Section 4 of 0.11 (with a standard error of 0.01) that we find based on estimation in levels with diffuse priors on initial conditions for the permanent components.

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 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 only did so 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.[12] To address a variety of data-reporting issues, we closely follow the sample-selection procedure 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 following BPP, but our estimates of transitory consumption responses 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 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 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

[12] In any wave, the PSID reports information for the previous year. For example, the data released in 1999 contain information collected for 1998. When reporting our results, we refer to the year the data correspond to rather than the year labelled in the PSID.

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.[13] 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.[14] Summary statistics for the HtM groups are

[13]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.

[14]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.

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.

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. Table 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. The lower liquid wealth and lower 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 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, higher 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 (2019) by only including households in a particular group at a given point of time if they are classified in the category for at least two consecutive waves including the current one. Furthermore, to minimize compositional changes for groups in our time-varying estimation, we include households in a group after the Great Recession only if, in addition to satisfying the two consecutive waves minimum, they were classified in the same category in the last wave prior to the Great Recession. However, we confirm that our results are qualitatively robust to excluding all households from a group that were only classified in a category either before or after the Great Recession. 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 we investigate whether the sensitivity of consumption changed with the Great Recession by dividing the sample period in half from before to after 2007. Finally, we explore implications of our results for why consumption fell during the Great Recession.

4.1 Consumption responses over the full sample

Table 3 reports estimates of constant consumption response parameters for the full sample period of 1998-2016, allowing for heteroskedasticity from before to after the Great Recession (results for all model parameters are provided in the appendix).[15] Before discussing

[15]In addition to allowing for heteroskedasticity across time, our group-level estimation allows for different shock variances across groups. However, we note that elasticity estimates when households are combined into larger groups are generally similar to weighted averages of estimates for subgroups, suggesting that an assumption of the same variances within a group does not distort elasticity estimates even if shock volatility estimates sometimes differ across groups, as can be seen in the appendix. When there is a larger discrepancy, such as, for example, 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 sample selection in terms of the two-consecutive-wave rule and, implicitly, within-group heterogeneity, as the relevant estimated shock

Table 3: Full-sample estimates of constant consumption response parameters

	All	**Renter**	**Homeowner**	**PHtM**	**WHtM**	**NHtM**
γ_η	0.38 (0.03)	0.49 (0.00)	0.32 (0.03)	0.46 (0.03)	0.47 (0.12)	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)	0.73 (0.00)	0.52 (0.00)	0.83 (0.00)	0.48 (0.00)	0.43 (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)
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 (0.07)	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)
$E[C_{it}/Y_{it}]$	0.57 (0.00)	0.48 (0.00)	0.55 (0.00)	0.50 (0.00)	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 (0.01)	0.07 (0.01)
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 constant elasticity of consumption with to a permanent income shock, $\bar{\gamma}_\epsilon$ is the long-run elasticity of consumption with respect to transitory income shocks, $\tilde{\gamma}_\epsilon$ is the transitory sensitivity of consumption with respect to 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 reported), and MPC is $\gamma_\epsilon \times E[C_{it}/Y_{it}]$ (reported standard error based on QMLE for γ_ϵ and takes the mean consumption-income ratio 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.

consumption responses to transitory income shocks and implied MPCs, we first look at consumption responses to permanent income shocks, which were the main focus of analysis using the semi-structural model in BPP. 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 sample, 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.[16] Meanwhile, as might be expected, homeowners, NHtM, higher liquid wealth, higher housing wealth, and lower leverage households all appear better able to absorb permanent income risk than their counterparts. 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 higher liquid wealth, higher housing wealth, and lower 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.[17]

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 perma-

variances in the appendix are very similar across these subgroups and to the estimates for all homeowners.

[16] There are many possible sources of this 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), these 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. Still, our estimate of consumption insurance is considerably higher than the comparable estimate of 36% reported in BPP. Possible reasons for this difference include the imprecision of BPP's GMM estimate and its sensitivity to weighting scheme highlighted by Chatterjee et al. (2021), as well as a large 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 for likelihood-based inference when we consider simulated data from the their model.

[17] Interestingly, however, we find 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 the sample selection, and the extended model specification compared to BPP and Chatterjee et al. (2021).

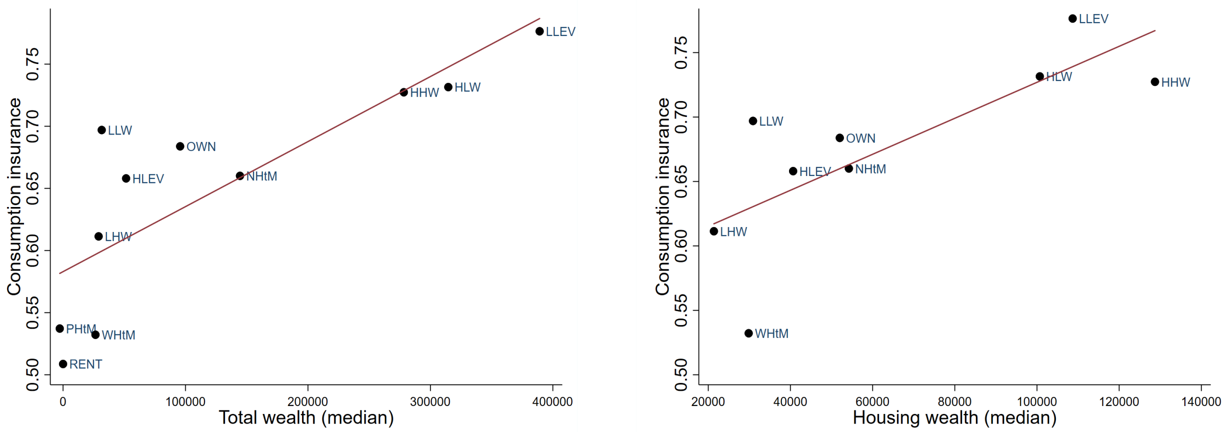

Figure 1: Consumption insurance vs. wealth

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.

nent income risk, wealthier households have a greater ability to absorb permanent income risk than poorer households. HtM status also appears to be important, although we find that liquid wealth is less important than housing wealth or homeownership status.

Returning to 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. As 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 always small for different household groups and often statistically insignificant. Thus, 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 $\tilde{\gamma}_\epsilon$. Notably, the estimates of $\tilde{\gamma}_\epsilon$ are statistically significant for all households and for all groupings of households. Thus, we can uniformly reject the implicit restriction in the original BPP model specification that $\tilde{\gamma}_\epsilon = 0$ and these results provide strong support for our more general model specification that allows for dynamic consumption elasticities with respect to transitory income shocks.

Examining the cross-sectional patterns of heterogeneity in the transitory sensitivity of consumption in more detail, we find that homeowners with lower liquid wealth, lower housing wealth, and higher leverage have larger transitory consumption responses parameters than their respective counterparts. Among all of these subgroups, homeowners with lower 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. 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 HtM households from this subgroup further increases the estimate of $\tilde{\gamma}_\epsilon$ to 0.25 (with a standard error of 0.05).[18] This suggests 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 somewhat larger transitory consumption response parameters compared to NHtM households, although the differences are not striking.[19]

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). Specifically, for each group, we calculate the implied MPC $\equiv \gamma_\epsilon \times E[C_{it}/Y_{it}]$, which, as noted in Commault (2020), provides a lower-bound estimate of the average across households in a particular group given a positive relationship between the elasticity and the consumption-income ratio across households within a group.[20] We use the sample average to estimate $E[C_{it}/Y_{it}]$, with standard

[18] Removing HtM households from low housing wealth and high leverage subgroups has either no impact or leads to a small decrease in the estimated transitory consumption response parameter. See the appendix for these estimates removing HtM households from the relevant subgroups of homeowners.

[19] While we find liquid wealth of homeowners is the key characteristic behind heterogeneity in the transitory sensitivity of consumption, we do not want to downplay the potential role of HtM status. In particular, we find more heterogeneity along the HtM dimension when we consider a sample selection that does not exclude transient households, i.e. households with the same 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.

[20] 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 $cov(X,Y) = E[XY] - E[X]E[Y]$. While 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. There are some outliers in these ratios that could be due to data-reporting issues, so we drop observations for which the ratio is

errors based on least squares, and because these estimates are extremely precise, we treat the mean consumption-income ratio as known when calculating standard errors of the MPCs. In principle, different ratios for different household groups could play a role in MPC heterogeneity. 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 clear evidence of heterogeneity related to these balance sheet characteristics, with the significant differences in estimates based on liquid wealth in particular confirmed by the precision of the MPC estimates reported in Table 3. The negative relationships between the MPCs and total wealth, liquid wealth, and housing wealth (top panels and bottom left panel) are consistent with what would be predicted by either one or two-asset incomplete markets models, e.g. Carroll (1997) and Kaplan and Violante (2014).[21] There is also a positive relationship between the MPCs and household leverage (bottom right panel), implying that highly-indebted homeowners tend to respond more to transitory income shocks.

below 0.05 or greater than 1 on the basis that these values could reflect reporting errors (this involves dropping 2,953 observations from our total sample of 31,830 observations). Confirming a positive relationship that makes our MPCs correspond to being 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 elastiticies 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 only be 0.02. Thus, 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.

