Who Are the Hand-to-Mouth?*

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May 30, 2023

Abstract

Many households hold little wealth. In standard precautionary savings models these households should not only display higher marginal propensities to consume (MPCs), but also higher future consumption growth. In contrast, we see from the PSID that such "hand-to-mouth" households do *not* display higher growth in spending. They also exhibit greater volatility of spending and adjust their spending to a greater extent through the number of categories consumed. Consistent with a role for preference heterogeneity, the panel data show that it is persistent differences across households, not current assets, that predict low consumption growth and other spending differences for the hand-to-mouth households. To identify the extent of preference heterogeneity, we consider the model of Kaplan and Violante (2014) with both liquid and illiquid assets, but allow heterogeneity in preferences. To match the data, many poor hand-to-mouth must be relatively impatient and have a high inter-temporal elasticity of substitution (IES). The model shows that preferences predominantly explain the higher MPCs for low-asset households. Preference heterogeneity notably increases the spending impact of fiscal transfers, but only if targeted, while reducing that from interest rate cuts.

*We thank Nataliya Gimpelson, Stephan Gordeev, Man Chon Iao, Federico Kochen, and Paulo Lins for excellent research assistance on this project. We also thank Martin Blomhoff Holm, Greg Kaplan, Matthew Knowles, Gianluca Violante, and Ivan Werning for their helpful comments.

1 Introduction

Many households hold little wealth. These ostensibly "hand-to-mouth" households are often estimated to exhibit larger marginal propensities to consume (MPCs).[1] For that reason, these households feature prominently in discussions of tax and transfer schemes to boost aggregate output.[2] To the extent that macro-policy relies on "getting the micro foundations right," it is crucial to answer why households hold so few assets, especially since their implied MPCs may hinge on that answer.

We document new facts on the spending behavior of hand-to-mouth (or $H2M$ for short) households from the Panel Study of Income Dynamics (PSID). These facts contradict predictions of the standard savings model unless households differ in their long-run targeted assets-to-income. They also point to a role of preference heterogeneity, rather than differences in income processes, to explain that heterogeneity in savings targets. Exploiting the panel dimension of the PSID, we use household fixed effects to capture long-run heterogeneity. Adding fixed effects helps bridge the gap between the standard model and the data. Motivated by these findings, we then calibrate a structural model so as to capture the extent of preference heterogeneity suggestd by the data. While that calibrated preference heterogeneity is fairly modest, we find it markedly increases the spending impact of a fiscal transfer targeted by wealth, while reducing that from a temporary interest rate cut.

The core paradigm of both the micro and macro literatures, and our starting point, is the precautionary saving model in which consumers self-insure by saving in a non-contingent asset subject to a borrowing constraint.[3] This model predicts that: (i) the MPC is strictly decreasing in wealth, and (ii) expected consumption growth is also decreasing in wealth, as low-wealth agents are either constrained or in the process of building up their buffer stock of savings. Guided by these predictions, we explore the spending behavior of households in the PSID. Following Zeldes (1989), we treat households with little net worth relative to labor earnings as empirical analogues to the model's low-wealth agents that are potentially "hand-to-mouth." Higher net worth households with negligible liquid assets, referred to by

[1] To that point, Havranek and Sokolova (2020) conduct a meta analysis of more than 100 studies estimating household MPCs. They identify a higher MPC for households classified as lower wealth or liquidity as the most robust finding across studies.

[2] Many papers model low-asset households as responding more to fiscal policies. Recent examples include Kaplan and Violante (2014), Jappelli and Pistaferri (2014), Farhi and Werning (2017), McKay and Reis (2016), Carroll, Slacalek, Tokuoka and White (2017), Kaplan, Moll and Violante (2018), and Auclert (2019). Many of these authors also make clear that the hand-to-mouth will display less direct inter-temporal substitution response to interest rates, though they may respond more via indirect channels, such as the income and wealth effects, resulting from interest rate changes (e.g., Auclert, 2019, Kaplan et al., 2018).

[3] Just a few of the many papers in this vein are Schechtman and Escudero (1977), Imrohoroglu (1989), Deaton (1991), Carroll (1992), Huggett (1993), Aiyagari (1994) and Krueger, Mitman and Perri (2016).

Kaplan, Violante and Weidner (2014) as the "wealthy hand-to-mouth," are an alternative group of interest. We label 40 percent of households as hand-to-mouth based on either low net worth or low liquid wealth.

From the PSID we document four new facts on the behavior of $H2M$ households. The first is that some households tend to be persistently hand-to-mouth. As one example, those households observed in year t to be hand-to-mouth based on net worth are more than ten times as likely to have that status in year $t+2$ than are those households that are not hand-to-mouth, based on wealth or liquidity, in t. Even by year $t+4$, these relative probabilities differ by a factor of nearly ten. These patterns reflect that households differ considerably in their tendency toward low wealth, possibly due to drawing specific sequences of shocks, but also possibly due to targeting diffening amounts of assets.

Our second fact is that consumption growth is not higher for $H2M$ households. The standard savings model exhibits a tight relationship between MPC and consumption growth. A financially-constrained household exhibits a high MPC because marginal utility is high relative to its expected future value. But, absent preference heterogeneity, that requires such households to expect higher future consumption. Our PSID panel follows households for up to twenty-one years, allowing us to control for household fixed effects as well as current $H2M$-status. Controlling for fixed effects, being currently $H2M$ does predict considerably higher consumption growth, 4% higher for the next two years for those $H2M$ by net wealth. But that effect is masked because households that are often hand-to-mouth *average* lower spending growth. A natural interpretation is that, beyond shocks, households exhibit heterogeneity in their targeted assets, with households targeting low assets displaying low consumption growth while frequently observed $H2M$.

One reason that $H2M$ households *might* target fewer assets is if they differ in their income process. For instance, if their income profiles are steeper they will hold less life-cycle savings, and if their income and consumption are more predictable they will hold less precautionary savings. But households that are often hand-to-mouth in the PSID display slower income growth. Moreover, these households exhibit greater volatility in both income and consumption – this is the third of the four new facts we highlight. So, absent preference heterogeneity, they should display a greater demand for precautionary savings. This reinforces heterogeneity in preferences, rather than in income processes, as a candidate for lower targeted savings by the hand-to-mouth.

Our fourth fact is that households observed hand-to-mouth spend differently than other households. Controlling for total spending, they purchase fewer expenditure categories. That within-period differential behavior should not reflect a different income process or a different rate of time discounting than other households. Furthermore, they adjust spending to a greater extent through the extensive margin of adding and dropping categories of spending. More active spending adjustment at the extensive margin is consistent, as we illustrate, with a greater elasticity of inter-temporal substitution in spending (higher IES).

The facts we document contradict the standard savings model in which agents are ex ante identical and relative $H2M$-status is solely due to bad luck. They also invalidate differences in income processes as an explanation for low wealth holdings. The facts suggest that differences in targeted assets are driven, at least in part, by preference heterogeneity. Because households with a low time discount factor β or a high IES target lower assets, we explore a quantitative model that allows households to differ in these two key parameters.[4]

We examine how such preference heterogeneity influences behavior key to macro policies: the distribution of MPCs across households and responsiveness to interest rates or other inter-temporal prices. To distinguish heterogeneity in discount factors from that in IES, we exploit portfolio choices in the two-asset model of Kaplan and Violante (2014) calibrated to allow preference heterogeneity. The model helps identify high-IES consumers because, being less averse to consumption varying over time, they are more willing to hold illiquid assets. We calibrate to match a number of facts about $H2M$ households from the PSID: e.g., shares of households that are hand-to-mouth, due to low wealth or lack of liquid assets; net worth by $H2M$-status; and the facts we present for persistence of being hand-to-mouth and expected spending growth by $H2M$-status.

We find that preference heterogeneity plays a major role in dispersion in MPCs despite nearly eighty percent of households having standard "macro" preferences, that is, being patient and inter-temporally inelastic. Consistent with the empirical literature, summarized by Havranek and Sokolova's (2020) meta study of MPC estimates, our model produces higher MPCs for agents classified as hand-to-mouth, especially those classified as $H2M$ due to low net worth (the poor $H2M$). We find that preference heterogeneity is crucial for the higher MPCs for $H2M$ agents, explaining about 84 percent of the higher MPCs for the poor $H2M$.

Our model results are relevant for the design of policies aimed at stimulating spending. In particular, we find that preference heterogeneity significantly increases the impact from *targeting* transfers to the poorest households. While the models with and without preference heterogeneity have similar average MPCs, heterogeneity dramatically increases the MPC gap between the poor and the rest of the wealth distribution. This reflects that the $H2M$ in

[4]When we refer to a household's low β this is actually shorthand for saying a low β times R, where R is the gross return they face in asset markets – β is only reflected in the consumer's first-order condition as the product βR. We also note that a low β could be motivated from behavioral models, rather than taken as a primitive. For instance, Lian (2021) shows that consumers who anticipate optimizing mistakes act as though they have a lower discount factor. Lian further shows this result holds regardless of whether the underlying behavioral cause of mistakes reflects inattention, mental accounting, rules of thumb, or hyperbolic discounting.

the heterogeneous-preference model represent the type that has a high MPC regardless of wealth. By contrast, allowing preference heterogneity in the calibrated model reduces the predicted spending impact of a temporary decline in the interest rate on liquid assets, with the relative response especially muted for the poorer $H2M$.

Related Work. Our paper is related to the literature studying the spending behavior of low-wealth households. Empirically, this literature focuses on how these households respond to income shocks and, more recently, interest rate shocks. As mentioned, Havranek and Sokolova (2020) reference many of the studies in the former group in their meta analysis. Cloyne, Ferreira and Surico (2019) and Holm, Paul and Tischbirek (2020) are examples of the latter. Quantitatively, the literature has focused on assessing the implications for fiscal and monetary policies (e.g., Kaplan and Violante, 2014 and Kaplan et al., 2018). We contribute to this line of work by pointing to a broader set of predictions of standard consumption theory regarding the behavior of low-wealth households for spending growth, spending volatility, and spending allocation. Testing these predictions using panel data allows us to uncover that the key predictor for a household's spending is not its current assets, but rather the longer-run positioning of its assets, pointing to a role for permanent differences between households as joint determinants of their wealth holding and spending behavior.

Our interpretation of these permanent differences as reflecting differences in preferences intersects with the literature identifying preference heterogeneity. Recent examples include Parker (2017), Gelman (2021), Athreya, Mustre-del-Río and Sánchez (2019), and Calvet, Campbell, Gomes and Sodini (2022). Our work is especially complementary to Calvet et al. (2022), who also find support for heterogeneity in both the IES and discount factors across a sample of Swedish households.[5]

The paper proceeds as follows. To guide the empirics, we begin in Section 2 by reviewing predictions of the standard buffer-stock savings model. In Section 3 we describe the PSID panel we employ as our primary data source and how we identify $H2M$ households. We present our empirical results in Section 4. After describing our strategy to highlight persistent versus transitory factors in their spending, we present our four facts for the hand-to-mouth, followed by a number of robustness results. In Section 5 we calibrate our version of the two-asset Kaplan and Violante (2014) model of precautionary savings that allows for preference heterogeneity. We explore its ability to generate the $H2M$ facts from the PSID, then show its implications for MPCs, especially those of the $H2M$, and consider its relevance for how spending responds to a fiscal transfer or an interest rate cut. We conclude in Section 6.

[5]They draw this conclusion from the heterogeneity in how households reduce savings as the need for precautionary savings declines. Although we target different moments, our estimated preference heterogeneity is broadly consistent with the distribution of preference parameters reported in their paper.

2 Hand-to-Mouth in the Canonical Consumption Model

To guide our empirical exploration of the hand-to-mouth, we review the canonical consumption-savings model in which agents use a non-contingent asset to smooth idiosyncratic income fluctuations. In Section 5, we extend the model to include both liquid and illiquid assets along the lines of Kaplan and Violante (2014); for the current motivational section, we present the standard single-asset environment.

Specifically, suppose an agent faces a volatile income stream and has access to a non-contingent savings vehicle that has gross return $R = 1 + r < \beta^{-1}$, where β is the discount factor. The level of assets is restricted to be above some threshold $\underline{a} \leq 0$. Assume the agent has power flow utility with an inter-temporal elasticity of substitution σ.

The first-order condition for the optimal consumption sequence is the familiar Euler equation:[6]

$$\mathbb{E}_t \left[\beta R \left(\frac{c_{t+1}}{c_t} \right)^{-\frac{1}{\sigma}} \right] \leq 1, \tag{1}$$

with equality when $a_{t+1} > \underline{a}$. If consumption growth is log-normally distributed, the Euler equation becomes:[7]

$$\mathbb{E}_t \Delta \ln c_{t+1} \geq \sigma \ln(\beta R) + \frac{1}{2\sigma} Var_t(\Delta \ln c_{t+1}). \tag{2}$$

Note that each of these terms may, in practice, be specific to an individual. That is, $\beta_i \neq \beta_j$ for agents i and j, $\sigma_i \neq \sigma_j$, etc. This implies a consumer will have higher expected consumption growth if (i) they are constrained; (ii) they are relatively patient (high βR); (iii) they have a relatively low IES (low σ, assuming $\beta R < 1$); and/or (iv) they have a relatively large demand for precautionary savings (a large conditional variance of consumption growth scaled by risk aversion $1/\sigma$).[8] A primary focus of the empirical and quantitative work is to assess whether the behavior implied by (2) is consistent with the data, and to what extent preference heterogeneity is necessary or useful to bring theory in line with data.

Let $\mathcal{C}_t(x, y)$ denote the associated optimal consumption function for a consumer of age t, where x is cash-on-hand and y is income; and let the *marginal propensity to consume* (MPC) be $\partial \mathcal{C}/\partial x$. As is well known (see Carroll and Kimball, 1996), in this environment $\mathcal{C}_t$

[6] The inequality in the Euler equation could be replaced with an equality by adding the non-negative multiplier from the $a_{t+1} \geq \underline{a}$ constraint to the left-hand side of (1) and the right-hand side of (2). This multiplier is zero if the constraint is slack, and positive when the constraint binds.

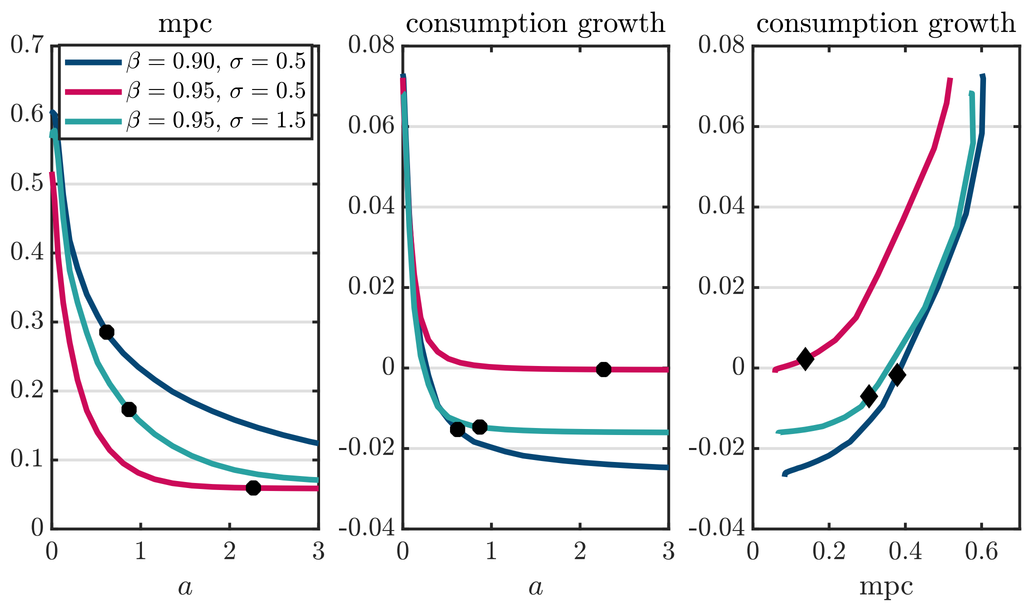
[7] See Deaton (1991).

[8] See Carroll (2000) and Carroll (2001) for a detailed discussion of sources of heterogeneity in the Euler equation and the challenges they pose to estimation.

is a strictly increasing and concave function of x.[9] Hence, the MPC is well-defined almost everywhere and decreasing in the level of assets.

We solve the model numerically for a calibrated lifecycle income process for three preference types. The details are provided in Appendix A1. In the left panel of Figure 1, we present how the MPC at age 40 varies with assets a for the three preference specifications listed in the figure.[10] In the center panel, we present how average consumption growth between t and $t+1$ varies with assets at age t. In the right panel, we plot consumption growth against MPC, as we vary assets. Of course, agents are distributed differently with respect to a_t for the differing preferences. As a point of reference, the black dots in the figure represent the mean value of a_t for each type.[11]

Figure 1: MPC and Consumption Growth



Note: The left panel depicts $\partial\mathcal{C}(x,y)/\partial x$ as a function of a. The middle panel depicts $\mathbb{E}\ln\left(\frac{\mathcal{C}(x',y')}{\mathcal{C}(x,y)}\right)$ as a function of a, where the expectation is over y' with $x' = Ra' + y'$ and $a' = x - \mathcal{C}(x,a)$. The right panel depicts $\partial\mathcal{C}(x,y)/\partial x$ on the x-axis and $\mathbb{E}\ln\left(\frac{\mathcal{C}(x',y')}{\mathcal{C}(x,y)}\right)$ on the y-axis. The black dots in the left and middle panels are the mean value of a. The black diamonds in the right panel are the mean MPC. All objects are for agents at age 40.

Given preferences, and the assumed income process, low-wealth households exhibit higher MPCs and higher expected consumption growth. But these predictions are conditional on a

[9] Carroll and Kimball (1996) show the concavity of the consumption function in an environment without borrowing constraints.

[10] Given the life-cycle setting, the policy functions will be age-specific. Since the model is annual, the MPC is also annual and the units are consistent with what is typically estimated in the data.

[11] The mean asset value is the ergodic distribution's counterpart to the target "buffer stock" of Deaton (1991) and Carroll (1992).

preference specification. The cross-sectional distribution of MPCs and average consumption growth within a population may reflect not only movements along a curve for a given type, but also movements across curves at a given level of wealth. Therefore, with preference heterogeneity, assets alone are not a sufficient statistic to predict consumption behavior.

If preference heterogeneity is required to explain consumption growth for low-asset households, then that heterogeneity will also play a role in mapping MPCs to these households. Consider those with assets at or near the borrowing constraint reflecting negative income draws – the standard interpretation of the hand-to-mouth. Such households exhibit both high MPCs and high expected consumption growth. This is illustrated in the right panel of Figure 1 for each preference type, with agents' MPCs displayed on the horizontal axis and expected consumption growth on the vertical. For a given type there is a tight relationship between MPC and expected consumption growth. By contrast, if $H2M$ status largely reflects low targeted assets, consistent with low consumption growth for the hand-to-mouth, the relationship between assets and MPC is driven by MPC differences across the curves. From the figure, that hetergeneity can clearly mask the clear, positive relation within types.

The literature typically – but not exclusively – assumes ex-ante identical individuals, with low wealth reflecting a history of bad income shocks. However, the analysis in this section points to (at least) three other explanations for low assets. One, also familiar from the literature, is that the agent is relatively impatient. The second, perhaps less familiar, is that the agent has a high elasticity of inter-temporal substitution (assuming that $\beta R < 1$). The third is that the agent has an income process, a high anticipated growth rate or low volatility, which reduces the demand for precautionary savings.[12] These three motives each generate low wealth positions due to low target wealth, as opposed to "bad luck." Identifying the strength of these forces in the data will be the focus of the following empirical work.

3 Data

We first describe the PSID panel we employ as our primary data source. We then discuss how we identify $H2M$ households and compare their characteristics to other households.

3.1 PSID Panel

Our empirical work is primarily conducted on the PSID, employing its biennial surveys from 1999 to 2019. 1999 was the onset of the PSID measuring wealth in each survey. It also

[12] A fourth explanation, not present in the benchmark, is that poverty itself lends itself to alternative saving behavior (above and beyond the precautionary term). See, for example, the experiences of those surveyed in Morduch and Schneider (2017). We further address this possibility in the empirical work.

initiated the PSID including spending more broadly than on food and housing. Appendix A2 discusses our variable constructions and sample restrictions in detail. Here we highlight the key variables for our analysis of earnings, income, wealth, and expenditures.

We identify households as hand-to-mouth, following Zeldes (1989) and Kaplan et al. (2014), by assets relative to a measure of earnings. Our earnings measure equals labor income, net of payroll taxes, plus government transfers received. We also consider a broader measure of after-tax income that sums earnings, transfers, net profits from business or farm, and net income from assets, minus the family's federal and state income tax liabilities calculated by TAXSIM. For homeowners we include 6 percent of the home value as implicit rent, while subtracting associated property taxes, mortgage interest, and home insurance.

Our division of assets by liquidity largely follows Kaplan et al. (2014). For liquid net worth we sum checking and savings balances, money market funds, certificates of deposit, treasury bills, and stocks outside of pension funds, while subtracting debts in the forms of credit and store cards, student loans, medical or legal debt, and debt owed to family. Illiquid assets reflect home and other real estate equity, IRA/pension holding, non-government bonds, insurance equity, and the net value of any business, farm, or vehicles.

Measured expenditures include shelter, utilities, food, gasoline, health insurance and medical expenses, education, child care, public transportation, and vehicles spending for purchases, repairs, insurance and parking. Spending on shelter equals rental payments for renters; for homeowners we set it to 6 percent of the respondent's valuation of their home. Summing categories, expenditures average 58.3 percent of after-tax income. Unless stated otherwise, our results reflect spending on all these categories, but are robust if we exclude spending on the durable categories of vehicle purchases and repair. (See Section 4.6.2.)

Our sample reflects only the PSID's nationally representative sample, including its "split-off" families and sample extensions to better represent dynasties of recent immigrants. All results reflect PSID longitudinal family weights. We include households with heads ages 25 to 64 and for which we can measure hand-to-mouth status from wealth and earnings for at least three surveys. We exclude households with less than $2,000 in annual earnings plus transfers, after-tax income, or expenditures. (All nominal variables are converted to 2009 CPI-deflated dollars.) Appendix A2 details the impact of these sample restrictions.

3.2 Identifying the Hand-to-Mouth

Various measures have been introduced to identify households in the data that are likely to have high marginal propensities to consume. The early and influential paper by Zeldes (1989) stratified households by net worth. Specifically, Zeldes considered a household "constrained" if its net worth was less than two months of its labor earnings. Following Zeldes, we therefore define a household as hand-to-mouth based on net worth (denoted $H2M_{NW}$) if their net worth is less than two months labor earnings.

Kaplan et al. (2014) (henceforth KVW) pursue an alternative measure of constraints focused on liquidity rather than wealth. They classify a household as constrained if its liquid wealth is below, or close to, a borrowing limit or if its liquid wealth is close to zero. The latter criteria is designed to identify those at a “kink” in the budget set near zero liquid assets due to a wedge between borrowing and saving interest rates. More exactly, they define constrained households as those with negative liquid wealth with absolute value greater than 16.5% of annual earnings,[13] or non-negative, but small, liquid wealth equal to a week or less of earnings. Note that KVW’s definition focuses only on liquid net worth, and is designed to include households potentially with substantial total net worth (the “wealthy hand-to-mouth”). We therefore assign households to be wealthy hand-to-mouth (denoted $H2M_{LIQ}$) if they are not $H2M_{NW}$, but have liquid wealth that satisfies the KVW criteria.

In our PSID sample, 40.6% of households are hand-to-mouth, with 23.3% denoted $H2M_{NW}$ and 17.3% denoted $H2M_{LIQ}$. That is, 17.3% of the sample is liquidity constrained according to the KVW definition, but have sufficient total net worth to be considered unconstrained by the Zeldes measure. As Table 1 shows, 16.9% of the sample is both net-worth and liquidity constrained. We assign these households to the low-net-worth $H2M_{NW}$ category. As a result, 73% of $H2M_{NW}$ households do satisfy the KVW liquidity-constrained definition.[14] We also constructed these shares for the seven waves of the Survey of Consumer Finance (SCF) from 1998 to 2016. The respective household shares for not hand-to-mouth, $H2M_{NW}$, and $H2M_{LIQ}$ are 62.5%, 25.0%, and 12.5%, similar to our counts from the PSID.

3.3 Characteristics of the Hand-to-Mouth

We provide summary statistics for the hand-to-mouth in Table 2. Specifically, we compute statistics based on whether a household is designated as one of our hand-to-mouth measures in a given year. This implies that the same household may be represented in multiple columns, albeit in different waves of the survey.

First compare the $H2M_{NW}$ in column (2) to those not hand-to-mouth in column (1). These $H2M$ are 7 years younger on average; their earnings and incomes are only half as

[13]They set the borrowing limit at 18.5% of annual earnings, but treat those above by less than a week’s earnings as effectively at the constraint, together implying a constraint at about 16.5% of annual earnings.

[14]For comparison, Zeldes classified 29% of his (earlier) PSID sample as hand-to-mouth by his net-worth definition. KVW classify 31% of their Survey of Consumer Finance sample as liquidity constrained, compared to 34.1% in our PSID sample (spread over both our measures). KVW classify 20% percent as “wealthy hand-to-mouth,” compared to 17.5% for our PSID sample.

Table 1: Hand-to-Mouth Groups

	Not $H2M$	$H2M_{NW}$	$H2M_{LIQ}$
Shares	59.3%	23.3%	17.3%

	By LIQ (KVW)	
By NW (Zeldes)	Not $H2M$	$H2M$
Not $H2M$	59.3%	17.3%
$H2M$	6.4%	16.9%

Note: Sample is PSID 1999-2019, with $H2M$ status observed at least three times. Sample size is 30,627.

much; and of course their wealth, both liquid and illiquid, is much lower. Turning to the $H2M_{LIQ}$, we see they are not really so wealthy. In particular their median net worth is only 30 percent that of households not classified as $H2M$. By other measures, they are intermediate to the groups: They more closely resemble those not $H2M$ in age, but better resemble those $H2M_{NW}$ in earnings and income.

Table 2: Summary Characteristics of the Hand-to-Mouth

	Not $H2M$	$H2M_{NW}$	$H2M_{LIQ}$
Age	46.7	40.0	44.8
Income	99,280	47,758	64,874
Earnings	90,263	45,464	56,335
Liq Wealth (median)	13,666	-7,776	-2,305
Net Worth (median)	174,182	-2,316	50,817
High Liquid Debt	24.7%	65.3%	54.3%
Sample Shares	59.3%	23.3%	17.3%

Note: All figures in 2009 dollars. High Liquid Debt equals one for households with credit card, store credit, student loans, medical or legal bills, or loans from family that sum to a month's or more of earnings, zero otherwise.

While the $H2M$ have lower average earnings, they are not dominated by households that are especially poor. For example, if we exclude households in the bottom quintile for long-run earnings, 18.4% and 15.5% of that sample are still classified respectively as $H2M_{NW}$

and $H2M_{LIQ}$.[15] As a corollary, 63% of households classified as $H2M_{NW}$ are in the upper four quintiles for long-run earnings, while for those classified as $H2M_{NW}$ that share is 71%.

Recall from the Euler equation (1) that a potential source of differences in consumption growth rates is heterogeneity in expected rates of return: If low-asset households face a lower marginal return on savings, this could push them towards lower expected consumption growth. The variable High Liquid Debt in Table 2 reports the fraction of households, by group, that have balances on credit cards, store credit, student loans, medical or legal bills, or loans from family that sum to at least one month of household earnings. A large share of $H2M$ households exhibit such high debts. More exactly, two-thirds of $H2M_{NW}$ and over half of $H2M_{LIQ}$ households do, compared to only a fourth for those not hand-to-mouth. The bulk of such debts, especially credit card debt, charge high interest rates. This suggests that many households classified as $H2M$ do face a high marginal return to saving.[16]

4 Empirical Results

In this section we examine the consumption behavior of $H2M$ households, guided by the predictions from the canonical model. We document four four facts about that behavior that challenge the standard model, and provide evidence that these departures reflect persistent differences across households. Based on that evidence, and further robustness checks, we argue that these differences reflect disparities in target wealth across households that are likely to stem from differences in preferences rather than income processes.

4.1 Empirical Strategy

For each fact, we follow a two-step empirical strategy. We first regress our variable of interest on the two indicators of $H2M$ status. Take, as an example, log consumption growth between years t and $t+2$ (as the PSID is biennial) for household i, $\Delta \ln c_{i,t+2}$. The benchmark specification (omitting the constant) is:

$$\Delta \ln c_{i,t+2} = \beta_{NW} H2M_{t,NW} + \beta_{LIQ} H2M_{t,LIQ} + \boldsymbol{\delta}' \boldsymbol{D}_t + \boldsymbol{\gamma}' \boldsymbol{X}_{i,t} + \varepsilon_{i,t+2}. \quad (3)$$

Growth rates, here for consumption, are log differences between year t and the subsequent wave in year $t+2$, where we divide those differences by two to annualize the growth rates.

[15] See Appendix A3.1 for the definition of household long-run earnings.

[16] PSID surveys after 2011 allow us to separately identify credit card debt. H2M households are twice as likely to have credit card debt of a month's earnings or more. The incidence is 28.7% and 30.1% respectively for $H2M_{NW}$ and $H2M_{LIQ}$, compared to 14% for households not hand-to-mouth.

The variables $H2M_{t,k}$, for $k = NW, LIQ$, take value one if household i is $H2M_k$ in *period* t, that is, at the initial period of the growth rate; so coefficients β_{NW} and β_{LIQ} reveal each group's *differential* consumption growth compared to households hand-to-mouth by neither measure. $\boldsymbol{D}_t$ is a vector of year dummies; and $\boldsymbol{X}_{i,t}$ is a vector of household demographics: a quadratic in age, two change-in-marital-status dummies (marriage and separation), and two change in family size dummies (increase and decrease).[17]

Regression equation (3) estimates to what extent having low assets or liquidity predicts the variable of interest. Other than demographic controls, it assumes the outcome of interest depends only on current wealth or liquidity. This is consistent with the standard model in which agents are ex ante identical (conditional on demographics), but differ in their current asset position due to a sequence of idiosyncratic income realizations.

This baseline specification frequently yields results counter to the standard model. Motivated by the discussion in Section 2, the next step in our empirical strategy is to explore whether permanent (or persistent) differences across households influence the mapping between $H2M$ status and observed outcomes. The panel dimension of the PSID allows us to control for such. To this end, our second specification adds household fixed effects to equation (3).