[21] A number of other empirical studies, including Zeldes (1989), Johnson, Parker, and Souleles (2006), Parker et al. (2013), Baker and Yannelis (2017), and Fagereng et al. (2020), have documented a significant negative correlation between MPCs and liquid wealth. This link is 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. This 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.

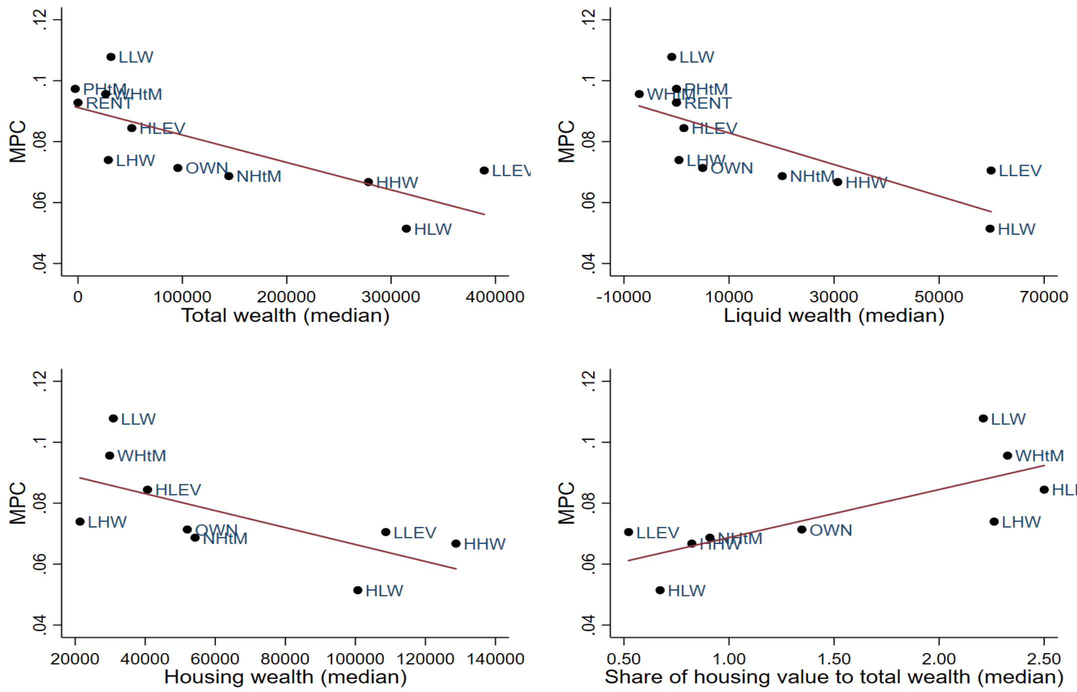

Figure 2: MPCs vs. wealth and leverage

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.

4.2 Did the sensitivity of consumption change with the Great Recession?

Next, we investigate whether parameters for our semi-structural model changed from before to after the Great Recession. Given heterogeneity related to balance sheet characteristics in Table 3 and substantial adjustments in household balance sheets around the Great Recession, we might expect to see changes in parameter estimates. Perhaps what is notable, then, 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.[22] Thus, the full-sample estimates of these parameters in Table 3, which again suggest permanent responses to transitory shocks are small and heterogeneity in consumption insurance is more related to homeownership status and housing wealth than liquid wealth, are still the most relevant. Based on a Wald test for a structural break using the Huber-White sandwich formula for the estimated parameter variance-covariance matrix, 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 for every group, although the change is significant when considering all households.

Table 4 reports structural break tests and time-varying estimates for the transitory consumption response parameter (results for all model parameters are provided in the appendix). The Wald statistics for the hypothesis of no structural break in the transitory sensitivity of consumption, 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, is significant for all households and homeowners at the 5% level and for lower liquid wealth homeowners at the 1% level. The fact that the Wald statistics are not significant for the other groups of households suggests the change in the transitory sensitivity of consumption for lower liquid wealth homeowners drives the significant change in the transitory consumption response parameter for homeowners and all households, although it should be noted that transitory consumption response parameter estimates increased for all groups, even if the increase is not always significant.[23] Then, as

[22]A motivating theoretical optimization problem for households with CRRA utility considered in BPP suggests that $\bar{\gamma}_\epsilon$ 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 expect this parameter to decrease from before to after the Great Recession given an apparent decline in real interest rates over the sample period; see, for example, Holston, Laubach, and Williams (2017). However, the time-varying estimates of $\bar{\gamma}_\epsilon$ are almost identical in the two subsample periods, suggesting the effect of a decline in interest rates is not enough to meaningfully change this parameter. Meanwhile, other aggregate and idiosyncratic effects of changes in interest rates on consumption are captured by time dummies in first-stage regression for household consumption and the idiosyncratic consumption shocks, respectively.

[23]The stronger link of the change in the transitory sensitivity of consumption to liquid wealth than other

Table 4: Structural break tests and time-varying estimates for consumption responses

	All	**Renters**	**Homeowners**	**PHtM**	**WHtM**	**NHtM**
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$	5.88 (0.02)	0.44 (0.52)	5.82 (0.02)	0.01 (0.92)	0.58 (0.45)	1.13 (0.29)
$\tilde{\gamma}_{\epsilon,\text{1998-2006}}$	0.09 (0.02)	0.10 (0.03)	0.08 (0.02)	0.07 (0.06)	0.09 (0.04)	0.09 (0.02)
$\tilde{\gamma}_{\epsilon,\text{2007-2016}}$	0.14 (0.02)	0.13 (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 (0.00)	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)	0.06 (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)	0.07 (0.05)	0.10 (0.03)	0.08 (0.01)
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.**
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{pre}}=\tilde{\gamma}_{\epsilon,\text{post}}}$	12.45 (0.00)	1.14 (0.29)	0.06 (0.81)	1.01 (0.31)	1.70 (0.19)	0.50 (0.48)
$\tilde{\gamma}_{\epsilon,\text{1998-2006}}$	0.13 (0.03)	0.08 (0.03)	0.12 (0.03)	0.08 (0.03)	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 (0.04)	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)
No. of households	1,631	1,429	1,663	1,440	1,462	1,334

Notes: Wald statistics with p-values based on a $\chi^2(1)$ distribution in parentheses are reported for the hypothesis of no structural break, where the pre-break period is 1998-2006 and the post-break period is 2007-2016. Point estimates with standard errors in parentheses for the corresponding subsample periods are reported based on QMLE for all other inferences unless otherwise noted below. $\tilde{\gamma}_\epsilon$ is the transitory sensitivity of consumption 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 reported), and MPC is $\gamma_\epsilon \times E[C_{it}/Y_{it}]$ (reported standard error based on QMLE for γ_ϵ and takes the mean consumption-income ratio as known given highly precise estimates), where γ_ϵ is the short-run elasticity with respect to transitory income shocks. 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.

also reported in Table 4, the increased transitory sensitivity of consumption given reasonably stable consumption-income ratios translates into higher implied MPCs after the Great Recession, an empirical insight that is only made possible given the inclusion of the transitory consumption response parameter $\tilde{\gamma}_\epsilon$ in our semi-structural model.[24] The estimated MPC for all households increased by more than 40% 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 lower 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). This result is consistent with the deterioration in housing wealth and liquidity constraints making consumption more sensitive to transitory income shocks for many households in the sample. This result is intuitive, but crucially we are able to precisely quantify the changes from before to after the Great Recession using a semi-structural model.

Because house prices rebounded somewhat by the end of our sample period, we consider how persistent the changes in consumption behavior were after the Great Recession. To examine this, we conduct two robustness checks, the full results for which are provided in the appendix. First, 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 behavior had been more transitory, we would expect larger estimated changes in parameters and test statistics for structural change with the shorter second subsample period. However, the results are generally quite similar to those reported in Table 4. Second, we consider the possibility of more frequent changes in model parameters for all households by allowing for a structural break after every two waves. Again, we find the same pattern of change in the transitory consumption response parameters as in Table 4, although the parameter estimates are not precise even given our focus on results for all households. The estimates clearly support a persistent change in the sensitivity of transitory consumption responses from before to after the Great Recession 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

balance sheet variables also suggests that the result is not being driven by an underlying demographic characteristic that is more related to the other balance sheet variables, such as geographic location with housing wealth or employment status with leverage.

[24]In particular, not only is the full-sample estimate of the MPC for all households smaller at 0.05 instead of 0.08 when considering 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 both before and after the Great Recession. Thus, it is only by allowing for dynamic consumption elasticities that we are able to detect higher MPCs that have increased from before to after the Great Recession.