As we shall see, adding the fixed effects typically changes the estimated β_{NW} and β_{LIQ} coefficients significantly, bringing the estimates closer to predictions of the standard model. This implies both that household fixed effects comprise an important share of variation in $H2M$ status and these fixed effects – households' tendencies to be hand-to-mouth– are significantly correlated with the variable of interest. For instance, with respect to equation (3), household fixed effects for being $H2M$ strongly predict a household's *average* rate of consumption growth. In Section 5, we compare these moments to models that do or do not allow for preference heterogeneity.[18]

To better understand the fixed effects, we also compute conditional means of $H2M$ status for each household.[19] We refer to the coefficients on each of the household dummy variables

[17]When the left-hand side variable of interest is a level, rather than a growth rate, we include a cubic in age and dummies to reflect two categories for marital status, five for family size ($\{1, 2, 3, 4, \geq 5\}$), and three for race (black, white, other). Race and age are those of the household head. When adding fixed effects, the race dummies are dropped.

[18]Carroll (2001) pointed out the pitfalls of estimating structural parameters from a linear (or even second-order) approximation of the Euler equation. Carroll does endorse specific "consumption growth regressions." While (3) is not explicitly discussed, it is consistent with his concern that preference (or other) sources of heterogeneity need to be taken into account. Our approach uses measures of $H2M$ status to proxy for (time-varying) binding borrowing constraints and consumption risk, and fixed effects to control for preferences. Moreover, our purpose is to document whether consumption growth varies by $H2M$ status, a clear implication of the baseline model, rather than estimate structural parameters. The latter requires a structural model, which we explore in Section 5.

[19]More specifically, we regress the sequence of zero-one indicators $H2M_{NW}$ and $H2M_{LIQ}$ for each

as that household's "fixed effect" for $H2M_{NW}$ and $H2M_{LIQ}$ status. We perform a similar exercise to obtain the conditional mean (fixed effect) for a household's consumption growth and other LHS variables.

4.2 Fact 1: Households Tend to Remain H2M

In the model of buffer stock savings from Section 2, households draw down assets in response to a negative income shock, but also have an incentive to rebuild savings when income rebounds. Thus observing a household that remains persistently hand-to-mouth suggests either a sequence of negative shocks or low targeted assets-to-income, possibly due to a high discount rate or a high willingness to intertemporally vary consumption.

For this reason, we start in Table 3 by reporting transition probabilities for PSID households between the $H2M$ categories. As the PSID waves are two years apart, we report two-year and four-year transition rates. The large diagonal elements reflect significant persistence in $H2M$ status. This persistence is particularly striking given that reporting errors for household income and wealth no doubt create spurious transitions. In particular Panel A shows that those classified as $H2M$ by net worth in a given year have a 65% chance of remaining in that status and a 16% chance of transitioning to the liquidity based measure of $H2M$ status; this leaves only a 20% chance that after two years an individual has become "unconstrained" by either definition. Stratifying by status at t, we see that $H2M_{NW}$ households at t are more than ten times as likely to occupy that status at $t+2$ as households that are not hand-to-mouth by either measure at time t (frequencies 0.65 versus 0.06).

Panel B shows that, even four years out, $H2M_{NW}$ households exhibit a 58% probability of having that status, and only a 24% probability of being hand-to-mouth by neither measure. By contrast, these probabilities for households not constrained by either measure at t are respectively 7% and 81%. So, even viewed four years later, $H2M_{NW}$ households at t are about ten times as likely to occupy that status as households $H2M$ by neither measure at t. For the wealthier $H2M_{LIQ}$, there is a 43% chance of transiting out of $H2M$ status altogether at $t+2$, and only a 47% chance of doing so by $t+4$. While higher than corresponding probabilities for the $H2M_{NW}$, these are still quite low given these households have median net worth exceeding $\$50,000$ (from Table 2).

In Appendix A3.1 we show that this high persistence remains even stratifying households by their long-term earnings or their average rate of growth in earnings.[20] Table A7 of the appendix reproduces the t to $t+4$ transition rates, separately for households in the bottom

household-year observation on a household identifier dummy, as well as year dummies, a cubic in age, and dummies for race, marital status, and number of children.

[20]See Appendix A3.1 for how household long-term earnings and earnings growth are constructed.

Table 3: Transition Rates for $H2M$ Status

	Not $H2M_t$	$H2M_{NW,t}$	$H2M_{LIQ,t}$
		Panel A	
Not $H2M_{t+2}$	.822	.195	.427
$H2M_{NW,t+2}$	.061	.648	.176
$H2M_{LIQ,t+2}$	.118	.157	.398
		Panel B	
Not $H2M_{t+4}$	.807	.244	.470
$H2M_{NW,t+4}$	.066	.578	.181
$H2M_{LIQ,t+4}$	.127	.178	.349

Note: Sample is PSID 1999-2019, with $H2M$ status observed at least three times.

quintile for long-term earnings and all other households. The high persistence in $H2M$ is not driven by a set of households that consistently have low earnings – based only on households in the upper four quintiles of long-term earnings, households $H2M_{NW}$ at t are an order of magnitude more likely to be observed in that status at $t + 4$ than those not $H2M$ at t.

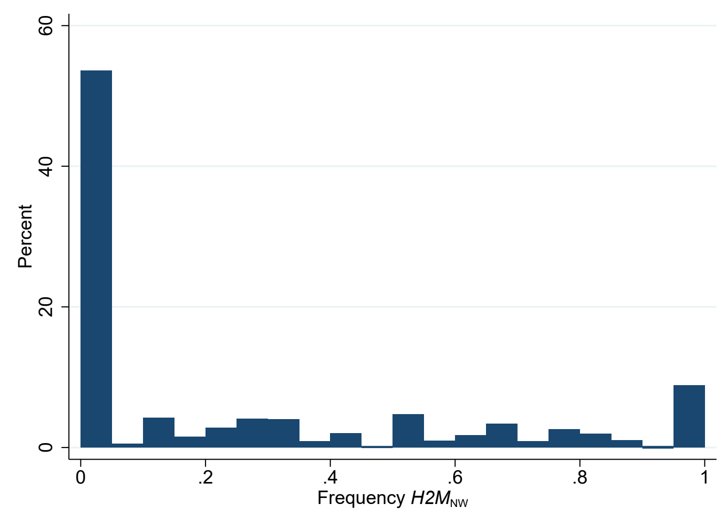
Table A8 in Appendix A3.1 stratifies households into three quantiles, low, middle, and high, by their average rate of growth in earnings. One concern might be that households remain poor $H2M$ because they experience a sequence of negative shocks. But the table shows that persistence in being $H2M_{NW}$ from t to $t + 4$ is similarly high, a little less than 0.6, for households that averaged low, medium, or high earnings growth. Conversely, the persistence in remaining not $H2M$ does not reflect a sequence of positive earnings shocks: 80% of ouseholds not $H2M$ at t remain that way four years later, regardless of being among households with low, middle, or high earnings growth.

Given our sample covers a time span of up to 21 years, we can also examine to what extent households differ in their proclivity to be observed $H2M$ over their PSID panel. Figure 2 plots the distribution of household frequencies for being observed $H2M_{NW}$. Along the horizontal axis is the frequency that a household is $H2M$ in our sample, with one frequency for each household.[21] For example, 0.4 denotes households observed $H2M_{NW}$ at forty percent of their observations. At the extremes, zero denotes households never $H2M_{NW}$ and 1 those always so. Greater persistence in being hand-to-mouth pushes mass to the extremes. We note that much of the distribution is in the extremes: Households never

[21] Household $H2M$ status is observed three to eleven times for our sample, with a median of seven times, spanning thirteen years.

observed $H2M_{NW}$ comprise 53.4% of households; second-most common, 8.9% of households, are always $H2M_{NW}$. This persistence is consistent with findings in Athreya et al. (2019) that less than 10 percent of households, those with repeat episodes of delinquent loans, account for half of all experiences of such financial distress.

Figure 2: Distribution of Frequencies $H2M_{NW}$



4.3 Fact 2: H2M Do *Not* Have Higher Consumption Growth

As discussed in Section 2, a constrained household's Euler equation holds as an inequality implying, all else equal, higher expected consumption growth. Moreover, even if the borrowing constraint is not binding, a low-wealth household should exhibit high expected growth in consumption as it rebuilds assets (see Figure 1). Here we document that the hand-to-mouth do not display higher growth in consumption. Adding household fixed effects brings the impact of *current* hand-to-mouth status more in line with the standard model.

Table 4 presents results for regression equation (3) relating (annualized) log growth in consumption from t to $t + 2$ on the dummies indicating $H2M$ status in t as well as the controls described in Section 4.1. Starting with column (1), which omits household fixed effects, we see there is little difference in future consumption growth between the $H2M_{NW}$ and those with higher net worth, while the wealthier hand-to-mouth ($H2M_{LIQ}$) show about a percentage point lower consumption growth than the other groups.

But these estimated effects change notably when we control for household fixed effects in column (2). Fixed effects control for (permanent) differences between households, including differences in preferences, rates of return, and consumption uncertainty. Controlling for fixed effects, low-net-worth households have a significantly higher rate of consumption growth –

Table 4: Consumption and Income Growth for the Hand-to-Mouth

	Consump Growth		Income Growth	
	(1)	(2)	(1)	(2)
$H2M_{NW}$	.002	.020	.010	.028
	(.004)	(.007)	(.004)	(.007)
$H2M_{LIQ}$	-.008	.002	.009	.025
	(.003)	(.005)	(.004)	(.006)
R^2	.08	.20	.05	.20
Fixed Effects	No	Yes	No	Yes

Note: Sample size is 24,214. Growth rates are annualized. Not-$H2M$ group is omitted in all regressions. Regressions include the controls described in Section 4.1. Standard errors are robust; for Columns (1) and (3) they are clustered by household.

the coefficient on $H2M_{NW}$ is 2.0 log points – as anticipated by the standard model of savings. Including fixed effects, the point estimate on $H2M_{LIQ}$ is essentially zero, suggesting that the wealthier hand-to-mouth have similar consumption growth going forward than wealthier households with more liquid wealth. One interpretation is that the wealthy hand-to-mouth need not reduce consumption in order to build up a buffer stock of precautionary saving, as they have the option of converting illiquid to liquid wealth in response to shocks to income.[22]

The significant impact from including fixed effects in Table 4 implies that: (a) Household fixed-effects account for much of the dispersion in $H2M$ status in the PSID, and (b) those fixed effects strongly correlate with a household's *average* rate of consumption growth. To point (a), we compute each household's fixed effects for the variables $H2M_{NW}$ and $H2M_{LIQ}$ by regressing each variable on household fixed effects and the usual controls. The household fixed effects account for 68% of the variance in $H2M_{NW}$ status and 43% of that in $H2M_{LIQ}$. To point (b), we similarly construct household fixed effects for consumption growth by regressing consumption growth on fixed effects and controls. We find that a household's consumption-growth fixed effect is negatively correlated with its fixed-effects for being $H2M_{NW}$ or $H2M_{LIQ}$, with respective correlations of -0.65 and -0.50. In short, households that tend to be repeatedly hand-to-mouth have lower average consumption growth.

[22] A concern might be that the household fixed effects conflate permanent differences across households with households having a sequence of "bad luck" over our sample. But, in contrast to the fixed effects, including a household's average rate of earnings (including transfers) growth over the sample as an added control has negligible impact on the results in Column (1): The coefficient for $H2M_{NW}$ is unchanged and that for $H2M_{LIQ}$ is reduced from -0.008 to -0.009. See Appendix A3.1 for a description of how we construct households' average growth rates in earnings.

$H2M$ households are not only poorer in terms of assets, but also in terms of earnings. In particular, the correlations between a household's long-term earnings and its fixed effects for being $H2M_{NW}$ and $H2M_{LIQ}$ are respectively -0.27 and -0.19.[23] But the negative correlation between household $H2M$ fixed effects and for consumption growth are not driven by the tendency of low-earnings households to be $H2M$. If we exclude households in the bottom quintile for long-run earnings, the correlations between fixed-effects for being $H2M_{NW}$ and $H2M_{LIQ}$ with that in consumption growth are respectively -0.68 and -0.55.

We also related consumption growth to $H2M$ status controlling for a household being in the bottom quintile for long-term earnings, rather than including fixed effects. Results are given in Column (1) of Table A9 in Appendix A3.2. Controlling for low earnings increases the coefficient of $H2M_{NW}$ for consumption growth from 0.002 to only 0.006, and it remains statistically insignificant, while having almost no impact on the coefficient for $H2M_{LIQ}$.

The right panel of Table 4 repeats the two specifications, but with log growth in income (earnings plus financial income) as the outcome variable. Standard consumption smoothing arguments suggest that households that anticipate higher future income will draw down assets or increase debt today, making them more likely to be observed as $H2M$. Hence, low-wealth households should exhibit higher income growth. Without fixed effects, both those $H2M_{NW}$ and those $H2M_{LIQ}$ display about one percent faster annual growth in income than the non-$H2M$. But, from Column (1), this does not translate into higher consumption growth. Controlling for fixed effects, the $H2M$ exhibit considerably higher income growth: 2.8% higher for $H2M_{NW}$, 2.5% for $H2M_{LIQ}$. Consistent with being constrained, that income growth is mirrored, under fixed effects, by higher consumption growth for households temporarily observed $H2M_{NW}$.

Summing up Fact 2, being $H2M$ does not predict higher consumption growth. But this fact conflates two underlying outcomes: (i) Households often observed $H2M$, especially by net worth, display lower *average* consumption growth, while (ii) controlling for those average outcomes, currently being $H2M_{NW}$ does predict significantly faster consumption growth. If we interpret households that are often $H2M$ as targeting lower assets, due to a low discount factor or high IES, then in Section 2 we saw that such households will simultaneously display high MPCs and low expected consumption growth. We consider several robustness exercises in Section 4.6, in particular with respect to how households are divided by net worth and how expenditures are measured. We also present results stratifying households by age or permanent income. In all cases these summary statements continue to apply.

[23] Again, see Appendix 4.2 for the construction of long-term earnings. These correlations are statistically highly significant, with respective standard errors of 0.013 and 0.014.

4.4 Fact 3: H2M Have More Volatile Consumption and Income

In the model of Section 2, low-wealth households are subject to higher anticipated consumption volatility given the absence of a buffer stock of savings. But, alternatively, low-wealth households might have lower volatility of income, thereby leading them to desire less precautionary savings. In this subsection we document that is not the case – hand-to-mouth households display *more* volatile growth in both income and consumption. Moreover, it is those households that are often hand-to-mouth, either by net worth or liquid assets, who display significantly more volatile income and consumption growth. This implies that other origins are required for the heterogeneity in targeted savings across households.

To explore these relationships in our PSID sample, we regress the volatility of consumption and income growth on lagged $H2M$ status as well as the controls outlined in Section 4.1. That is, growth rates between t and $t+2$, are related to $H2M$ indicators as of t. This specification is designed to capture whether $H2M$ households face greater uncertainty about the near future. We measure spending volatility by the absolute value of spending growth after first removing consumption growth predicted from the regressions in Table 4. Denote that variable by $|\Delta \ln(c)_{res}|$. We consider predicted growth that does or does not condition on household fixed effects; but the results for volatility are extremely similar. For brevity, the table results reflect residual consumption growth conditional on household fixed effects. We proceed in parallel fashion for measuring volatility of income growth.

Results are reported in Table 5. From Column (1), we see that the hand-to-mouth, especially those $H2M_{NW}$, exhibit more variable future consumption growth. For context, the mean of the dependent variable is 0.13. So the coefficients on $H2M_{NW}$ and $H2M_{LIQ}$ of 0.018 and 0.006 represent respectively 13% and 5% of that mean.[24]

But, turning to Column (2), these effects are eliminated once we include individual fixed effects. The implication is that it is those households that are often hand-to-mouth that exhibit more volatile consumption growth.[25] To further illustrate that point, we construct household fixed effects for volatility of consumption growth by regressing that variable, $|\Delta \ln(c)_{res}|$, on fixed effects and our standard controls. A household's fixed effect for

[24]If we instead judge volatility of consumption growth based on predicted growth without fixed effects, the coefficients corresponding to Column (1) of Table 5 are 0.024 (0.003) for $H2M_{NW}$ and 0.008 (0.003) for $H2M_{LIQ}$, with a mean for the dependent variable of 0.14; while the estimates corresponding to Column (2) of the table are 0.003 (0.004) for $H2M_{NW}$ and -0.004 (0.003) for $H2M_{LIQ}$.

[25]We also examined whether households that are often $H2M$ exhibit more volatile *levels* of consumption, as well as more volatile consumption growth. To do so, we first regress log expenditure on household fixed effects and controls, including age and year effects. We then compute the standard deviation of the residuals for each household. The correlation of a household's standard deviations with its fixed effects for being $H2M_{NW}$ and $H2M_{NW}$ are respectively 0.11 and 0.06. While these correlations are positive and statistically significant, they are considerably lower than the correlations of the household's fixed effect in consumption-growth volatility with its $H2M$ fixed effects.

consumption-volatility displays respective correlations of 0.60 and 0.46 with its fixed-effects for being $H2M_{NW}$ and $H2M_{LIQ}$.

The correlations between household fixed effects for being $H2M$ and its volatility of consumption growth are not driven simply by spending for poorer households – they are similar, at 0.64 and 0.51, if we exclude households in the bottom quintile for long-run earnings. Furthermore, in Appendix A3.2 we reestimate the specification from Column (2) controlling for a household being in the bottom earnings quintile, in lieu of fixed effects. While households in the bottom quintile of earnings do exhibit more volatile spending, controlling for that, we still see that being $H2M_{NW}$ predicts more volatile consumption growth

Table 5: Consumption and Income Volatility for the Hand-to-Mouth

	$\|\Delta \ln(c)_{res}\|$		$\|\Delta \ln(y+ra)_{res}\|$	
	(1)	(2)	(3)	(4)
$H2M_{NW}$	.018	.001	.018	.005
	(.003)	(.004)	(.003)	(.004)
$H2M_{LIQ}$	.006	-.005	.020	.007
	(.003)	(.003)	(.004)	(.004)
R^2	.01	.38	.01	.44
Fixed Effects	No	Yes	No	Yes

Note: Sample size is 24,214. Growth rates are annualized. Not-$H2M$ group is omitted in all regressions. Regressions include the controls described in Section 4.1. Standard errors are robust; for Columns (1) and (3) they are clustered by household.

Results for volatility in income growth are presented in Columns (3) and (4) of the table. These largely parallel those for consumption: (i) Hand-to-mouth households exhibit greater income volatility over the subsequent two years; (ii) those effects are sharply reduced by controlling for household fixed effects. That is, it is those households that are often observed hand-to-mouth who display more volatile income growth.

In Section 4.6 we consider robustness of these results to alternative measures of spending and to the impact of measurement error in expenditure and income. We continue to see that hand-to-mouth households exhibit more volatile income and consumption growth. But this volatility is predicted by a household's fixed effect, not its current asset position.

Given that income heterogeneity is a natural explanation for differences in targeted savings, in Appendix A1.2 we simulate the standard savings model allowing households to differ by income process. We calibrate that heterogeneity by first dividing PSID households into two roughly equal-sized groups based on how frequently they are $H2M_{NW}$. For each group we estimate an earnings process, allowing group-specific means, life-cycle growth, and volatility for persistent and transitory income shocks. Most notably, those often hand-to-mouth have much larger transitory shocks to their earnings. We then simulate the savings model under each of the two income processes to reveal whether frequent $H2M$ status reflects that group's differential income process. The model's predictions for being hand-to-mouth are precisely opposite the data. That is, the empirical income process for the frequently hand-to-mouth, given its large transitory income risk, in the model predicts *lower* likelihood of being hand-to-mouth. So the exercise, consistent with the evidence presented in this subsection, indicates that differences in income processes are not a compelling explanation for why certain households are often hand-to-mouth.

4.5 Fact 4: H2M Are More Elastic at Extensive Spending Margin

The savings problem of Section 2 illustrates that low wealth-to-income may reflect a household's poor luck, its income process, or its preferences – specifically a high rate of time preference or a high IES. Section 4.3 implies differences in asset targets, not just luck, are important for explaining the hand-to-mouth, while Section 4.4 suggests differences in income processes do not align with the implied target differences. In this section, we look at the extensive margin of consumption behavior of low-wealth individuals (i.e. whether a category is consumed at all) to establish a role for IES differences, in addition to differences in patience, as drivers of hand-to-mouth behavior.

We first show that households who are often $H2M$ allocate their spending differently, spreading it over fewer categories than other households with the same total spending. These static differences not only imply that $H2M$ households differ in preferences from non-$H2M$, but also those differences extend beyond rates of time discounting. Furthermore, adjustment in the number of categories consumed (the extensive margin) comprises more of a given change in spending for households that are often hand-to-mouth.

Those close to adjustment on an extensive margin may exhibit a highly elastic response of total spending to changes in inter-temporal prices.[26] In Appendix A4, we provide a simple framework to show how the results presented in this section are suggestive of a relatively high IES for those prone to adjust spending at the extensive margin, a group that empirically aligns with those frequently hand-to-mouth.

To document these facts we divide nondurable expenditure into the categories listed in

[26]This idea has been applied to labor markets by Rogerson (1988) and to portfolio choice by Grossman and Laroque (1990). Chetty and Szeidl (2007) make a related argument in the context of risk preference in the presence of consumption commitments.

Table A5 in Appendix A2. We have a finer decomposition of expenditure into categories using the Consumer Expenditure Survey (CE), reported in Table A5 in Appendix A2.

Our first exercise shows that the $H2M$ consume a different number of distinct categories conditional on total nondurable expenditure. That is, they allocate a given total spending differently in terms of number of goods versus spending per good. To document this, we regress the log number of categories with positive expenditure on log total expenditure as well as our $H2M$ dummies, year dummies, and demographic controls. The presence of total expenditure as a regressor controls for the Engel curve for variety of categories with respect to total spending.

The results are reported in Table 6. Columns 1 and 2 use the PSID and our benchmark measures of $H2M$ status. We cannot construct identical measures of $H2M$ in the CE as it does not have as detailed wealth data as the PSID. Instead, we define a measure using only liquid assets, denoted $H2M_{KVW}$, equal to one if liquid assets are less than a week's earnings above the borrowing limit or, while positive, are less than one week's earnings. This is exactly the hand-to-mouth measure in Kaplan et al. (2014). We classify 37.5% of the CE sample to be $H2M_{KVW}$. The final two columns estimate the impact of $H2M_{KVW}$ on the log number of categories in our PSID and CE samples.

Table 6: Number of Categories Consumed

Dependent variable is $\ln N$

	PSID (1)	PSID (2)	PSID (3)	CE (4)
$\ln c$	.220	.166	.221	.456
	(.005)	(.004)	(.005)	(.002)
$H2M_{NW}$	-.048	-.024		
	(.007)	(.005)		
$H2M_{LIQ}$	-.036	-.010		
	(.006)	(.004)		
$H2M_{KVW}$			-.043	-.115
			(.005)	(.002)
R^2	.38	.70	.38	.57
Fixed effects	No	Yes	No	No

Note: Samples sizes are 30,626 for the PSID sample and 192,299 for the CE. Categories are restricted to nondurables and services. Households on average spend on 7.5 of 15 categories in PSID, on 12.1 of 27 categories in the CE. Regressions include the controls described in Section 4.1. Standard errors are robust; for Columns (1) and (3) they are clustered by household.

The estimates show a clear pattern that low-wealth and low-liquidity households consume fewer categories of goods conditional on total expenditure. The effect is also economically significant. For instance, comparing the coefficients for total expenditure and for being $H2M_{NW}$, we see that the $H2M_{NW}$ coefficient is opposite in sign and over one-fifth the magnitude of that for $\ln c$. That implies that being $H2M_{NW}$ predicts the same impact on number of categories as a 22% reduction in total spending.

Column 2 of Table 6 includes household fixed effects. This greatly cuts the impact of current $H2M$ status – by half for $H2M_{NW}$ and by 70% for $H2M_{LIQ}$. Households who are often $H2M$, by either measure, are those who consume fewer categories conditional on total spending. We can also see this by taking a household's fixed effect for number of categories purchased (constructed by regressing *ln* number of categories on fixed effects, *ln* total household expenditures, and controls) and correlating it with the household's fixed effects for $H2M$ status. A household's consumption-variety fixed effect exhibits respective correlations of -0.65 and -0.49 with its fixed-effects for being $H2M_{NW}$ and $H2M_{LIQ}$. Furthermore, these correlations are not driven by low-earnings households. Excluding households in the bottom quintile for long-run earnings, the respective correlations are -0.64 and -0.53.[27] Thus, as for our results for consumption growth and consumption volatility, it is a household's propensity to be $H2M$, not its current status, that largely predicts spending behavior.

Our second exercise shows that *at the margin* of changing total nondurable expenditure, the $H2M$ allocate added spending differently than the non-$H2M$ along the extensive versus intensive margins. To that end, we regress $\Delta \ln N_t$ on $\Delta \ln c_t$, interacting the growth of total expenditure with our $H2M$ indicators.[28]

Results are reported in Table 7. We see from Column 1 that the category elasticity is higher for the $H2M_{NW}$.[29] The second column also interacts a household's expenditure growth with its estimated fixed effects for being observed as $H2M_{NW}$ or $H2M_{LIQ}$. This shows that it is actually those households who are regularly $H2M_{NW}$ who adjust more likely on the extensive margin, with current $H2M_{NW}$ status no longer relevant. Finally, the third column also interacts the change in spending with whether the household is in the bottom quintile for average household earnings over the sample. Households in that bottom quintile

[27]In Appendix A3.2 we reestimate the regression from Column (2) of Table 6 controlling for a household being in the bottom earnings quintile instead of fixed effects. We see that households in the bottom quintile of earnings allocate their spending to fewer categories, even controlling for total spending. But being $H2M_{NW}$ or $H2M_{NW}$ still predicts purchasing significantly fewer categories.

[28]The regressions also include the hand-to-mouth indicators as well as the year and demographic controls. $H2M_{NW}$ and $H2M_{LIQ}$ are both as of $t-1$, where a period is two years. Coefficients are all annualized.

[29]In Appendix A3.5 we explore this further by decomposing the growth in nondurable consumption between $t-1$ and t into an intensive change, reflecting the change in spending on goods consumed in both periods, and an extensive margin reflecting the adding and dropping goods. There we see that the extensive margin is about twenty percent more important for $H2M_{NW}$ households.

also show a greater responsive of spending through number of categories. But, controlling for that, we see nearly the same impact of the household fixed effect for being $H2M_{NW}$. That is, it remains true it is households who are often $H2M_{NW}$ who vary spending more through the extensive category margin.

Table 7: Regression of $\Delta \ln N$ on $\Delta \ln c$

Dependent variable is $\Delta \ln N$

	(1)	(2)	(3)
$\Delta \ln c$	.138	.144	.134
	(.006)	(.006)	(.006)
$\Delta \ln c \times H2M_{NW}$	.038	.008	-.003
	(.011)	(.015)	(.015)
$\Delta \ln c \times H2M_{LIQ}$	.015	.020	.012
	(.012)	(.015)	(.017)
$\Delta \ln c \times$ $H2M_{NW}$ fixed effect		.049	.045
		(.018)	(.018)
$\Delta \ln c \times$ $H2M_{LIQ}$ fixed effect		-.001	-.012
		(.024)	(.024)
$\Delta \ln c \times$ Lowest earnings quintile			.057
			(.018)
R^2	.11	.11	.12

Note: Sample size is 24,214 in Column (1), 21,894 in Columns (2) and (3). Regressions include controls for $H2M$ status, in addition to the controls described in Section 4.1. Column (2) also includes a fixed effect as well as interacts the conditional mean of $H2M$ status (“$H2M$ fixed effect”). Standard errors clustered at household level.

The results of Tables 6 and 7 document heterogeneity across consumers in the relevance of their extensive margin of consumption that correlates with the tendency to have low assets. As discussed above, and illustrated in Appendix A4, how total spending responds to relative prices (or interest rates) may be sensitive to whether adjustments occur primarily along the extensive or intensive margins. The empirical results therefore suggest that differences in the effective IES are a plausible candidate for explaining why some households are prone to $H2M$ status. In Section 5 we allow for such differences as one candidate in calibrating preference heterogeneity.

4.6 Robustness Checks

In this section we examine robustness of our results to several measurement issues: (i) How households are classified as low net worth and liquity; (ii) the type of goods in expenditures; (iii) measurement error in income and expenditure; and (iv) dividing the sample by age and long-term earnings. The results continue to align qualitatively, and usually quantitatively, with those presented above, including that households often $H2M$ display lower consumption growth and more volatile spending.

4.6.1 Results Further Dividing Households by Net Worth

We have focused on the impact on spending of being classified as $H2M$ based on low net worth, those $H2M_{NW}$, or only by virtue of low liquidity, those $H2M_{NW}$. From the buffer-stock model, for a given preference type, MPCs and consumption growth decline monotonically with assets, though that relationship is steeper at low asset levels (Figure 1). In this section we examine how spending differs more generally with respect to net worth.

Table 8 presents results for spending growth, volatility of spending, and number of categories purchased by household asset holdings. But the specifications now reflect respective dummy variables for a household being in each of the first three quartiles in terms of its net-worth-to-earnings ratio, with the top quartile being the reference group, and a separate dummy for a household being liquidity constrained as defined by Kaplan et al. (2014).

We see from Column (1) that, conditional on liquidity status, low net worth predicts higher subsequent consumption growth: Being in the first quartile predicts 1.1% higher growth than being in the second, and 1.1% higher growth than being in either the third or fourth quartiles. Column (1) also shows that, conditional on net-worth quartile, low liquidity is associated with significantly lower subsequent consumption growth, by 1.2%. These results are consistent with the finding from Table 4 that $H2M_{NW}$ households do not exhibit faster subsequent consumption growth. $H2M_{NW}$ households are a subset, barely a proper one, of households in the first quartile of net worth. But, at the same time, nearly three quarters of $H2M_{NW}$ households would be classified as liquidity constrained by Kaplan et al. (2014), compared to only about a fifth for households not $H2M_{NW}$. Thus, the combined effects of being poorest quartile for net-worth and much more likely liquidity constrained would predict only modestly higher consumption growth for the $H2M_{NW}$.