(with a standard error of 0.05) even being a bit higher than the 2009-2012 subsample period estimate of 0.13 (with a standard error of 0.03).[25]

We conduct a number of other robustness checks for the time-varying estimates, with the full results also 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 do not increase given the comparatively lower consumption-income ratios for this measure of consumption. Second, given substantial overlaps between lower liquid wealth homeowners, higher leverage homeowners, and HtM households, 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 sensitivity of consumption in the post-break period is in the same direction after removing the overlapping households. We find that excluding HtM households from the low liquid wealth subgroup alters the estimated post-break transitory consumption response parameter $\tilde{\gamma}_{\epsilon,\text{2007-2016}}$ 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 break test still significant at the 1% level in this case), while excluding higher leverage homeowners leads to a similar estimate of 0.25 (with a standard error of 0.10) as before. By contrast, excluding lower liquid wealth homeowners from high leverage subgroup alters the estimated post-break transitory consumption response parameter $\tilde{\gamma}_{\epsilon,\text{2007-2016}}$ 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 the sensitivity of consumption to transitory income shocks from before to after the Great Recession.[26] Third, to further

[25]One possibility is that consumption behavior during the housing boom was more unusual than in the bust, perhaps due to the ubiquity of home equity lines of credit at the time, and the Great Recession led to more of a "return to normal" than a structural break for consumption behavior. Although the data are not directly comparable for a variety of reasons, we find an estimate of $\tilde{\gamma}_{\epsilon}$ of 0.09 (with a standard error of 0.02) for all households in the BPP sample from 1978-1992. 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 BPP 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 Great Recession is more of a return to normal than a break from the past.

[26]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 are 0.14 and 0.13 (with standard errors of 0.03 and 0.05, respectively) in the respective pre- and post-break periods, suggesting this leverage-related balance sheet characteristic is not relevant for explaining the structural break

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. Again, lower liquid wealth homeowners stand out and their transitory consumption responses parameters increased significantly, statistically and economically, from before to after the Great Recession.

4.3 Why did consumption fall during the Great Recession?

Our estimated MPCs are smaller than those typically found in natural experiments.[27] This could reflect possible downward biases in reported consumption in the survey or the lower-bound nature of the estimates given a positive relationship between the short-run elasticity and the consumption-income ratio across households. It could also reflect our focus on non-durable components of annual consumption, while transitory income shocks might lead to intertemporal substitution of durable goods purchases within the year that would result in larger estimated short-run MPCs for natural experiments. Likewise, it could reflect our 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.

To put our results into 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 (2020) find an average MPC of 0.08 or $40 for one-time windfall of $500, although it is higher at 0.14 or $700 for a one-time windfall of $5,000.[28] 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

in the average transitory sensitivity of consumption.

[27] However, we note that our estimated MPCs are uniformly larger than the semi-structural estimate of 0.04 reported in Table 4 of Commault (2020) for the PSID over the same 1998-2016 sample period.

[28] Also see Christelis, Georgarakos, Jappelli, Pistaferri, and Van Rooij (2019) on hypothetical consumption responses to income shocks.

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.[29]

But our findings of relatively small estimated consumption responses to income shocks do beg the question as to why consumption fell so much during the Great Recession. The more than 40% increase in the estimated average MPC with the Great Recession reported in Table 4 suggests that greater sensitivity to transitory income shocks, especially for lower liquid wealth households, is part of the story. However, a more complete answer can be provided by the fact that even our relatively small MPC estimates turn out to imply sizeable consumption elasticities with respect to house prices. In particular, given the decline in house prices by as much as 30% between 2007 and 2009 according to the Case-Shiller index, there is a large implied negative wealth effect on the level of consumption, an effect that is amplified by the heightened sensitivity of consumption with the Great Recession.[30]

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, Guerrieri, Lorenzoni, and Vavra (2018):

$$\gamma_{\text{hp}} \approx \text{MPC} \times (1-\delta)\frac{P_{t-1}H_{it-1}}{C_{it}} \tag{9}$$

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

[29]Again see the household optimization problem in BPP corresponding to the permanent income hypothesis with self-insurance, which suggests that, under MA(0) dynamics for transitory income, the proportionate response to a transitory shock compared to a permanent shock would simply be equal to $r/(1+r)$, where r is the interest rate.

[30]Given the housing-market bust associated with 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.

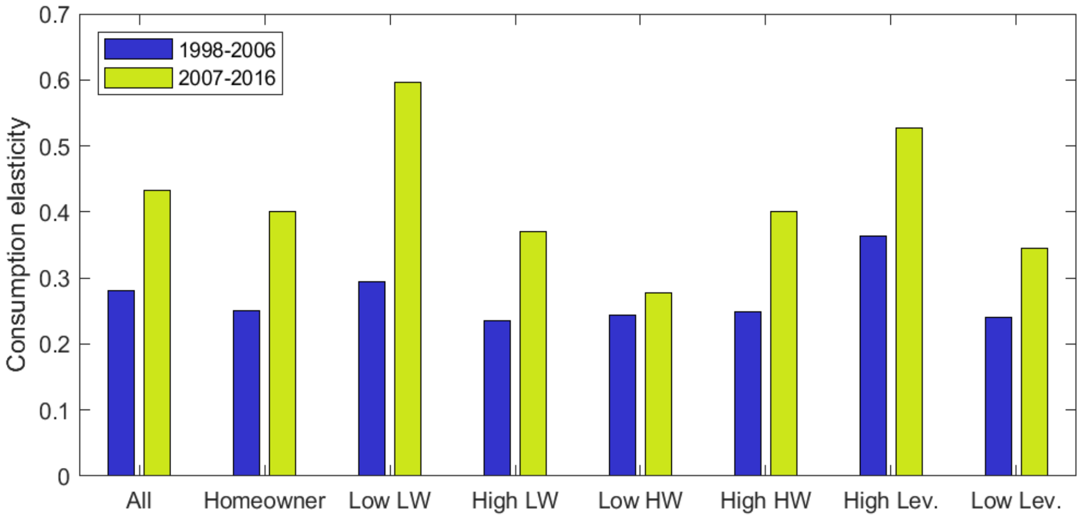

Figure 3: Implied consumption elasticities with respect to house prices

Notes: Implied consumption elasticities with respect to house prices for different household groups are reported for subsample periods of 1998-2006 (blue bars) 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.

more than 40% from before to after the Great Recession, we should expect γ_{hp} to increase for all households even at a maximum decline in house prices of about 30%, especially given that consumption also fell during the Great Recession, thus partially offsetting the decrease in the PH/C ratio.

Figure 3 shows that the implied consumption elasticities with respect to house prices increased substantially after 2007. The estimate of γ_{hp} for all households is 0.28 in the subsample period before the Great Recession and 0.43 in the subsample period afterwards, 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 in line with the estimates in Berger et al. (2018).[31] As with the MPCs, the increase in the estimate of γ_{hp} is largest for

[31] 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. Estimates in the literature 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 (2020), and Graham and Makridis (2020). We note that the scale of our consumption elasticities may be high if the self-reported house values are overly optimistic in the PSID 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

lower 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. Indeed, even given a somewhat lower median level of consumption for lower liquid wealth homeowners than for higher leverage homeowners reported in Table 2, the lower liquid wealth homeowners have a largest implied absolute fall in their consumption given the same percentage decrease in house prices. Furthermore, the fact that the largest change in the sensitivity of consumption was for lower liquid wealth homeowners, not higher leverage homeowners, is consistent with the arguments in Kaplan et al. (2020a,b) that a decline in housing wealth rather than proportionately larger consumption responses for deleveraging households is behind the fall in consumption.

5 Conclusion

Taken together, our empirical results suggest that a decline in house prices combined with liquidity constraints led to a persistent rise in MPCs and a large fall in consumption with the Great Recession. Before the Great Recession, the households with comparatively high MPCs were mainly renters and WHtM households, while homeowners with lower liquid wealth or higher leverage could not be distinguished from WHtM households in terms of their MPCs. However, since the Great Recession when household balance sheets changed substantially, our estimates suggest that these homeowners, particularly those with lower liquid wealth, have higher MPCs than renters and WHtM households. A simple explanation for this key role of homeowner liquidity in understanding changes in 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 period, in line with the empirical evidence in Hurst and Stafford (2004) that households use 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 house prices declined and housing wealth deteriorated, credit constraints became tighter for many homeowners due to a fall in the value of their collateral. This made it more difficult for them to borrow to smooth consumption in the event of transitory shocks to their income; see also Gross, Notowidigdo, and Wang (2019), 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

show that it works well as an approximation in many settings.

similar magnitude to the increase in the average MPC that we find in our sample.