Turning to Column (2), consistent with Table 4, adding fixed effects eliminates the impact of being liquidity constrained on consumption growth, while revealing a strong relation between *transitorily* low net worth, and subsequent consumption growth. The latter relationship is quite monotonic: Compared to households in the top quartile for net worth, those in the bottom quartile display nearly 5% faster subsequent consequent spending growth; those in the next poorest display 1.7% faster; and those in the next-to-richest only 0.5% faster. So, with fixed effects, this pattern closely conforms to the predictions for a single-preference type from the buffer-stock model in the middle panel of Figure 1.

The results for volatility of consumption growth and variety of spending also largely align with the takeaways from our sparser specification in Tables 5 and 6. From Column (3) of Table 8, households in the bottom quartile for net worth or liquidity constrained, keeping in mind that with $H2M_{NW}$ households are typically both, each show more volatile consumption growth. But, from Column (4), these effects project on the household fixed effects, not on current status in terms of net worth or liquidity. From Column (5) it is low-liquidity households that predictably spread spending over fewer categories. This arguably supports our interpretation that elastic preferences, high σ, should yield both a lower demand for liquidity and a willingness to concentrate spending by category. (See Appendix A4.) But, again, this tendency is removed by controlling for fixed effects, Column (6), implying it reflects those households often with low liquidity, not transitorily so.

4.6.2 Excluding Durables

Our empirical results in Sections 4.3 and 4.4 include all categories of spending available in the PSID beginning with the 1999 wave. This includes two categories that reflect NIPA durables: vehicle purchases and leases, and vehicle repair. In Appendix A3.3 we explore robustness of the results to excluding these two categories. Table A10 gives results for consumption growth, $\Delta \ln c$, and volatility of that growth, $|\Delta \ln c_{res}|$. These align with the results above. Consumption growth for H2M-households is slightly lower, but considerably more volatile. Controlling for household fixed effects eliminates that higher volatility while altering the coefficient on current $H2M_{NW}$ to predict higher expected consumption growth.

4.6.3 Tests of Measurement Error

One caveat with the volatility measures is that they also capture error in the measures of consumption and income. Such error is undoubtedly significant (see, for example, Bound, Brown, Duncan and Rodgers, 1994, Aguiar and Bils, 2015, and Carroll, Crossley and Sabelhaus, 2015). However, it is less clear that the magnitude of the error varies with $H2M$ status, which is relevant for the exercises performed above. To explore this, we posit that measurement error is *iid* over different waves of the survey. If the persistence of the true variable is similar across $H2M$ status, then the observed autocorrelation will be lower for the group with the greater mis-measurement.

Table 8: Results for Finer Breakdown by New Worth

	$\Delta \ln(c)$		$\lvert\Delta \ln(c)_{res}\rvert$		$\ln N$	
	(1)	(2)	(3)	(4)	(5)	(6)
NW Q1	.017	.047	.012	−.002	.010	−.0004
	(.004)	(.009)	(.004)	(.005)	(.009)	(.007)
NW Q2	.006	.017	.003	−.0005	.016	.006
	(.002)	(.004)	(.002)	(.002)	(.003)	(.003)
NW Q3	.001	.005	−.001	−.001	.009	.002
	(.001)	(.002)	(.001)	(.001)	(.002)	(.001)
Illiquid	−.012	−.003	.006	−.004	−.042	−.015
($H2M_{KV}$)	(.003)	(.005)	(.003)	(.003)	(.005)	(.004)
$\ln c$					.222	.166
					(.005)	(.004)
R^2	.08	.20	.01	.38	.38	.70
Fixed effects	no	yes	no	yes	no	yes

Note: Sample size is 24,214 in Columns (1) to (4); it is 30,626 in Column (5). Growth rates are annualized. N in Column (5) denotes the number of categories with positive spending. Omitted groups are the top quartile in terms of net-worth to income and not hand-to-mouth based on liquidity. Regressions include the controls described in Section 4.1. Robust standard errors are in parentheses, clustered at household for Columns (1), (3), and (5).

Table 9 reports the estimated auto-regressive coefficients for the growth of income and consumption for each hand-to-mouth status. Specifically, we compute the correlation of growth between years $t-4$ and $t-2$ and the growth between $t-2$ and t for each group defined by period $t-2$ $H2M$ status. Looking across the rows, there is little evidence that the $H2M$ have a significantly lower autocorrelation for either income or consumption. Under the assumption that the true process is the same for all groups, this suggests that classical measurement error (in logs) is not more or less severe for the $H2M$ households.

4.6.4 Dividing the Sample by Age and Earnings

From Table 2, households that are $H2M$ are younger and have lower earnings. In Appendix A3.4 we examine rates of spending growth and volatility of spending dividing the sample between households with heads ages 25 to 39 versus those 40 to 64 (recall that the benchmark regressions above also include age controls) and dividing households by their long-term

Table 9: Autocorrelation of Income and Spending Growth

	Not $H2M$	$H2M_{NW}$	$H2M_{LIQ}$
$\rho(\Delta \ln y^d_t, \Delta \ln y^d_{t-1})$	-.338	-.275	-.386
	(.019)	(.021)	(.029)
$\rho(\Delta \ln c_t, \Delta \ln c_{t-1})$	-.367	-.358	-.348
	(.011)	(.019)	(.021)

Note: Regressions include the controls described in Section 4.1. Standard errors are clustered at household level. For brevity, we denote $y^d \equiv y + ra$. R^2 is 0.23 in row 1, 0.19 in row 2.

earnings.[30] Of course, there is no presumption that differences in preferences are orthogonal to earnings.[31] But it is useful to examine high and low-earnings households separately because it partially controls for: (a) the possibility of scale effects in savings returns, and (b) a differential importance of government savings (e.g., Social Security) in discouraging savings.

The results above qualitatively continue to hold. We point to appendix tables A11 and A12 for the detailed results. Here we highlight the takeaways, especially any discrepancies from the results for the full sample. Across the groups, subsequent consumption growth is *not* higher for households that are hand-to-mouth. As above, currently being $H2M_{NW}$ does predict higher consumption growth once one controls for household fixed effects. But this is fairly weak for households with heads ages 25-39, while being much stronger for ages 40-64. When the sample is divided by long-term earnings, the coefficient on $H2M_{NW}$ is similar across groups and essentially the same as for the full sample. Finally, $H2M_{NW}$ households, as in Table 5 for the full sample, display more volatile consumption growth across each subgroup. But this effect is smaller, though still statistically significant, when the sample is divided by long-term earnings.

5 Calibrating Preference Heterogeneity

The facts documented in Section 4 indicate the importance of persistent differences across households in their targeted assets-to-income. By largely determining a household's propensity to have low net worth or liquidity, these differences can mask or reverse behavior for $H2M$ households as predicted by the standard model of homogeneous agents. A logical

[30]Long-term earnings, see Appendix A3.1, equal a household's average natural log of earnings after removing year dummies and a cubic function of the head's age.

[31]In fact, Dynan, Skinner and Zeldes (2004) argue that an important reason that lower-income households save less may reflect a lower demand for precautionary savings. This aligns with our conclusions, and those of Calvet et al. (2022) that the behavior of hand-to-mouth households is consistent with a high IES.

candidate to model such differences is heterogeneity in the stochastic process for income; however, the results of Section 4.4 indicate that this, at least on its own, is not a fruitful avenue to pursue. An alternative is heterogeneous preference parameters. A number of papers have found evidence that discount factors vary across individuals.[32] The extensive margin analysis of Section 4.5 also suggests a role for IES differences across individuals, as does prior empirical work.[33]

In this section, we explore a quantitative model in which households differ in these two key parameters. The purpose is twofold: (i) explore to what extent key moments of the wealth distribution and the empirical results from Section 4, filtered through a state-of-the-art model, suggest heterogeneity in discount factors or IES; and (ii) study the implications of that calibrated heterogeneity for describing behavior that is key to macroeconomic policy.

As noted in Section 2, it is difficult to distinguish impatience (β) from a high IES (σ) when the interest rate is less than the discount rate.[34] To do so, we move to a two-asset model, using portfolio choices to distinguish between the two. A consumer with a high IES is both sensitive to interest rate differences across assets and has a lower need for liquidity. That is, a high-IES consumer cares less *when* consumption occurs and so is more willing to tie up savings in illiquid assets. It is also useful to distinguish high-IES behavior from that driven by risk aversion, as achieved by Epstein-Zin preferences. The model of Kaplan and Violante (2014) (henceforth KV) uses Epstein-Zin preferences and includes a meaningful liquidity decision; so we therefore employ their model to a very large extent.

5.1 Model Environment

In this section, we recap the key elements of the KV model. We depart from the setting in their paper by solving the model at annual frequency, allowing for a richer income process and, importantly, allowing for preference heterogeneity.[35]

Agents live $J = 58$ years, spending $J^w = 38$ at work and $J^r = 20$ retired. Consumer i

[32]This includes evidence from surveys eliciting respondent preferences, e.g., Barsky, Juster, Kimball and Shapiro (1997), Parker (2017), and from structural estimates, with Calvet et al. (2022) as a recent example.

[33]Both Barsky et al. (1997) and Calvet et al. (2022) find evidence for heterogeneity in IES as well as the rate of time discount. The latter estimate an IES standard deviation across Swedish households of 0.99.

[34]Also noted above, a low market return to savings acts like a low β in discouraging household savings. We calibrate heterogeneity in households "internal return" to savings purely as differences in β's. This is partly for parsimony. But it also reflects that households classified as $H2M$ in the data disproportionately hold debt charging high rates (see Section 3.3), providing a high marginal return to saving.

[35]We thank the authors for sharing their code.

has Epstein-Zin preferences given recursively at age j by:

$$V_{ij} = \left[(c_{ij}^{\phi} s_{ij}^{1-\phi})^{1-1/\sigma_i} + \beta_i \left\{ \mathbb{E} V_{i,j+1}^{1-\gamma} \right\}^{\frac{1-1/\sigma_i}{1-\gamma}} \right]^{\frac{1}{1-1/\sigma_i}},$$

where c is nondurable consumption; s is the service flow from durables (described below); γ is the coefficient of relative risk aversion, which we set to 4 as in KV; and σ is the inter-temporal elasticity of substitution. Note that we allow the time-preference parameter β and σ to vary by individual.[36] Following KV, we set $\phi = 0.85$, which is based on the ratio of housing expenditures to total consumption in the US National Income and Product Accounts.

Earnings are given by the exogenous process:

$$\ln y_{ij} = \chi_j + \alpha_i + z_{ij} + \varepsilon_{ij},$$

where χ_j is a deterministic function of age, j, and α_i is an individual fixed effect. The idiosyncratic risk is represented by z_{ij}, which is a random walk, and ε_{ij}, which is iid across time. KV estimate a fourth-order polynomial for χ_j using the PSID. The variance of the fixed effect is set to 0.18 and that of the (mean-zero) innovations to random walk z_{ij} is set at 0.012. We set the variance of the transitory shock ε_{ij} to 0.05, as in Blundell, Pistaferri and Preston (2008). The income process yields mean earnings equal to $\$53,000$ dollars.

Two assets are available. Liquid asset m has an annual after-tax return:

$$r_m(m) = \begin{cases} 5.77\% \text{ if } m \in [\underline{m}_j, 0); \\ -1.41\% \text{ if } m \geq 0, \end{cases}$$

where $\underline{m}_j$ is an age- and income-specific borrowing limit.[37] The illiquid asset $a \geq 0$ has a higher return, but consumers must pay a fixed cost κ to alter their stock of a.[38] Again following KV, we set the illiquid after-tax return to 2.21%. In addition to a financial return, illiquid assets generate a significant service flow.[39]

Consumption and rental housing are taxed at a rate of 7.2%. Earnings and assets are taxed, with the tax rate a function of earnings and the consumer's portfolio: $\mathcal{T}(y_{ij}, m_{ij}, a_{ij})$.

[36]We do not allow γ to vary by individual. In the PSID data, we find no covariance between our $H2M$ indicators and the relative risk aversion estimates of Kimball, Sahm and Shapiro (2009). The assumption is also consistent with Calvet et al. (2022), who find little heterogeneity in risk aversion in the Swedish data.

[37]Specifically, for $j \leq J^w$, $\underline{m}_j = 0.74 y_j$. For $j > J^w$, $\underline{m}_j = 0$.

[38]KV calibrate the fixed cost to match that one-third of households in the Survey of Consumer Finance are $H2M$. We re-calibrate κ together with the preference parameters to match moments in our PSID sample.

[39]The service flow is given by: $s_{ij} = \zeta a_{ij} + h_{ij}$, where $h_{ij} \geq -\zeta a_{ij}$ represents housing services obtained from a rental market. KV set $\zeta = 1\%$, quarterly, so we set it to 4% in our annual model. The units of rental housing h are normalized such that the relative price of c to h is one.

Retirees receive social-security benefits given by $p(\chi_{J^w}, \alpha_i, z_{i,J^w})$; these are taxed according to the same function $\mathcal{T}$ faced by workers, but with p replacing y as an argument. We refer the reader to KV for the exact functional forms and parameters for $\mathcal{T}$ and p and note that we adjust those to reflect that we solve the model at an annual frequency.

5.2 Calibrating the Hand-to-Mouth

In calibrating preferences we strive to generate realistic $H2M$ behavior while adding heterogeneity parsimoniously, so as to depart minimally and intuitively from standard models. We therefore take a conservative approach and consider three preference types.

A preference type is a pair (β, σ) representing time preference and IES. In all cases, we set risk aversion to $\gamma = 4$, as in KV. In addition to the preference parameters, we also calibrate each type's share of the population, as well as the fixed portfolio adjustment cost κ. We search for the three preference types, their population weights and the fixed cost parameter that best match the 18 moments listed in Column 1 of Table 11: the shares of the population that are $H2M_{NW}$ and $H2M_{LIQ}$; the mean net-worth and illiquid wealth to income ratios; the mean net-worth to income ratio conditional on being observed in each of the three $H2M$ statuses; the median net-worth, illiquid, and liquid wealth to income ratios; the shares of households that are always and never observed $H2M_{NW}$ and $H2M_{LIQ}$; and the four slope coefficients from regressing consumption growth from t to $t+2$ on dummies indicating $H2M$ status at t, without and with fixed effects (i.e. Columns 1 and 2 in Table 4). The table is divided into two panels, as we discuss them separately. We weight the $H2M$ shares 10 times more heavily than the other moments. We compute the model moments on a simulated sample of 10,000 households that mimics the structure of the PSID sample: households are observed every two years, for at least 3 and at most 11 times. The distribution over the number of times a household is observed is the same as in the PSID sample, with a median of 7 biannual observations.[40] Because our PSID sample reflects working-age households, we base the comparable moments from the simulated data only on agents pre-retirement.

As the objective function is likely non-convex, we follow Guvenen (2011) and use a multi-start algorithm to search for the parameterization that best fits the data. Specifically, we draw a Sobol sequence of 500 quasi-random parameter guesses and solve the model for each of these 500 guesses. We then restrict attention to the 10 best guesses and perform a local search with a simplex algorithm using each of these as starting points. As suggested by Guvenen (2011), we perform the local searches iteratively, using a convex combination of the current starting point and the best starting point thus far. Starting from the optimum

[40]Specifically, we randomly draw from the simulated data observations of length $\tau = 3, 4, \ldots, 11$ to match the PSID frequencies of observing a household for that number of periods.

of this iterative local search, we increase the number of grid points of the asset space and perform a one last local search.

5.2.1 The Baseline Calibration

The calibration delivers nine parameters: Two governing relative population shares across three preference types; six reflecting preference parameters (β, σ) for each type, and the adjustment cost, κ. Table 10 reports the calibrated preferences and shares by type, while the second column of Table 11 reports the simulated moments. The calibrated cost of adjusting assets is \$4,504. For comparison, KV calibrate a cost of \$1,000 in a quarterly model.