Our finding of a much larger increase in MPCs for lower liquid wealth homeowners compared to highly leveraged homeowners supports the argument in Kaplan et al. (2020a,b) that a negative housing wealth shock more than deleveraging drove down consumption during the Great Recession. Meanwhile, the large increase in MPCs 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". Therefore, our estimates also 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 MPCs supports the view 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 precise inferences that support heterogeneity and time variation in MPCs across different household groups classified by 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. Furthermore, likelihood-based inference avoids the large downward bias in estimating consumption insurance with respect to permanent income risk that Kaplan and Violante (2010) highlight afflicts the BPP approach when considering simulated data from their 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 allow for dynamic consumption elasticities with respect to transitory income shocks. This is done by adding a parameter to capture the transitory sensitivity of consumption, addressing concerns raised in Commault (2020) with estimation of the BPP model if consumption does not actually follow a random walk and is consistent with non-zero transitory consumption responses for constrained households in simulated data from the calibrated Kaplan and Violante (2010) life-cycle model. As we show, this transitory consumption response parameter 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 liquid wealth drives the time variation in MPCs from before to after the Great Recession.

We conclude by noting that future directions for research using a semi-structural approach include an in-depth analysis of possible asymmetries in consumption responses and of links between unobserved income shocks and observables, both of which require extending estimation methods, as recently considered in Ballantyne (2021) and Braxton, Herkenhoff, Rothbaum, and Schmidt (2021).

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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.

Suppressing household-specific subscripts for simplicity and letting z denote the accumulation of a shock, the observation equation for our model in levels is

$$\mathbf{y_t} = \mathbf{HX_t},$$

where

$$\mathbf{y_t} = \begin{bmatrix} y_t \\ c_t \end{bmatrix}, \mathbf{H} = \begin{bmatrix} 1 & \theta & 0 & 1 & 0 & 0 \\ \tilde{\gamma}_\epsilon & 0 & 1 & \gamma_\eta & \bar{\gamma}_\epsilon & 1 \end{bmatrix}, \text{ and } \mathbf{X_t} = \begin{bmatrix} \epsilon_t \\ \epsilon_{t-1} \\ v_t \\ \tau_t \\ z_{\epsilon t} \\ z_{ut} \end{bmatrix}.$$

The state equation is

$$\mathbf{X_t} = \mathbf{FX_{t-1}} + \mathbf{v_t},$$

where

$$\mathbf{F} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \mathbf{v_t} = \begin{bmatrix} \epsilon_t \\ 0 \\ v_t \\ \eta_t \\ \epsilon_t \\ u_t \end{bmatrix},$$

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

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

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. 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 $\tau_{0|0} = y_1$,

$z_{\epsilon 0|0} = 0$, and $z_{u0|0} = c_1 - \gamma_\eta y_1$ (or first available values given missing observations) with variances of 100 along with $\epsilon_{0|0} = \epsilon_{-1|0} = v_{0|0} = 0$ and variances of these shocks to initialize the Kalman filter. This would be equivalent to estimation of the model in growth rates in the absence of missing observations and, therefore, implicitly allows for fixed effects. 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.

We closely follow the sample-selection procedure 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 selection 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 in a particular group in 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 in 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 relatively less transient, with 75% of homeowners appearing in 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 were WHtM before the Great Recession remained as WHtM after the Great Recession. Similarly, the results for subgroups of homeowners based on balance sheet variables presented in the right panel of

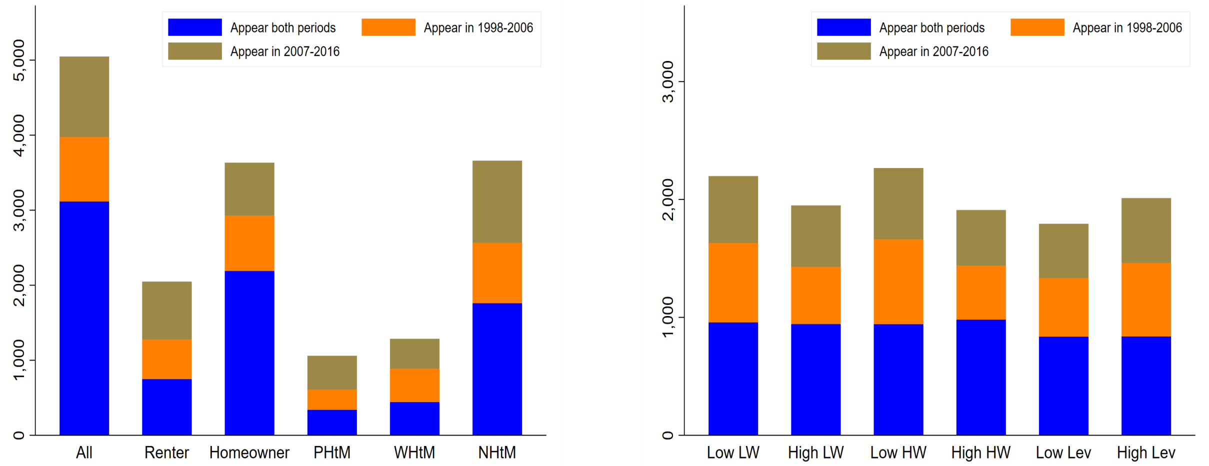

Figure B–1: Number of households in one or both subsample periods

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.

Figure B–1 suggest a lot of transitions, with only just over 50% of homeowners in each of the low liquid wealth, low housing wealth, and high leverage subgroups before the Great Recession remaining in that subgroup classification after the Great Recession.

For our analysis of time-varying MPCs, we classify households into groups based on their status before the Great Recession and do not consider households who only appear in a group after the Great Recession. 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 sample 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 period before 2007 who also remained in that same group in the period after 2007. Therefore, only the households in the blue bars in Figure B–1 are included in this robustness analysis.

C 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.

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

		All	Renters	Homeowners
			INCOME	
σ_η	1998-2006	0.12 (0.00)	0.12 (0.01)	0.12 (0.01)
	2007-2016	0.13 (0.00)	0.14 (0.01)	0.11 (0.00)
σ_ϵ	1998-2006	0.26 (0.00)	0.31 (0.01)	0.24 (0.00)
	2007-2016	0.26 (0.00)	0.32 (0.01)	0.22 (0.01)
			CONSUMPTION	
σ_u	1998-2006	0.08 (0.01)	0.08 (0.04)	0.08 (0.01)
	2007-2016	0.10 (0.00)	0.11 (0.01)	0.09 (0.00)
σ_v	1998-2006	0.26 (0.01)	0.34 (0.02)	0.21 (0.01)
	2007-2016	0.30 (0.00)	0.36 (0.01)	0.24 (0.00)
$\bar{\gamma}_\epsilon$		0.03 (0.01)	0.01 (0.01)	0.03 (0.03)
$\tilde{\gamma}_\epsilon$		0.11 (0.01)	0.12 (0.02)	0.11 (0.02)
γ_η		0.38 (0.03)	0.49 (0.00)	0.32 (0.03)
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.

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

		PHtM	WHtM	NHtM	HtM$_{nw}$
				INCOME	
σ_η	1998-2006	0.12 (0.02)	0.11 (0.01)	0.11 (0.01)	0.12 (0.01)
	2007-2016	0.15 (0.02)	0.09 (0.01)	0.11 (0.01)	0.13 (0.01)
σ_ϵ	1998-2006	0.34 (0.01)	0.26 (0.01)	0.24 (0.01)	0.29 (0.01)
	2007-2016	0.33 (0.01)	0.26 (0.01)	0.24 (0.01)	0.30 (0.01)
				CONSUMPTION	
σ_u	1998-2006	0.16 (0.06)	0.07 (0.04)	0.08 (0.01)	0.06 (0.04)
	2007-2016	0.13 (0.02)	0.10 (0.02)	0.10 (0.01)	0.10 (0.01)
σ_v	1998-2006	0.35 (0.04)	0.27 (0.02)	0.22 (0.01)	0.33 (0.02)
	2007-2016	0.34 (0.01)	0.26 (0.01)	0.27 (0.01)	0.34 (0.01)
$\bar{\gamma}_\epsilon$		0.00 (0.00)	0.03 (0.01)	0.03 (0.01)	0.00 (0.00)
$\tilde{\gamma}_\epsilon$		0.12 (0.03)	0.13 (0.03)	0.10 (0.02)	0.13 (0.03)
γ_η		0.46 (0.03)	0.47 (0.12)	0.34 (0.04)	0.48 (0.01)
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.

Table C–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	0.12 (0.01)	0.11 (0.01)	0.11 (0.01)	0.12 (0.01)	0.10 (0.01)	0.13 (0.01)
	2007-2016	0.10 (0.01)	0.11 (0.01)	0.11 (0.01)	0.11 (0.01)	0.09 (0.01)	0.12 (0.01)
σ_ϵ	1998-2006	0.24 (0.01)	0.24 (0.01)	0.22 (0.01)	0.25 (0.01)	0.22 (0.01)	0.25 (0.01)
	2007-2016	0.23 (0.01)	0.22 (0.01)	0.20 (0.01)	0.23 (0.01)	0.20 (0.01)	0.24 (0.01)
					CONSUMPTION		
σ_u	1998-2006	0.08 (0.01)	0.08 (0.01)	0.07 (0.01)	0.07 (0.01)	0.08 (0.01)	0.08 (0.01)
	2007-2016	0.10 (0.01)	0.09 (0.01)	0.08 (0.01)	0.09 (0.01)	0.08 (0.01)	0.10 (0.01)
σ_v	1998-2006	0.23 (0.01)	0.18 (0.01)	0.21 (0.01)	0.20 (0.01)	0.18 (0.01)	0.20 (0.01)
	2007-2016	0.25 (0.01)	0.23 (0.01)	0.26 (0.01)	0.23 (0.01)	0.22 (0.01)	0.25 (0.01)
$\bar{\gamma}_\epsilon$		0.02 (0.01)	0.03 (0.01)	0.02 (0.01)	0.02 (0.01)	0.03 (0.01)	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_η		0.30 (0.08)	0.27 (0.05)	0.39 (0.05)	0.27 (0.05)	0.34 (0.07)	0.22 (0.05)
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.

Table C–4: Full-sample estimates for lower wealth and higher leverage homeowners excluding HtM

		Low LW	Low HW	High Lev
			INCOME	
σ_η	1998-2006	0.12 (0.01)	0.10 (0.01)	0.09 (0.01)
	2007-2016	0.08 (0.01)	0.11 (0.01)	0.09 (0.01)
σ_ϵ	1998-2006	0.22 (0.01)	0.23 (0.01)	0.21 (0.01)
	2007-2016	0.21 (0.01)	0.18 (0.01)	0.19 (0.01)
			CONSUMPTION	
σ_u	1998-2006	0.08 (0.01)	0.07 (0.01)	0.08 (0.01)
	2007-2016	0.10 (0.01)	0.08 (0.01)	0.07 (0.01)
σ_v	1998-2006	0.21 (0.01)	0.21 (0.01)	0.17 (0.01)
	2007-2016	0.25 (0.01)	0.26 (0.01)	0.23 (0.01)
$\bar{\gamma}_\epsilon$		0.00 (0.03)	0.01 (0.02)	0.02 (0.01)
$\tilde{\gamma}_\epsilon$		0.25 (0.05)	0.13 (0.03)	0.12 (0.03)
γ_η		0.13 (0.09)	0.41 (0.06)	0.38 (0.07)
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 C–5: Time-varying estimates for all households and groups by homeownership status

		All	Renters	Homeowners
			INCOME	
σ_η	1998-2006	0.12 (0.00)	0.12 (0.01)	0.12 (0.00)
	2007-2016	0.12 (0.00)	0.13 (0.01)	0.10 (0.00)
σ_ϵ	1998-2006	0.26 (0.00)	0.31 (0.01)	0.24 (0.00)
	2007-2016	0.24 (0.00)	0.28 (0.01)	0.22 (0.00)
			CONSUMPTION	
σ_u	1998-2006	0.08 (0.01)	0.08 (0.04)	0.08 (0.01)
	2007-2016	0.10 (0.00)	0.10 (0.01)	0.09 (0.00)
σ_v	1998-2006	0.26 (0.01)	0.34 (0.02)	0.21 (0.01)
	2007-2016	0.28 (0.00)	0.33 (0.01)	0.24 (0.01)
$\bar{\gamma}_\epsilon$	1998-2006	0.03 (0.01)	0.02 (0.02)	0.03 (0.01)
	2007-2016	0.03 (0.01)	0.02 (0.02)	0.03 (0.01)
$\tilde{\gamma}_\epsilon$	1998-2006	0.09 (0.02)	0.10 (0.03)	0.08 (0.02)
	2007-2016	0.14 (0.02)	0.13 (0.04)	0.14 (0.02)
γ_η	1998-2006	0.36 (0.00)	0.49 (0.14)	0.31 (0.03)
	2007-2016	0.39 (0.02)	0.51 (0.00)	0.32 (0.03)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,1998\text{-}2006}=\tilde{\gamma}_{\epsilon,2007\text{-}2016}}$		5.88	0.44	5.82
N		3,977	1,278	2,930

Notes: The table reports estimates of all model parameters, with standard errors in parentheses. A Wald statistic for a test of parameter stability with a 5% critical value of 3.84 based on a $\chi^2(1)$ distribution under the null hypothesis $H_0 : \tilde{\gamma}_{\epsilon\ 1998\text{-}2006} = \tilde{\gamma}_{\epsilon\ 2007\text{-}2016}$ is also reported. These results are for the time-varying analysis also reported in Table 4.

Table C–6: Time-varying estimates for groups by HtM status

		PHtM	WHtM	NHtM
			INCOME	
σ_η	1998-2006	0.12 (0.02)	0.11 (0.01)	0.11 (0.01)
	2007-2016	0.14 (0.02)	0.07 (0.01)	0.11 (0.00)
σ_ϵ	1998-2006	0.34 (0.01)	0.26 (0.01)	0.24 (0.01)
	2007-2016	0.31 (0.02)	0.27 (0.01)	0.23 (0.01)
			CONSUMPTION	
σ_u	1998-2006	0.16 (0.06)	0.07 (0.04)	0.08 (0.01)
	2007-2016	0.12 (0.02)	0.10 (0.02)	0.10 (0.00)
σ_v	1998-2006	0.35 (0.04)	0.27 (0.02)	0.22 (0.01)
	2007-2016	0.31 (0.02)	0.24 (0.02)	0.24 (0.01)
$\bar{\gamma}_\epsilon$	1998-2006	0.01 (0.03)	0.04 (0.02)	0.04 (0.01)
	2007-2016	0.01 (0.03)	0.03 (0.03)	0.04 (0.01)
$\tilde{\gamma}_\epsilon$	1998-2006	0.07 (0.06)	0.09 (0.04)	0.09 (0.02)
	2007-2016	0.08 (0.07)	0.13 (0.05)	0.12 (0.03)
γ_η	1998-2006	0.66 (0.14)	0.47 (0.04)	0.30 (0.04)
	2007-2016	0.59 (0.12)	0.50 (0.00)	0.33 (0.04)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,1998\text{-}2006}=\tilde{\gamma}_{\epsilon,2007\text{-}2016}}$		0.01	0.58	1.13
N		612	890	2,566

Notes: The table reports estimates of all model parameters, with standard errors in parentheses. A Wald statistic for a test of parameter stability with a 5% critical value of 3.84 based on a $\chi^2(1)$ distribution under the null hypothesis $H_0 : \tilde{\gamma}_{\epsilon\ 1998\text{-}2006} = \tilde{\gamma}_{\epsilon\ 2007\text{-}2016}$ is also reported. These results are for the time-varying analysis also reported in Table 4.

Table C–7: Time-varying estimates for subgroups of homeowners

		Low LW	High LW	Low HW	High HW	High Lev.	Low Lev.
					INCOME		
σ_η	1998-2006	0.12 (0.01)	0.12 (0.01)	0.11 (0.01)	0.12 (0.01)	0.10 (0.01)	0.13 (0.01)
	2007-2016	0.09 (0.01)	0.10 (0.01)	0.10 (0.01)	0.11 (0.01)	0.08 (0.01)	0.11 (0.01)
σ_ϵ	1998-2006	0.24 (0.01)	0.23 (0.01)	0.22 (0.01)	0.24 (0.01)	0.22 (0.01)	0.25 (0.01)
	2007-2016	0.23 (0.01)	0.22 (0.01)	0.21 (0.01)	0.23 (0.01)	0.20 (0.01)	0.25 (0.01)
					CONSUMPTION		
σ_u	1998-2006	0.08 (0.01)	0.08 (0.01)	0.07 (0.01)	0.07 (0.01)	0.08 (0.01)	0.08 (0.01)
	2007-2016	0.09 (0.01)	0.10 (0.01)	0.08 (0.01)	0.09 (0.01)	0.08 (0.01)	0.10 (0.01)
σ_v	1998-2006	0.23 (0.01)	0.18 (0.01)	0.21 (0.01)	0.20 (0.01)	0.18 (0.01)	0.20 (0.01)
	2007-2016	0.25 (0.01)	0.21 (0.01)	0.26 (0.01)	0.22 (0.01)	0.20 (0.01)	0.23 (0.01)
$\bar{\gamma}_\epsilon$	1998-2006	0.02 (0.02)	0.02 (0.02)	0.03 (0.02)	0.01 (0.03)	0.04 (0.02)	0.01 (0.02)
	2007-2016	0.02 (0.02)	0.02 (0.02)	0.03 (0.02)	0.01 (0.03)	0.04 (0.02)	0.01 (0.02)
$\tilde{\gamma}_\epsilon$	1998-2006	0.13 (0.03)	0.08 (0.03)	0.12 (0.03)	0.08 (0.03)	0.12 (0.03)	0.10 (0.03)
	2007-2016	0.26 (0.04)	0.12 (0.04)	0.13 (0.05)	0.12 (0.04)	0.17 (0.04)	0.12 (0.04)
γ_η	1998-2006	0.29 (0.05)	0.25 (0.05)	0.41 (0.08)	0.26 (0.04)	0.28 (0.07)	0.23 (0.05)
	2007-2016	0.33 (0.05)	0.25 (0.05)	0.40 (0.07)	0.28 (0.04)	0.31 (0.07)	0.23 (0.05)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,1998\text{-}2006}=\tilde{\gamma}_{\epsilon,2007\text{-}2016}}$		12.45	1.14	0.06	1.01	1.70	0.50
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. A Wald statistic for a test of parameter stability with a 5% critical value of 3.84 based on a $\chi^2(1)$ distribution under the null hypothesis $H_0 : \tilde{\gamma}_{\epsilon\ 1998\text{-}2006} = \tilde{\gamma}_{\epsilon\ 2007\text{-}2016}$ is also reported. These results are for the time-varying analysis also reported in Table 4.