Turning to the first two columns of Table 10, we see that the preferences of the first two types, who constitute nearly 80% of the population, are fairly patient and intertemporally inelastic. Type I, 45% of the population, are especially patient and inelastic with preference parameters $\beta = 0.97$ and $\sigma = 0.53$; whereas Type II, 34% share, are a little less patient, $\beta = 0.94$, and more elastic, $\sigma = 0.98$. Averaging β and σ's over these groups would yield respectively 0.96 and 0.67, values similar to those typically employed in the macro literature. By contrast, Type III, the remaining 22% of the population, are both quite impatient, $\beta = 0.72$, as well as highly elastic, $\sigma = 2.87$.

Table 10: Calibrated Preferences and $H2M$ Shares

Type	Preferences	Share	Share of Not $H2M$	Share of $H2M_{NW}$	Share of $H2M_{LIQ}$
I	β=0.97, σ=0.53	44.7%	58.1%	2.02%	62.3%
II	β=0.94, σ=0.95	33.7%	41.9%	13.7%	37.4%
III	β=0.72, σ=2.87	21.6%	0.03%	84.3%	0.34%

The simulated moments are reported in the second column of Table 11. The model does well matching most empirical moments. Given our focus, we highlight that the model matches well the shares of $H2M_{NW}$ and $H2M_{LIQ}$ – we show below that its modest preference heterogeneity is important to that matching. As Kaplan and Violante (2022) recently stressed, many models have difficulty matching both the mean and median wealth to income ratios, the so-called "missing middle." The baseline model with three types matches both these moments (overall and by $H2M$ status) quite well. The main "misses" are the slope coefficients on being $H2M_{LIQ}$ in the consumption growth regressions reported in Panel B. We defer a detailed discussion of this panel to its own Section 5.3 below.

To see more clearly "who are the hand-to-mouth," in the last three columns of Table 10

Table 11: Moments Used in Parameterization

	Data	Baseline	Single type	KV	Only β heterog
			Panel A		
share $H2M_{NW}$	0.233	0.255	0.178	0.102	0.250
share $H2M_{LIQ}$	0.173	0.193	0.249	0.247	0.232
net-worth to income	3.927	2.822	3.002	2.553	2.750
illiquid wealth to income	2.912	2.756	2.984	2.534	2.752
net-worth to income $H2M_{NW}$	-0.390	-0.110	0.010	0.033	-0.109
net-worth to income $H2M_{LIQ}$	2.536	3.203	3.510	2.804	3.204
net-worth to income not $H2M$	5.010	3.912	3.708	3.177	3.743
median net-worth to income	0.890	0.998	0.685	0.807	0.915
median illiquid wealth to income	0.011	0.000	-0.007	0.000	-0.010
median liquid wealth to income	0.833	0.888	0.627	0.808	0.887
share never $H2M_{NW}$	0.536	0.683	0.735	0.791	0.686
share always $H2M_{NW}$	0.089	0.220	0.117	0.030	0.215
share never $H2M_{LIQ}$	0.518	0.368	0.265	0.210	0.332
share always $H2M_{LIQ}$	0.018	0.002	0.006	0.004	0.006
			Panel B		
slope $\Delta c_{t,t+2}$ on $H2M_{NW}$	0.002	0.009	0.015	0.016	0.020
slope $\Delta c_{t,t+2}$ on $H2M_{LIQ}$	-0.008	0.057	0.083	0.063	0.081
slope $\Delta c_{t,t+2}$ on $H2M_{NW}$, FE	0.020	0.024	-0.008	0.013	0.010
slope $\Delta c_{t,t+2}$ on $H2M_{LIQ}$, FE	0.002	0.063	0.094	0.069	0.091

Note: Agents from the simulated models are sampled over periods ranging from 3 to 11 binannual observations in accordance with the distribution of histories reflected in the PSID data moments. Slope coefficients for consumption growth are annualized.

we report the composition of the three $H2M$ states by preference type. The two patient types exclusively make up the non-$H2M$, while the impatient/elastic Type III constitute 84% of the $H2M_{NW}$, despite being only 22% of the simulated population. Type I, being the most patient/inelastic almost never transit to $H2M_{NW}$, while those Type II are under-represented in that status by a factor of nearly three (14% versus its population share of 34%). By contrast, Type III are rarely classified as $H2M_{LIQ}$. These households typically do not hold positive liquid wealth, but their low net worth classifies them as $H2M_{NW}$. Consequently, both Types I and II are overrepresented among the $H2M_{LIQ}$.

Consider the thought experiment of removing Type III agents from this economy. As mentioned, the preference parameters of the remaining agents would exhibit average values of $\beta = 0.96$ and $\sigma = 0.67$, comparable to typical preferences calibrated to hit wealth targets.

But the flipside of Type III agents constituting 84% of the $H2M_{NW}$ is that, removing them from the economy, the remaining agents come up short by a factor of one-fifth in accounting for the share of $H2M_{NW}$ in the PSID. For the same reason, if we simulate a model imposing preferences similar to those of our Type I or II, it falls far short in accounting for the $H2M_{NW}$.

This provides a sense of the importance of bad luck versus preferences in determining who are the poor hand-to-mouth. Type III, who make up 84% of the poor hand-to-mouth, are nearly always ($> 99\%$ of time) observed $H2M_{NW}$. This reflects that their combination of impatience and high IES results in low targeted savings. Thus only the remaining 16% of the $H2M_{NW}$ can be viewed as transiting that status due to income realizations.

5.2.2 The One-Type Models

For comparison, we also calibrate a one-type model to match the same 18 moments. The parameters (β, σ, and κ) are reported in the second row of Table 12 and the simulated moments are in the column labelled "Single-type" of Table 11. As an alternative one-type specification, we also report the preference parameters from KV's original paper in the last row of Table 12 and the moments it produces in the column labelled "KV" of Table 11. The calibrated one-type model puts the adjustment cost κ at $\$6,008$, a third higher than our baseline model's $\$4,504$. Our annual version of the KV model uses $\kappa = \$4,000$.

Both of the one-type models have relatively patient ($\beta = 0.94$) agents, but with a large parameter σ governing the inter-temporal elasticity: KV have $\sigma = 1.5$, while σ for the moment-matching model is much higher, at 2.85. The calibrated one-type model is able to match the overall share of $H2M$ agents, but it, like the KV model, reverses the composition by under-estimating the share who are poor hand-to-mouth. Essentially, the single-type models generate the overall $H2M$ share via a high IES that generates frequently illiquid households. The data, on the other hand, call for relatively low net-worth households to make up the dominant share of the hand-to-mouth.

The especially high intertemporal elasticity for the moment-matching model is dictated by its attempt to match the data moments we introduce in Section 4: the shares of both hand-to-mouth types, the persistence of $H2M$ status, and the relationship between $H2M$ and subsequent consumption growth. To match these without preference heterogeneity, the model requires that agents are largely indifferent to varying consumption intertemporally and thus have a high IES of 2.85. But that elasticity is far above values estimated in the literature (Havrnek, 2015). Our benchmark 3-type model has a small group with σ nearly this large. But the calibrated average σ across agents is only 1.12, while the average value for β is only modestly lower than the single-type model at 0.91.

Table 12: Calibrated Parameters: Single-Type Models

Model	Preferences	Fixed cost κ
Calibrated	β=0.94, σ=2.85	\$6,008
KV	β=0.94, σ=1.50	\$4,000

Note: For the baseline model $\kappa = \$4,504$. KV calibrate κ to be $\$1,000$ for a model at quarterly frequency.

5.3 Revisiting Consumption Behavior: Model versus Data

Table 4 documented that, absent controls for type (i.e. fixed effects), being $H2M$ does not predict faster consumption growth. This runs counter to the standard model without preference heterogeneity. However, once we control for fixed effects, the data do show being currently $H2M_{NW}$ predicts faster growth. We repeat those results in Panel B of Table 11 along with the coefficients from the same regressions obtained from the simulated models.

We start with the annualized slope of consumption growth on $H2M_{NW}$ status. The one-type models predict counterfactually that $H2M_{NW}$ agents exhibit much higher consumption growth. Our model overpredicts the coefficient as well, but less so. That better performance reflects the selection effect in our model: Agents observed as $H2M_{NW}$ are disproportionately Type III; and Type III agents *on average* exhibit lower consumption growth due to their low β and high σ. Including a fixed effect acts as a partial control for that selection effect. Thus our model successfully produces the empirical finding that controlling for a fixed effect greatly increases predicted consumption growth from being $H2M_{NW}$. The one-type models, having no selection effect, fail to produce that finding: Controlling for fixed effects actually reduces predicted consumption growth for those $H2M_{NW}$. In fact, the calibrated single-type model actually yields, opposite the data, that being $H2M_{NW}$ predicts lower consumption growth controlling for fixed effects.

Turning to the consumption growth coefficients for $H2M_{LIQ}$ status, we see that all of the models mistakenly predict high future consumption growth for liquidity-constrained households. Our baseline model, as well as KV, predict about 6% higher annualized consumption growth for those $H2M_{LIQ}$, while the data show a small negative effect. The calibrated one-type model is particularly off, predicting agents $H2M_{LIQ}$ agents to display 8.3% faster consumption growth. Adding a fixed effect increases the estimated $H2M_{LIQ}$ coefficient modestly both in the data and in each of the models.

Recall that, in the model, being liquidity constrained implies a strict inequality in the agent's Euler equation, assuming the shock is not sufficient to induce tapping into illiquid assets. This predicts high subsequent consumption growth, something we do not see in the data. One interpretation of this discrepancy is that, contrary to the model, actual low-liquidity households do not face a strict inequality in their Euler equation. Rather, high-net-worth households, though holding little liquid wealth, may have alternative means to smooth consumption. In any event, there is something missing from all versions of the two-asset model for describing the consumption behavior of the wealthy hand-to-mouth.

Taking stock, the two-asset KV model, re-calibrated to allow for heterogeneity in patience and intertemporal elasticity parameters, matches surprisingly well the behavior of those $H2M_{NW}$. The model pinpoints a high willingness to substitute intertemporally, as well as impatience, for a relatively small subset of agents as crucial to explain the behavior of the $H2M_{NW}$. The model has more limited success in matching the behavior of those $H2M_{LIQ}$.

The literature has more typically introduced heterogeneity through discount rates, rather than elasticities of intertemporal substitution. Before moving to discuss the implications of the estimated preference heterogeneity, we first ask to what extent a model with only β heterogeneity can capture the moments in Table 11. The last column of the table reports the fit of such a model.

The estimation effectively produces two preference types: a patient type with $\beta = 0.94$ and an impatient type with $\beta = 0.68$. The share of the patient is 79.7%, with that of the impatient 19.6%. There is also a third calibrated type, but with a share of only 0.7%, with an intermediate $\beta = 0.77$. All agents are very elastic, with an IES of 1.84. The impatient type predominates among the $H2M_{NW}$, comprising 76% of agents in that status, four times their population share. Those $H2M_{LIQ}$ are essentially all of the patient type.

Many moments from the calibration are fairly similar to those from our three-type model with β and σ heterogeneity. For instance it produces a similar share of $H2M_{NW}$, 0.255 versus 0.250 in the baseline. It does predict more agents to be $H2M_{LIQ}$, 0.232 versus 0.193 in the baseline and 0.173 in the data, reflecting that all agents are highly elastic intertemporally.

The primary differences from the baseline are with respect to the slope coefficients on $H2M$-status for consumption growth. With β-only heterogeneity, the model far overstates consumption growth from being $H2M_{NW}$, in fact, even more so than the single-type models. Like the baseline model, the model with only β heterogeneity exhibits a strong selection effect, with the impatient type much more likely to be $H2M_{NW}$. But, unlike the baseline, that selection effect acts opposite that in the data. Low β's actually exhibit higher average consumption growth. While their low β is a force for low consumption growth, see Equation (2), these agents also exhibit much more volatile consumption growth due to having little or no buffer savings. This generates a sufficiently strong precautionary motive to dominate the more direct impact of their low β. While this force also exists in our baseline model, its impact is lessened given that our Type III agents also exhibit a higher σ than others, reducing their precautionary saving motive.

Because the model with β-only heterogeneity generates that low-β, frequently-$H2M_{NW}$ agents exhibit higher average consumption growth, controlling for fixed effects *decreases* the coefficient on $H2M_{NW}$ for consumption growth, cutting it in half from 0.02 to 0.01. This is directly opposite the impact of controlling for fixed effects in the PSID data.

Finally, we point out that the model with β-only heterogeneity, like all the models, performs poorly in predicting consumption growth for agents who are observed $H2M_{LIQ}$. In fact, like the calibrated one-type model, it performs especially poorly. This discrepancy from the data is equally large controlling for fixed effects. The extreme prediction for consumption growth of these two calibrated models partly reflects that all agents exhibit very high intertemporal elasticities, making them tolerant of large predictable shifts in consumption.

5.4 Implications of Preference Heterogeneity for Policy

Using the calibrated model, we address how preference heterogeneity affects the cross-sectional distributions of marginal propensities to consume and the sensitivity of consumption to interest rates, both key objects to macroeconomic policy.

5.4.1 The Marginal Propensity to Consume

Table 13 reports the marginal propensity to consume out of a $1,000 transfer for the simulated sample.[41] This is calculated for a pure transfer, not offset by taxes, although we discuss a tax-financed transfer below.[42] The first row of the table reports the average MPC in the simulated sample, as well as the MPCs conditional on being not hand-to-mouth, $H2M_{NW}$, or $H2M_{LIQ}$. The average MPC is 32%. This is comparable to numbers targeted in calibrations in the literature, though larger than Havranek and Sokolova (2020) find from their meta analysis of 144 studies after controlling for publication bias.[43]

Going across the top row of Table 13, for the non-$H2M$ the average MPC from our simulated model is 5%. But the MPCs for the hand-to-mouth, especially poor hand-to-mouth, are much larger – the $H2M_{NW}$ and $H2M_{LIQ}$ respectively have average MPCs of 72% and 34%. Thus the results clearly reinforce the conventional view of a relatively high

[41] MPCs are calculated for the entire sample (all ages), not just the working age that we use to calibrate to the PSID, in order to measure the aggregate response of the full simulated population.

[42] Using the policy functions, we subtract consumption conditional on a liquid asset position of m from that for position m plus $1,000$, dividing this difference by $1,000. This is equivalent to randomly giving a fraction of the simulated population $1,000, then regressing the change in consumption on the amount received (either zero or $1,000). The coefficient is therefore the percentage consumed by the recipients.

[43] They report an average "excess sensitivity" to transitory or anticipated income shocks of 11%.

MPC for those with low-wealth, while attaching relatively less importance to being $H2M$ based solely on low liquidity.