Table C–8: Time-varying estimates (1998-2006) and (2007-2012) for all households and groups by homeownership status

		All	Renters	Homeowners
			INCOME	
σ_η	1998-2006	0.12 (0.00)	0.12 (0.01)	0.12 (0.01)
	2007-2012	0.13 (0.01)	0.15 (0.01)	0.11 (0.01)
σ_ϵ	1998-2006	0.26 (0.00)	0.31 (0.01)	0.24 (0.00)
	2007-2012	0.25 (0.01)	0.28 (0.01)	0.22 (0.01)
			CONSUMPTION	
σ_u	1998-2006	0.08 (0.01)	0.09 (0.04)	0.08 (0.01)
	2007-2012	0.10 (0.01)	0.10 (0.02)	0.09 (0.00)
σ_v	1998-2006	0.26 (0.01)	0.34 (0.02)	0.21 (0.01)
	2007-2012	0.25 (0.01)	0.31 (0.02)	0.21 (0.01)
$\bar{\gamma}_\epsilon$	1998-2006	0.04 (0.01)	0.03 (0.02)	0.04 (0.01)
	2007-2012	0.04 (0.01)	0.03 (0.02)	0.04 (0.01)
$\tilde{\gamma}_\epsilon$	1998-2006	0.09 (0.02)	0.09 (0.04)	0.08 (0.02)
	2007-2012	0.15 (0.02)	0.12 (0.05)	0.14 (0.03)
γ_η	1998-2006	0.34 (0.03)	0.48 (0.10)	0.28 (0.03)
	2007-2012	0.36 (0.03)	0.49 (0.03)	0.29 (0.03)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,1998\text{-}2006}=\tilde{\gamma}_{\epsilon,2007\text{-}2012}}$		5.88	0.32	4.15
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 with a 5% critical value of 3.84 based on a $\chi^2(1)$ distribution under the null hypothesis $H_0 : \tilde{\gamma}_{\epsilon\ 1998\text{-}2006} = \tilde{\gamma}_{\epsilon\ 2007\text{-}2012}$ is also reported. These results are for a time-varying analysis using the same group classification as in Table 4, however the second subsample period ends in 2012 instead of 2016 as a robustness check.

Table C–9: Time-varying estimates (1998-2006) and (2007-2012) for groups by HtM status

		PHtM	WHtM	NHtM
			INCOME	
σ_η	1998-2006	0.13 (0.02)	0.11 (0.01)	0.11 (0.01)
	2007-2012	0.15 (0.02)	0.10 (0.02)	0.10 (0.01)
σ_ϵ	1998-2006	0.34 (0.02)	0.26 (0.01)	0.24 (0.01)
	2007-2012	0.32 (0.02)	0.27 (0.02)	0.23 (0.01)
			CONSUMPTION	
σ_u	1998-2006	0.16 (0.07)	0.07 (0.04)	0.08 (0.01)
	2007-2012	0.11 (0.04)	0.09 (0.02)	0.10 (0.01)
σ_v	1998-2006	0.35 (0.02)	0.27 (0.02)	0.22 (0.01)
	2007-2012	0.30 (0.02)	0.23 (0.02)	0.21 (0.01)
$\bar{\gamma}_\epsilon$	1998-2006	0.00 (0.08)	0.04 (0.05)	0.04 (0.02)
	2007-2012	0.01 (0.09)	0.04 (0.05)	0.04 (0.02)
$\tilde{\gamma}_\epsilon$	1998-2006	0.09 (0.05)	0.09 (0.05)	0.10 (0.02)
	2007-2012	0.17 (0.07)	0.09 (0.07)	0.13 (0.03)
γ_η	1998-2006	0.55 (0.11)	0.47 (0.08)	0.24 (0.05)
	2007-2012	0.48 (0.11)	0.49 (0.03)	0.27 (0.05)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,1998\text{-}2006}=\tilde{\gamma}_{\epsilon,2007\text{-}2012}}$		1.31	0.00	0.53
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 with a 5% critical value of 3.84 based on a $\chi^2(1)$ distribution under the null hypothesis $H_0 : \tilde{\gamma}_{\epsilon}$ 1998-2006 $= \tilde{\gamma}_{\epsilon}$ 2007-2012 is also reported. These results are for a time-varying analysis using the same group classification as in Table 4, however the second subsample period ends in 2012 instead of 2016 as a robustness check.

Table C–10: 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	0.12 (0.01)	0.12 (0.01)	0.11 (0.01)	0.12 (0.01)	0.10 (0.01)	0.13 (0.01)
	2007-2012	0.11 (0.01)	0.10 (0.01)	0.12 (0.01)	0.11 (0.01)	0.09 (0.01)	0.10 (0.01)
σ_ϵ	1998-2006	0.23 (0.01)	0.24 (0.01)	0.22 (0.01)	0.24(0.01)	0.22 (0.01)	0.25 (0.01)
	2007-2012	0.22 (0.01)	0.23 (0.01)	0.20 (0.01)	0.25 (0.01)	0.20 (0.01)	0.26 (0.01)
				CONSUMPTION			
σ_u	1998-2006	0.08 (0.01)	0.08 (0.01)	0.07 (0.01)	0.07(0.01)	0.08 (0.01)	0.08 (0.01)
	2007-2012	0.09 (0.01)	0.10 (0.01)	0.07 (0.01)	0.10 (0.01)	0.06 (0.01)	0.10 (0.01)
σ_v	1998-2006	0.23 (0.01)	0.18 (0.01)	0.21 (0.01)	0.20 (0.01)	0.18 (0.01)	0.20 (0.01)
	2007-2012	0.23 (0.01)	0.17 (0.01)	0.23 (0.01)	0.19 (0.01)	0.19 (0.01)	0.20 (0.01)
$\bar{\gamma}_\epsilon$	1998-2006	0.03 (0.02)	0.02 (0.02)	0.04 (0.02)	0.02 (0.02)	0.04 (0.02)	0.03 (0.02)
	2007-2012	0.03 (0.02)	0.02 (0.02)	0.04 (0.02)	0.02 (0.02)	0.04 (0.02)	0.03 (0.02)
$\tilde{\gamma}_\epsilon$	1998-2006	0.12 (0.03)	0.10 (0.03)	0.12 (0.03)	0.08 (0.02)	0.11 (0.03)	0.11 (0.03)
	2007-2012	0.22 (0.05)	0.13 (0.04)	0.09 (0.06)	0.11 (0.04)	0.13 (0.05)	0.12 (0.04)
γ_η	1998-2006	0.30 (0.06)	0.19 (0.06)	0.38 (0.07)	0.23 (0.05)	0.33 (0.05)	0.15 (0.05)
	2007-2012	0.33 (0.06)	0.19 (0.06)	0.37 (0.07)	0.24 (0.05)	0.36 (0.05)	0.16 (0.06)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,1998\text{-}2006}=\tilde{\gamma}_{\epsilon,2007\text{-}2012}}$		4.10	0.17	0.17	0.60	0.17	0.01
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 with a 5% critical value of 3.84 based on a $\chi^2(1)$ distribution under the null hypothesis $H_0 : \tilde{\gamma}_{\epsilon\ 1998\text{-}2006} = \tilde{\gamma}_{\epsilon\ 2007\text{-}2012}$ is also reported. These results are for a time-varying analysis using the same group classification as in Table 4, however the second subsample period ends in 2012 instead of 2016 as a robustness check.