Table 13: Breakdown of Aggregate MPC out of \$1,000

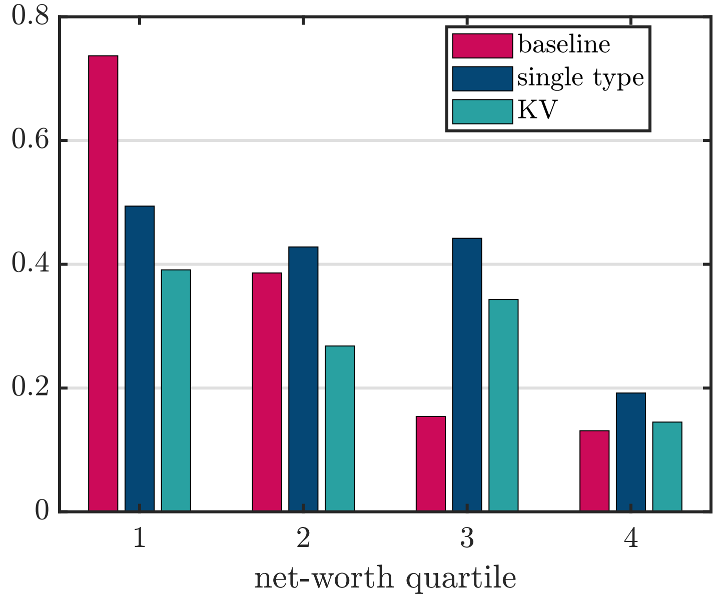
	Share	All	not $H2M$	$H2M_{NW}$	$H2M_{LIQ}$
			Baseline		
All preference groups	100%	0.316	0.050	0.722	0.336
β=0.97, σ=0.53	44.7%	0.121	0.024	0.519	0.243
β=0.94, σ=0.95	33.7%	0.277	0.090	0.520	0.463
β=0.72, σ=2.87	21.6%	0.783	0.775	0.783	0.793
			Single type (calibrated and KV)		
β=0.94, σ=2.85	100%	0.389	0.113	0.532	0.589
β=0.94, σ=1.5	100%	0.287	0.068	0.498	0.484

The remaining rows of the top panel of Table 13 show the role played by preference heterogeneity. Each row reflects a distinct preference type, with Column 1 repeating its population share. Recall from Section 2 that, conditional on assets, MPCs are higher if consumers are less patient or more elastic (higher σ). Row 2 gives MPCs for the largest preference group, Type I, who are patient ($\beta = 0.97$) and with an IES of 0.53. For these standard macro preferences, the average MPC is 12%, but reaches 52% when wealth is low. Type II (Row 3) are also fairly patient ($\beta = 0.97$) with a nearly unitary IES. Those preferences translate into a markedly higher MPC than for Type I, with an unconditional MPC of 28%. Types I and II average the same MPC of 52% when observed $H2M_{NW}$; but Type II are about nine times more likely to be observed with low wealth. (See Table 10.) MPCs for the impatient/elastic Type III, who comprise 84% of those observed $H2M_{NW}$, are reported in Row 4. Their average MPC is high, averaging 78%. Furthermore, their MPCs average essentially 78% regardless of $H2M$ status.

The bottom panel of Table 13 reports the MPCs for the two one-type models. The calibrated version generates an overall MPC of 39%, so modestly above that of our baseline, while that for the KV model is slightly lower than the baseline at 29%.

However, these similarities across environments do not extend to a closer look at how MPCs vary with wealth. In Figure 3, we split each model's simulated sample into net-worth quartiles and compute the average MPC out of the \$1,000 transfer for each quartile. For all models, the lowest wealth quartile has the highest MPC, as indicated by Table 13. For the benchmark model, there is a sharp decline in average MPC as we move across wealth quartiles. Conversely, the single type models show fairly modest differences across

Figure 3: MPC Across Models



Note: The figure plots MPCs out of a \$1,000 cash transfer by net-worth quintiles.

the first three wealth quartiles, before declining sharply at the top quartile. Thus, in the single type models, the difference in MPCs is primarily driven by the difference between the very wealthy and the rest of the distribution. In the benchmark model, we observe strong differences throughout the wealth distribution.

To get a better sense of what drives the higher MPC of the $H2M$, we can decompose the difference in MPCs between the $H2M$ and the non-$H2M$ into the portion due to wealth and the portion due to preferences. Specifically, consider the following decomposition for the average MPC for agents observed in a particular status k, e.g., $H2M_{NW}$, versus that for all agents. Let s_{jk} denote the share of the population that is both in status k and has preference type j; let s_j denote the share of the population with preference type j (the first column of Table 10); and let s_k denote the share of the population in $H2M$ status k. Note that this implies that s_{jk}/s_k is the share of status k that is of type j, corresponding to the last three columns of Table 10. We then have for each $H2M$ status k:

$$\begin{aligned}\mathbb{E}[MPC_i|k] - \mathbb{E}[MPC_i] = &\sum_j \frac{s_{jk}}{s_k} \left(\mathbb{E}[MPC_i|j,k] - \mathbb{E}[MPC_i|j]\right) \\ &+ \sum_j \left(\frac{s_{jk}}{s_k} - s_j\right) \mathbb{E}[MPC_i|j].\end{aligned} \tag{4}$$

The term on the left is the average MPC in $H2M$ status k minus the unconditional average.

In particular, let k refer to those $H2M_{NW}$, whose average MPC from Table 13 exceeds the overall average by 0.40 ($= 0.72 - 0.32$).

This is broken into the two terms on the right-hand side of equation (4). The first captures the importance of $H2M$ status given a preference type. More exactly, the term in parentheses is the average MPC of type j when in status k versus the average MPC for that preference type across all H2M states. The summation then averages across preference types, weighting each types by its representation in $H2M$ status k. This term would be zero if MPCs do not vary by $H2M$ status. This first term is small, equalling 0.065 for $k = H2M_{NW}$, or only 16% of the left-hand side.

The second term on the right captures whether high MPC preference types are over- or under-represented in status k. Specifically, the term in parentheses is the share of status k that is type j minus the share of the population that is type j. This term then multiplies the average MPC for type j. The summation therefore reflects the extent that high-MPC preference types are disproportionately in $H2M$ status k. This term is zero absent preference heterogeneity, but in the simulation accounts for 84% of the difference in MPCs between those $H2M_{NW}$ and the average MPC. Thus preference heterogeneity mostly explains the higher MPCs for the poor hand-to-mouth.

A variance decomposition provides another perspective on the role of preference heterogeneity in MPCs. We can decompose the variance of MPCs across individuals into the amount contributed by within-type variation and that explained by type differences. Letting $i \in I$ index individuals, $j \in J$ type, and s_j denoting the population share of type j, we have

$$Var(MPC_i) = \sum_j s_j Var(MPC_i|j) + \sum_j s_j \left(\mathbb{E}[MPC_i|j] - \mathbb{E}[MPC_i]\right)^2 .$$

The first term on the right is the weighted sum of within-type variances. The second term captures how the conditional mean MPC varies by type.

Table 14 reports the results of this decomposition for the simulated sample. We distinguish between respondents who do not change their decision to adjust the stock of illiquid assets in response to the \$1,000 transfers and those who do.[44] The latter group represents only 1.1% of the sample, but features extreme MPCs which greatly influence the variance. Focusing on the former group, the variance of the MPC is 0.11. The average within-type variance is 0.06, or 52% of the total. The remaining 48% reflects the differences in means across types, which total 0.05.[45] The results of this decomposition are consistent with Gel-

[44] By not changing the adjustment decision we mean agents do not adjust when receiving the transfer if they would not have adjusted otherwise, or still withdraw/deposit when receiving the transfer if they would have withdrawn/deposited otherwise.

[45] For comparison, the model with β-only heterogeneity predicts a much smaller role for preferences in

man (2021) and Lewis, Melcangi and Pilossoph (2021), who also establish a potentially important role for differences across types as drivers of MPC dispersion.

Table 14: Sources of MPC Heterogeneity

	Population share	Variance MPC	Across type variation (%)	Within-type variation (%)
All	100%	0.717	9.00	91.0
Not change adj decision	98.9%	0.112	47.5	52.5
Change adj decision	1.1%	32.94	12.7	82.5

5.4.2 Responsiveness to Fiscal Transfers

The patterns discussed above provide a valuable guide to refining transfer schemes. In particular, consider the following alternative fiscal policies to boost aggregate demand. The first is a one-time transfer of $1,000 to all households. The alternative is to direct the same aggregate transfer only to households in the bottom net-worth quartile. We compare the aggregate MPC in partial equilibrium for the multi-type and single-type models.

Table 15 reports the results. In the top panel we assume the transfer is not financed, while in the bottom panel we assume the government imposes a proportional tax on total income to finance the transfer under a balanced budget. When not financed, an untargeted transfer has similar impacts on aggregate consumption across the three alternative models. However, targeting the transfer to the poorest households generates a much bigger overall MPC in the baseline multi-type model, consistent with the illustration in Figure 3.

The bottom panel of Table 15 indicates that untargeted transfers financed by a proportional tax have a much lower aggregate impact. But, imposing a balanced budget, it remains true that the spending impact of targeted transfers to the bottom wealth quartile is much higher in the benchmark model than in the single-type environments.

The bottom line of this exercise is that the highest impact to aggregate consumption is by targeting the impatient, elastic Type III agents. In the benchmark model, these are easily identifiable due to their low wealth. In the single-type model, low wealth is a much less reliable guide to identifying those that have a high propensity to consume out of transfers.

explaining the variance of MPCs (0.16): the within-type variation accounts for 83% of the total variance, while the across-type variation accounts for the remaining 17%.

Table 15: Aggregate MPC out of Fiscal Transfers

	Untargeted	Targeted
	Not financed	
Baseline	0.316	0.738
Single type, calibrated	0.389	0.462
Single type, KV	0.287	0.320
	Financed	
Baseline	0.053	0.579
Single type, calibrated	0.125	0.413
Single type, KV	0.096	0.292

Note: The proportional tax rates required to finance the transfers in the three economies are 2.58%, 2.56% and 2.62%, respectively.

5.4.3 Responsiveness to the Interest Rate

Another standard policy designed to boost aggregate demand is a cut in the interest rate. We evaluate this, again in partial equilibrium, by considering a one-period, unanticipated decline in the interest rate. Specifically, we solve the optimal consumption response for each agent assuming the path of interest rates on liquid assets is reduced by one percentage point in the current period, but then returns to its benchmark level thereafter. The decline is on both positive and negative liquid asset positions. We compute the percentage change in consumption for the period of the rate cut, expressing that change relative to the no-cut baseline. We report the results in Table 16, with responses expressed as fractions of a percent in consumption.

Table 16: Consumption Response to a Temporary Interest Rate Cut

	All	not $H2M$	$H2M_{NW}$	$H2M_{LIQ}$
Baseline	0.080	0.088	0.151	0.031
Single type, calibrated	0.156	0.141	0.643	0.064
Single type, KV	0.153	0.176	0.451	0.083

In the baseline model with preference heterogeneity (first row), consumption increases by 0.08 of one percent in response to a 100 basis point cut in the liquid-asset interest rate. Going across the columns, we see that the response is largest for the $H2M_{NW}$.

There are several forces that drive the relative responsiveness of $H2M$ households. First of all, $H2M$ agents, both the $H2M_{NW}$ and $H2M_{LIQ}$, are typically at a borrowing constraint or have a high MPC, both of which dampen their response to the rate cut. For agents observed $H2M_{NW}$, there are two additional factors that act to raise their response absolutely and relative to the others. For one, the $H2M_{NW}$ are disproportionately high IES agents, leading to a larger response for those not literally constrained. Secondly, many $H2M_{NW}$ agents have negative balances of liquid assets, so they enjoy a positive income effect from a cut in interest rates, increasing their consumption.

From Table 16, we see that the response of agents observed as not-$H2M$ is intermediate to the two $H2M$ groups. This is surprising, as these agents are not near a borrowing constraint or budget kink. For this group, the key is that a subset, 3.5%, respond to the rate cut by moving assets from their liquid to their illiquid account (or delay withdrawals from the illiquid account) due to the larger interest differential between liquid and illiquid accounts. This reduces consumption for adjusters, lowering the consumption response of the relatively wealthy agents. For the 96.5% who do no such re-balancing, the consumption response is considerably larger than for either $H2M$ group, at 0.43%. By contrast neither the $H2M_{NW}$ nor $H2M_{LIQ}$ agents undertake such a transfer, since they hold little or no liquid assets.

Looking across the rows, we see that the spending response to the rate cut is considerably larger for the models with a single preference type. For those not $H2M_{NW}$, this greater response can be related to these agents having a much higher IES in these models than in our baseline. But the response is also larger, in fact especially so, for agents observed $H2M_{NW}$. In turn, this largely reflects that those $H2M_{NW}$ in our baseline model have higher MPCs (see Table 13) than in the one-type models. As discussed by Auclert (2019) and Slacalek, Tristani and Violante (2020), to a first-order, the magnitude of the substitution response to the interest rate is proportional to an agent's marginal propensity to save, i.e., one minus their MPC. In the one-type models, that marginal propensity to save for those $H2M_{NW}$ is nearly double that in our baseline with preference heterogeneity.

The upshot of the two policy experiments is that, bringing in modest preference heterogeneity to meet the empirical moments, targeted fiscal transfers have a larger impact on spending, while the impact from an interest rate change becomes more muted. Both these results are driven by the predicted spending responses of those agents that are observed as being poor hand-to-mouth.

6 Conclusion

A workhorse model of savings in the literature has consumers self-insuring their income risk subject to a borrowing constraint. This model has a number of predictions for the spending of low-asset households, including that they should exhibit higher expected consumption growth as well as a higher marginal propensity to consume. But these predictions are masked or muddled in the data if differences in asset holdings also reflect heterogeneity in preferences. We show that, if either a low discount factor or a high IES drives households to hold few assets, then these $H2M$ households can display lower spending growth. Moreover, such households have relatively high MPCs, even if they are at their target level of assets.

We see in the data that that households labeled as $H2M$ based on low net worth or lack of liquid assets do not exhibit faster spending growth. In addition, low-asset households exhibit more volatile spending and adjust their spending to a greater extent by varying the number of categories consumed. The latter cannot be explained by heterogeneity in discount factors, but is consistent with $H2M$ households exhibiting a higher IES *because* they have a more active extensive margin to vary consumption.

Strikingly, the spending "puzzles" we see for $H2M$ households project on their tendency to be hand-to-mouth, captured by their household fixed effects, rather than their current asset position. That is, it is households typically observed holding few assets that display lower spending growth, more volatile spending, and more volatility in terms of categories of spending. We view these findings as consistent with important and relatively stable differences in preferences for $H2M$ versus other households.

To identify the consequences of this heterogeneity we consider the setting in Kaplan and Violante (2014), where agents allocate wealth between liquid and illiquid assets, but allow for heterogeneity both in households' discount factors and IES. To match empirical targets, we find that much of the model population, 84%, must exhibit quite standard preferences, with a high discount factor and a low to medium IES. But to explain the significant shares of $H2M$ households, and our other data moments from the PSID, requires the remaining population be quite impatient and elastic. This last group accounts for 84% of the poor hand-to-mouth, despite comprising only 22% of the calibrated overall population. We find that preference heterogeneity is key for dispersion in MPCs across consumers, with preferences explaining about 84% of the higher MPCs for the poor $H2M$. From the model, we find that allowing for that modest preference heterogeneity markedly increases the spending impact of a fiscal transfer targeted by wealth, while reducing that from a temporary interest rate cut.