Table C–11: Time-varying estimates for all households allowing for a structural break every two waves

		All
		INCOME
σ_η	1998-2000	0.13 (0.01)
	2001-2004	0.13 (0.01)
	2005-2008	0.12 (0.01)
	2009-2012	0.11 (0.01)
	2013-2016	0.13 (0.01)
σ_ϵ	1998-2000	0.25 (0.01)
	2001-2004	0.26 (0.01)
	2005-2008	0.26 (0.01)
	2009-2012	0.25 (0.01)
	2013-2016	0.22 (0.01)
		CONSUMPTION
σ_u	1998-2000	0.10 (0.02)
	2001-2004	0.09 (0.01)
	2005-2008	0.06 (0.02)
	2009-2012	0.10 (0.01)
	2013-2016	0.13 (0.01)
σ_v	1998-2000	0.24 (0.01)
	2001-2004	0.25 (0.01)
	2005-2008	0.26 (0.01)
	2009-2012	0.26 (0.01)
	2013-2016	0.32 (0.01)
$\bar{\gamma}_\epsilon$	1998-2000	0.03 (0.01)
	2001-2004	0.04 (0.01)
	2005-2008	0.03 (0.01)
	2009-2012	0.03 (0.01)
	2013-2016	0.03 (0.01)
$\tilde{\gamma}_\epsilon$	1998-2000	0.09 (0.03)
	2001-2004	0.09 (0.02)
	2005-2008	0.13 (0.02)
	2009-2012	0.13 (0.03)
	2013-2016	0.15 (0.05)
γ_η	1998-2000	0.28 (0.02)
	2001-2004	0.36 (0.02)
	2005-2008	0.39 (0.02)
	2009-2012	0.39 (0.02)
	2013-2016	0.39 (0.03)
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 C–12: Time-varying estimates excluding (imputed) rent for all households and groups by homeownership status

		All	Renters	Homeowners
			INCOME	
σ_η	1998-2006	0.12 (0.00)	0.12 (0.01)	0.12 (0.01)
	2007-2016	0.12 (0.00)	0.13 (0.01)	0.10 (0.00)
σ_ϵ	1998-2006	0.26 (0.00)	0.31 (0.01)	0.24 (0.00)
	2007-2016	0.24 (0.00)	0.28 (0.01)	0.22 (0.00)
			CONSUMPTION	
σ_u	1998-2006	0.09 (0.01)	0.10 (0.05)	0.09 (0.01)
	2007-2016	0.12 (0.00)	0.14 (0.01)	0.12 (0.01)
σ_v	1998-2006	0.33 (0.01)	0.42 (0.02)	0.29 (0.01)
	2007-2016	0.36 (0.01)	0.41 (0.01)	0.32 (0.01)
$\bar{\gamma}_\epsilon$	1998-2006	0.02 (0.01)	0.02 (0.02)	0.00 (0.07)
	2007-2016	0.02 (0.01)	0.02 (0.02)	0.00 (0.07)
$\tilde{\gamma}_\epsilon$	1998-2006	0.13 (0.02)	0.16 (0.03)	0.11 (0.04)
	2007-2016	0.17 (0.03)	0.13 (0.04)	0.18 (0.04)
γ_η	1998-2006	0.30 (0.03)	0.45 (0.03)	0.24 (0.04)
	2007-2016	0.34 (0.03)	0.51 (0.01)	0.27 (0.04)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{1998-2006}}=\tilde{\gamma}_{\epsilon,\text{2007-2016}}}$		3.13	0.34	2.46
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 with a 5% critical value of 3.84 based on a $\chi^2(1)$ distribution under the null hypothesis $H_0 : \tilde{\gamma}_{\epsilon\ \text{1998-2006}} = \tilde{\gamma}_{\epsilon\ \text{2007-2016}}$ is also reported. 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 C–13: Time-varying estimates excluding (imputed) rent for groups by HtM status

		PHtM	WHtM	NHtM
			INCOME	
σ_η	1998-2006	0.12 (0.02)	0.11 (0.01)	0.11 (0.01)
	2007-2016	0.14 (0.02)	0.08 (0.02)	0.11 (0.00)
σ_ϵ	1998-2006	0.34 (0.01)	0.26 (0.01)	0.24 (0.01)
	2007-2016	0.31 (0.02)	0.27 (0.02)	0.23 (0.01)
			CONSUMPTION	
σ_u	1998-2006	0.22 (0.07)	0.08 (0.04)	0.09 (0.01)
	2007-2016	0.14 (0.03)	0.11 (0.02)	0.12 (0.01)
σ_v	1998-2006	0.40 (0.04)	0.37 (0.04)	0.28 (0.01)
	2007-2016	0.41 (0.02)	0.32 (0.02)	0.32 (0.01)
$\bar{\gamma}_\epsilon$	1998-2006	0.01 (0.03)	0.03 (0.02)	0.02 (0.02)
	2007-2016	0.01 (0.03)	0.03 (0.02)	0.02 (0.02)
$\tilde{\gamma}_\epsilon$	1998-2006	0.14 (0.05)	0.12 (0.05)	0.12 (0.02)
	2007-2016	0.02 (0.09)	0.15 (0.07)	0.16 (0.04)
γ_η	1998-2006	0.64 (0.08)	0.41 (0.07)	0.24 (0.04)
	2007-2016	0.65 (0.09)	0.41 (0.07)	0.27 (0.04)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,1998\text{-}2006}=\tilde{\gamma}_{\epsilon,2007\text{-}2016}}$		1.86	0.17	1.26
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 with a 5% critical value of 3.84 based on a $\chi^2(1)$ distribution under the null hypothesis $H_0 : \tilde{\gamma}_{\epsilon}$ 1998-2006 $= \tilde{\gamma}_{\epsilon}$ 2007-2016 is also reported. 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 C–14: 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	0.12 (0.01)	0.12 (0.01)	0.11 (0.01)	0.12 (0.01)	0.10 (0.01)	0.13 (0.01)
	2007-2012	0.09 (0.01)	0.10 (0.01)	0.10 (0.01)	0.11 (0.01)	0.08 (0.01)	0.11 (0.01)
σ_ϵ	1998-2006	0.24 (0.01)	0.24 (0.01)	0.22 (0.01)	0.24 (0.01)	0.22 (0.01)	0.25 (0.01)
	2007-2012	0.23 (0.01)	0.22 (0.01)	0.21 (0.01)	0.24 (0.01)	0.20 (0.01)	0.25 (0.01)
					CONSUMPTION		
σ_u	1998-2006	0.08 (0.02)	0.09 (0.01)	0.08 (0.02)	0.09 (0.01)	0.09 (0.01)	0.10 (0.01)
	2007-2012	0.11 (0.01)	0.12 (0.01)	0.10 (0.01)	0.12 (0.01)	0.09 (0.01)	0.13 (0.01)
σ_v	1998-2006	0.32 (0.02)	0.26 (0.01)	0.27 (0.01)	0.30 (0.02)	0.26 (0.01)	0.29 (0.02)
	2007-2012	0.32 (0.01)	0.30 (0.01)	0.32 (0.01)	0.33 (0.01)	0.29 (0.01)	0.32 (0.01)
$\bar{\gamma}_\epsilon$	1998-2006	0.01 (0.01)	0.00 (0.01)	0.02 (0.04)	0.00 (0.00)	0.03 (0.02)	0.00 (0.05)
	2007-2012	0.01 (0.01)	0.00 (0.01)	0.02 (0.04)	0.00 (0.00)	0.03 (0.02)	0.00 (0.05)
$\tilde{\gamma}_\epsilon$	1998-2006	0.16 (0.03)	0.10 (0.03)	0.14 (0.05)	0.10 (0.03)	0.15 (0.04)	0.11 (0.04)
	2007-2012	0.30 (0.05)	0.17 (0.05)	0.17 (0.07)	0.14 (0.04)	0.21 (0.05)	0.16 (0.05)
γ_η	1998-2006	0.27 (0.06)	0.13 (0.06)	0.35 (0.08)	0.18 (0.06)	0.18 (0.09)	0.17 (0.05)
	2007-2012	0.31 (0.06)	0.16 (0.06)	0.34 (0.08)	0.22 (0.06)	0.24 (0.09)	0.18 (0.05)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,1998\text{-}2006}=\tilde{\gamma}_{\epsilon,2007\text{-}2016}}$		8.59	2.34	0.23	0.85	0.95	1.38
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 with a 5% critical value of 3.84 based on a $\chi^2(1)$ distribution under the null hypothesis $H_0 : \tilde{\gamma}_\epsilon$ 1998-2006 $= \tilde{\gamma}_\epsilon$ 2007-2016 is also reported. 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 imputed rent as a robustness check.

Table C–15: Time-varying estimates for miscellaneous subgroups of homeowners

		Low LW w/o HtM	Low LW w/o High Lev	High Lev. w/o Low LW	High DtA	Low DtA
				INCOME		
σ_η	1998-2006	0.12 (0.01)	0.15 (0.02)	0.10 (0.02)	0.11 (0.01)	0.12 (0.01)
	2007-2016	0.09 (0.01)	0.11 (0.02)	0.08 (0.02)	0.11 (0.01)	0.11 (0.01)
σ_ϵ	1998-2006	0.23 (0.01)	0.26 (0.01)	0.19 (0.02)	0.21 (0.01)	0.25 (0.01)
	2007-2016	0.19 (0.02)	0.23 (0.02)	0.20 (0.03)	0.19 (0.01)	0.25 (0.01)
				CONSUMPTION		
σ_u	1998-2006	0.09 (0.01)	0.10 (0.02)	0.09 (0.02)	0.08 (0.01)	0.08 (0.01)
	2007-2016	0.08 (0.02)	0.11 (0.02)	0.06 (0.01)	0.09 (0.01)	0.10 (0.01)
σ_v	1998-2006	0.21 (0.01)	0.26 (0.02)	0.14 (0.01)	0.19 (0.01)	0.20 (0.01)
	2007-2016	0.24 (0.02)	0.29 (0.02)	0.20 (0.01)	0.22 (0.01)	024 (0.01)
$\bar{\gamma}_\epsilon$	1998-2006	0.00 (0.07)	0.02 (0.02)	0.01 (0.04)	0.03 (0.02)	0.00 (0.00)
	2007-2016	0.00 (0.07)	0.02 (0.02)	0.01 (0.04)	0.03 (0.02)	0.00 (0.00)
$\tilde{\gamma}_\epsilon$	1998-2006	0.14 (0.07)	0.14 (0.07)	0.13 (0.06)	0.14 (0.03)	0.11 (0.02)
	2007-2016	0.39 (0.10)	0.25 (0.10)	0.07 (0.08)	0.13 (0.05)	0.15 (0.03)
γ_η	1998-2006	0.22 (0.10)	0.22 (0.12)	0.39 (0.10)	0.29 (0.07)	0.23 (0.05)
	2007-2016	0.30 (0.11)	0.23 (0.12)	0.37 (0.10)	0.31 (0.07)	0.25 (0.05)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,1998\text{-}2006}=\tilde{\gamma}_{\epsilon,2007\text{-}2016}}$		7.00	1.26	0.55	0.04	1.87
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 with a 5% critical value of 3.84 based on a $\chi^2(1)$ distribution under the null hypothesis $H_0 : \tilde{\gamma}_{\epsilon\ 1998\text{-}2006} = \tilde{\gamma}_{\epsilon\ 2007\text{-}2016}$ is also reported. 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 HtM households, respectively. Column 5 reports the estimates for higher 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 C–16: Time-varying estimates for all household and groups by homeownership status using an alternative sample selection

		All	Renters	Homeowners
			INCOME	
σ_η	1998-2006	0.12 (0.00)	0.12 (0.01)	0.12 (0.01)
	2007-2016	0.12 (0.00)	0.13 (0.01)	0.11 (0.00)
σ_ϵ	1998-2006	0.26 (0.00)	0.33 (0.01)	0.23 (0.00)
	2007-2016	0.24 (0.00)	0.28 (0.01)	0.22 (0.00)
			CONSUMPTION	
σ_u	1998-2006	0.08 (0.01)	0.06 (0.04)	0.08 (0.01)
	2007-2016	0.10 (0.00)	0.11 (0.01)	0.09 (0.00)
σ_v	1998-2006	0.25 (0.01)	0.33 (0.02)	0.20 (0.01)
	2007-2016	0.28 (0.00)	0.33 (0.01)	0.24 (0.00)
$\bar{\gamma}_\epsilon$	1998-2006	0.03 (0.01)	0.04 (0.02)	0.03 (0.01)
	2007-2016	0.03 (0.01)	0.03 (0.02)	0.03 (0.01)
$\tilde{\gamma}_\epsilon$	1998-2006	0.10 (0.02)	0.12 (0.04)	0.09 (0.02)
	2007-2016	0.14 (0.02)	0.13 (0.04)	0.14 (0.02)
γ_η	1998-2006	0.35 (0.03)	0.45 (0.04)	0.30 (0.03)
	2007-2016	0.38 (0.02)	0.47 (0.03)	0.32 (0.03)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,\text{1998-2006}}=\tilde{\gamma}_{\epsilon,\text{2007-2016}}}$		3.66	0.08	3.72
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 with a 5% critical value of 3.84 based on a $\chi^2(1)$ distribution under the null hypothesis $H_0 : \tilde{\gamma}_\epsilon$ 1998-2006 $= \tilde{\gamma}_\epsilon$ 2007-2016 is also reported. These results are for a time-varying analysis using an alternative sample selection described in Appendix B as a robustness check.

Table C–17: Time-varying estimates for groups by HtM status using an alternative sample selection

		PHtM	WHtM	NHtM
			INCOME	
σ_η	1998-2006	0.12 (0.02)	0.11 (0.01)	0.11 (0.01)
	2007-2016	0.14 (0.02)	0.08 (0.02)	0.11 (0.00)
σ_ϵ	1998-2006	0.35 (0.02)	0.25 (0.01)	0.24 (0.01)
	2007-2016	0.31 (0.02)	0.27 (0.02)	0.22 (0.02)
			CONSUMPTION	
σ_u	1998-2006	0.03 (0.09)	0.06 (0.05)	0.08 (0.01)
	2007-2016	0.13 (0.02)	0.10 (0.02)	0.10 (0.00)
σ_v	1998-2006	0.37 (0.03)	0.29 (0.04)	0.21 (0.01)
	2007-2016	0.31 (0.02)	0.24 (0.02)	0.24 (0.01)
$\bar{\gamma}_\epsilon$	1998-2006	0.01 (0.03)	0.04 (0.03)	0.04 (0.02)
	2007-2016	0.02 (0.03)	0.04 (0.03)	0.04 (0.02)
$\tilde{\gamma}_\epsilon$	1998-2006	0.11 (0.07)	0.08 (0.06)	0.08 (0.03)
	2007-2016	0.09 (0.07)	0.12 (0.05)	0.12 (0.03)
γ_η	1998-2006	0.61 (0.15)	0.46 (0.03)	0.30 (0.04)
	2007-2016	0.55 (0.04)	0.49 (0.01)	0.33 (0.04)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,1998\text{-}2006}=\tilde{\gamma}_{\epsilon,2007\text{-}2016}}$		0.16	0.45	1.31
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 with a 5% critical value of 3.84 based on a $\chi^2(1)$ distribution under the null hypothesis $H_0 : \tilde{\gamma}_{\epsilon\ 1998\text{-}2006} = \tilde{\gamma}_{\epsilon\ 2007\text{-}2016}$ is also reported. These results are for a time-varying analysis using an alternative sample selection described in Appendix B as a robustness check.

Table C–18: 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	0.11 (0.01)	0.12 (0.01)	0.10 (0.01)	0.12 (0.01)	0.09 (0.01)	0.13 (0.01)
	2007-2016	0.09 (0.01)	0.10 (0.01)	0.10 (0.01)	0.11 (0.01)	0.08 (0.01)	0.11 (0.01)
σ_ϵ	1998-2006	0.23 (0.01)	0.23 (0.01)	0.22 (0.01)	0.23 (0.01)	0.20 (0.01)	0.25 (0.01)
	2007-2016	0.23 (0.01)	0.22 (0.01)	0.21 (0.01)	0.24 (0.01)	0.20 (0.01)	0.25 (0.01)
				CONSUMPTION			
σ_u	1998-2006	0.07 (0.01)	0.08 (0.01)	0.07 (0.02)	0.07 (0.01)	0.07 (0.01)	0.08 (0.01)
	2007-2016	0.09 (0.01)	0.10 (0.01)	0.08 (0.01)	0.09 (0.01)	0.08 (0.01)	0.10 (0.01)
σ_v	1998-2006	0.23 (0.02)	0.18 (0.01)	0.21 (0.01)	0.19 (0.02)	0.17 (0.01)	0.20 (0.01)
	2007-2016	0.25 (0.01)	0.221 (0.01)	0.26 (0.01)	0.22 (0.01)	0.20 (0.01)	0.23 (0.01)
$\bar{\gamma}_\epsilon$	1998-2006	0.02 (0.03)	0.01 (0.02)	0.03 (0.02)	0.01 (0.02)	0.06 (0.02)	0.01 (0.02)
	2007-2016	0.02 (0.03)	0.01 (0.02)	0.03 (0.02)	0.01 (0.02)	0.06 (0.02)	0.01 (0.02)
$\tilde{\gamma}_\epsilon$	1998-2006	0.12 (0.04)	0.10 (0.03)	0.10 (0.03)	0.10 (0.03)	0.13 (0.04)	0.12 (0.03)
	2007-2016	0.25 (0.04)	0.12 (0.03)	0.12 (0.03)	0.12 (0.03)	0.16 (0.05)	0.13 (0.04)
γ_η	1998-2006	0.32 (0.06)	0.22 (0.06)	0.41 (0.08)	0.25 (0.05)	0.29 (0.08)	0.22 (0.05)
	2007-2016	0.36 (0.06)	0.23 (0.06)	0.40 (0.07)	0.26 (0.05)	0.31 (0.08)	0.23 (0.05)
$\text{Wald}_{H_0:\tilde{\gamma}_{\epsilon,1998\text{-}2006}=\tilde{\gamma}_{\epsilon,2007\text{-}2016}}$		9.60	0.36	0.13	0.38	0.36	0.06
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 with a 5% critical value of 3.84 based on a $\chi^2(1)$ distribution under the null hypothesis $H_0 : \tilde{\gamma}_{\epsilon}$ 1998-2006 $= \tilde{\gamma}_{\epsilon}$ 2007-2016 is also reported. These results are for a time-varying analysis using an alternative sample selection described in Appendix B as a robustness check.