It is interesting to revisit the results of the "US Financial Diaries" (USFD) described in Morduch and Schneider (2017) through the lens of our empirical and quantitative exercises. The USFD project consists of detailed and repeated interviews with 235 low-wealth households over 12 months. The experiences documented by the diaries indicate volatile income and spending, with the ability to partially save for the short-term but not the long-term. Related to our discussion of income volatility, Morduch and Schneider note (p. 63): "The paradox is that the very people who need a buffer of savings are often the ones who have the hardest time creating it." Related to our low discount factor and the lack of persistent accumulation of assets, one respondent states (p. 66): "The discipline for us to not dip into that rainy-day fund – for entertainment or something fun – is too much." Our rationale in Appendix A3.5 for the high IES, namely, the relevance of fixed costs, also has clear echoes in the diaries. For example, one respondent was saving for the first month's rent to be able to get an apartment on his own. The surveyors note (p. 96) that "[the respondent] was trying to put money aside for the short-term goal of renting his own apartment, not a long-term goal like a home purchase or retirement." Interestingly, the authors of the study use this type of "short-term saving" behavior to argue against financial illiteracy as a primary cause of low wealth. Our study confirms many of these vignettes in a nationally representative survey. Moreover, we assess the prevalence of such "types" and provide quantitative implications of including such households in a model's population.

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Appendices for "Who Are the Hand-to-Mouth?"

A1 Consumption Model

A1.1 Parameterization

We solve the model in Section 2 numerically to illustrate its key predictions. We assume agents enter the labor market at age 22, work until age 60, then live until age 80. During working age, they receive labor endowment y_t. We assume the endowment has a deterministic component that depends on age and a stochastic component. Specifically, we postulate that:

$$\begin{aligned} \ln y_t &= f(t) + z_t + \varepsilon_t \\ z_t &= \rho z_{t-1} + \eta_t, \end{aligned}$$

where $f(t)$ is a cubic age polynomial, $\varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right)$, $\eta_t \sim N\left(0, \sigma_\eta^2\right)$. We set the parameters of the age polynomial to replicate the hump-shaped profile of earnings and we set $\rho = 0.98$, $\sigma_\eta = 0.11$ and $\sigma_\varepsilon = 0.29$ following Karahan and Ozkan (2013). We assume retirement income is constant and is a function of average earnings in the economy and the average career earnings of an agent, as predicted by earnings before retirement, according to the pension schedule in Guvenen, Kuruscu and Ozkan (2013). Finally, we set $R = 1.04$ and consider three preference types (β, σ): $(0.95, 0.5)$, $(0.9, 0.5)$, and $(0.95, 1.5)$.[46] We load the heterogeneity on preference parameters, but the alternative discount factors can also proxy for (permanent) differences in financial returns. That is, if an individual has access to a high-return savings vehicle that another individual with the same preferences lacks, then βR will differ across the two in the same fashion as a difference in discount factors. A separate issue is if returns vary by scale, say, due to a fixed cost of access. In this case, the level of assets will also reflect variation in returns, mitigating the negative impact of wealth on expected consumption growth. We discuss this point in more detail in the empirical section.

A1.2 Target Savings and Heterogeneity in Income Processes

A natural hypothesis is that some agents face less idiosyncratic income risk and in response hold less precautionary savings. Similarly, some could face a steeper life-cycle profile of earnings, and therefore desire to borrow rather than save. Both points suggest differences in

[46] Havrnek (2015) conducts a meta-study of IES estimates in the literature, reporting a median of 0.5. Kaplan and Violante (2014), citing the asset-pricing literature, choose an IES of 1.5.

income processes as a potential explanation for the persistent hand-to-mouth. However, our empirical analysis indicates that those often hand-to-mouth have lower income growth and more volatility. Given the plausibility of the income-difference hypothesis, a closer study is warranted. Hence, in this subsection we explore in greater detail the relative income processes for the frequently hand-to-mouth.

To this end, we divide the PSID sample in half based on the frequency of $H2M$ status over the sample. The median household finds itself in either $H2M$ status two times. We therefore group the 51.9 percent of the sample that are hand-to-mouth two times or less in the "Below Median" category, and the remaining 48.1 percent in the "Above Median." (We find similar patterns splitting only by frequency of $H2M_{NW}$ status.)

For each subsample we estimate a standard specification of the process for household earnings. Specifically, we estimate:

$$\ln y_{ijt} = \beta_t + \mathbf{X_{ijt}}\boldsymbol{\gamma} + \tilde{y}_{ijt},$$

where y_{ijt} is total after-tax labor earnings for household i in wave t with a head of age j, β_t is a year fixed effect, $\boldsymbol{X}$ is a vector of demographic controls, and $\tilde{y}_{ijt}$ is the residual income that we analyze below in a second stage. The vector $\boldsymbol{X}$ includes a cubic in age (normalized to zero at 25), as well as dummy controls for educational attainment (for less than high school, high school, some college, and college degree), the number of earners ($0, 1$ or 2), family size ($1, 2, 3, 4,$ or $5+$), and three race categories. We estimate the specification for each subsample separately. The results are reported in Table A1. The coefficients are similar across the two groups. Those often hand-to-mouth have a slightly shallower age profile, in line with Table 4, but the difference is small relative to the standard errors.

Table A1: First-Stage Income Process Parameters

	Rarely $H2M$	Frequently $H2M$
Age-25	.053	.049
	(.005)	(.004)
(Age-25)^2	-.002	-.002
	(<.001)	(<.001)
(Age-25)^3	(<.001)	(<.001)
	(<.001)	(<.001)
Observations	16,712	15,559

Note: Not reported are controls for education, household status, number of earners, family size and time.

Table A2: Residual Income Process Parameters

	Rarely $H2M$	Frequently $H2M$
ρ	.891	.902
	[.852 .936]	[.837 .925]
σ^2_η	.057	.044
	[.025 .075]	[.029 .062]
σ^2_ν	.019	.091
	[.000 .126]	[.061 .132]
σ^2_α	.145	.051
	[.084 .184]	[.029 .087]

Note: The table reports point estimates of the parameters of the income process and the 95% confidence interval in brackets.

We now study the residual income process $\tilde{y}_{ijt}$, estimating the standard specification:

$$\tilde{y}_{ij} = \alpha_i + \epsilon_{ij} + \nu_{ij}$$
$$\epsilon_{ij} = \rho\epsilon_{ij-1} + \eta_{ij},$$

where α_i is a mean-zero household fixed effect with cross-sectional variance σ^2_α; ϵ is a persistent AR(1) process with parameter ρ; and ν and η are mean-zero *iid* shocks with variances σ^2_ν and σ^2_η, respectively. All shocks are assumed to be orthogonal. We estimate the parameter vector $\{\rho, \sigma_k\}$, where $k = \alpha, \nu, \eta$, by method of moments. We follow Tonetti (2011) and use the (available) covariances between agents of ages j and j' as moments.[47] The results are reported in Table A2, along with bootstrapped 95% confidence intervals.

We see that households frequently hand-to-mouth have less volatile innovations to the AR(1) coefficient, but with slightly more persistence. Together the estimates indicate an unconditional variance of ϵ is 0.28 for the rarely hand-to-mouth compared to 0.24 for the frequently hand-to-mouth. Thus the frequently hand-to-mouth have slightly less long-run uncertainty. On the other hand, variance of the *iid* component of earnings is nearly five times as large for the frequently hand-to-mouth.

To put these differences in perspective, we simulated the standard model under each of the residual income processes, that estimated for households rarely hand-to-mouth and that estimated for those often so, separately for each of our three preference specifications. This reveals whether frequent *H2M* status reflects the differential income process for these

[47]See Tonetti (2011) for details. We are grateful to Chris Tonetti for sharing the Matlab code to compute the estimates.

Table A3: Simulated Moments for Alternative Income Specifications

	Frequency $H2M$		Wealth/Earnings	
	(1)	(2)	(1)	(2)
$\beta = 0.95, \sigma = 0.5$	.161	.113	3.823	3.753
$\beta = 0.95, \sigma = 1.5$	.351	.255	2.020	2.030
$\beta = 0.90, \sigma = 0.5$	.412	.312	1.296	1.313

Note: The columns labelled (1) use the residual income process parameters estimated for the Rarely Hand-to-Mouth reported in Table A2, setting $\sigma_\alpha^2 = 0$; the columns labelled (2) use the income parameters estimated for the Frequently Hand-to-Mouth. $H2M$ status in the model is whether the agent has assets a less than two months of annual earnings, $y/6$.

households. We set the borrowing constraint and the fixed effect equal to zero for each exercise. In Table A3, we report the frequency of $H2M_{NW}$ status (computed as $a' < y/6$, as in the data) and average wealth divided by average income.

In all simulations, the model's predictions by frequency of $H2M$ status are opposite the data. That is, the empirical income process for the frequently $H2M$ predicts less frequent $H2M$ status in the model. There is no clear pattern with respect to average wealth. Recall that the frequently-$H2M$ income process has much more transitory risk. This generates a large incentive to save near the borrowing constraint and quickly exit the low-asset region. This explains their infrequent $H2M$ status. Far from the constraint, however, the fact that the empirical $H2M$ income process has slightly less persistent risk plays a role, making the prediction for the long-run mean of wealth depend on the preference specification.

A2 Data Appendix

A2.1 Description of PSID sample

Our primary data source is the Panel Study of Income Dynamics (PSID) biennial surveys from 1999 to 2019. The advantage of the PSID for our purposes is that it provides measures of income, assets, and expenditures. Income measures were a focus of the PSID from it onset in 1968 (hence its name). The PSID introduced a module to measure assets and liabilities in 1984 that reappeared every five years. Beginning 1999 the PSID includes a wealth module in every survey. That is one reason we begin our sample in 1999. The second reason is that the PSID first began surveying households on a number of expenditure categories, beyond food and housing, with the 1999 survey.

We focus here on our variable constructions for the key variables of earnings, income, wealth, and expenditures. We then detail the sample restrictions we employ.

The analysis separately considers earnings income and a broader measure of after-tax income that includes net income from assets, including owner-occupied housing. We measure earnings by wage and salary income, net of payroll taxes, plus the head of household's labor component of income from any unincorporated business, and one half of family farm income. We add to these earnings any receipts of government transfer payments from AFDC, supplemental security income, other welfare payments, veteran's pensions, unemployment benefits, worker's compensation, or social security benefits. To construct after-tax income, we first sum taxable income (earnings, net profits from business or farm, and income from assets), transfer income, and social security income for the husband and wife as well as other family members. From this we subtract the family's federal and state income tax liabilities as measured by the TAXSIM program. For homeowners we then add 6 percent of the respondent's assessed value of their home to account for the implicit rent on their home, while subtracting payments for property taxes, mortgage interest, and home insurance.

We define a household net worth as the sum of its liquid and illiquid assets net of debts. We treat liquid net worth as the sum of balances in checking or savings accounts, money market funds, certificates of deposit, holdings of treasury bills and other government savings bonds, the value of stocks outside of pension funds, minus the value of all debts. The values for checking or savings accounts, money market funds, certificates of deposit, treasuries and other government bonds are multiplied by 1.055, to reflect cash holdings that are not reported in the survey. See Foster, Schuh and Zhang (2013) for justification. Illiquid wealth is the sum of a household's home equity, equity in other real estate, holdings of IRAs and other pensions, the value of bonds (not including treasury or other government bonds), insurance holdings, the value of any business or farm net of debts, and the value of any vehicles (including motor homes), boats, and trailers net of debt owed. These distinctions for liquid versus illiquid assets largely follow Kaplan et al. (2014), while fitting within the grouping of assets within the PSID questionnaire. Our stratification of households into not $H2M$, $H2M_{NW}$, and $H2M_{LIQ}$ are based on these measures of assets relative to our broad measure of earnings, as discussed at the beginning of Section 4.

Our measured expenditures include spending categories for shelter, utilities (by type), food for consumption at home, food for consumption away from home, gasoline, health insurance, medical expenses (separately for doctors, hospitals, and prescription drugs), education, child care, purchases or lease of vehicles, vehicle repair, vehicle insurance, parking, and public transportation (by type). Spending on shelter reflects rent payments for renters; for homeowners we set it to 6 percent of respondent's valuation of the home. Our measured expenditures relative to after-tax income averages 58.3 percent. For our measure of nondurable and services spending, we exclude spending on vehicles or their repair.

In addition to controlling for year and age effects, our regression analysis includes controls for marital status (single or married/cohabiting), race (three values), and family size. Family size takes five distinct values, with 5 representing family sizes of 5 and above. For regressions in growth form, e.g., growth rate of expenditures over two years, the controls reflect year and age dummies, and a set of dummies for the conceivable changes in marital status and for whether family size increased, stayed the same, or decreased.

Respondents report earnings, income, and taxes for the previous calendar year, whereas they report assets and liabilities as of the interview. Expenditures are reported for differing time frames. Among categories available from the 1999 survey, education spending is for the prior calendar year, health spending (including health insurance) for the previous two calendar years, and vehicle spending for since the survey two years prior. Other categories are in terms of the household's usual (typically monthly) expenditures. We treat these variables as aligned with respect to the previous calendar year, with assets viewed as end of period. We deflate nominal variables by the corresponding CPI measured in 2009 dollars.

Our sample reflects only the PSID's nationally representative core sample (i.e., we use the Survey Research Center sample, excluding the Survey of Economic Opportunity.). This sample includes "split-off" families from the orignal sample as well as the PSID sample extensions to better represent the families of immigrants and recent immigrants. Throughout the analysis we employ the PSID longitudinal family weights, which are designed to correct for non-random sample attrition as well as failures to draw an entirely random sample.

We restrict our sample to households with heads ages 25 to 64. We exclude households with less than \$2,000 (2009 \$'s) in any of annual earnings (including transfer receipts), after-tax income, or annual expenditures. We also exclude households with extreme responses on expenditures in which food purchases for consumption at home are zero, or spending on housing and food (home and away) is less than 5% or greater than 90% of total expenditures. Finally, we include only households whose $H2M$ status, from their earnings and asset information, can be measured for at least three surveys. Table A4 displays the impact of these restrictions sequentially for our resulting sample, both in terms of households and number of observations. It also shows the sample impact of examining two-year growth rates, such as income or expenditure growth.

Each household's annual expenditures are divided into distinct categories. Consider nondurable expenditure at two adjacent dates. Divide spending at t among N_t distinct goods: $c_t = \sum_{n=1}^{N_t} x_{n,t}$, where $x_{n,t}$ is the amount devoted to good n in period t. A similar decomposition can be done for the prior period. In this spirit, we divide nondurable expenditure into

Table A4: Impact of Sample Restrictions

Restriction	Households	Observations
Ages 25 to 64	8,227	40,469
Expenditures≥$2000	8,223	40,308
No odd spending	8,047	38,275
Earnings & Inc.≥$2000	7,947	37,351
$H2M$ status 3+ times	5,565	33,498
WRT 2-year changes	5,415	26,956

Note: PSID data, 1999 to 2019 survey waves.

the categories listed in Table A5. We exclude basic utilities like water, heat, and electricity as these may be included in rental contracts. For each category, we list its share of total nondurable expenditure as well as the fraction of households who report spending on that category in a given survey. The final two columns are the average probability of addition or deletion of that category, respectively.

Table A5: Categories

Category	Share	Positive	Add	Drop
Food at home	0.344	1.00	0.00	0.00
Food away	0.153	0.95	0.03	0.03
Gasoline	0.131	0.92	0.03	0.02
Car insurance	0.104	0.92	0.03	0.02
Health insurance	0.083	0.72	0.09	0.09
Education	0.053	0.29	0.10	0.13
Doctors	0.035	0.79	0.10	0.10
Prescription drugs	0.022	0.79	0.10	0.09
Other transport	0.022	0.30	0.17	0.17
Childcare	0.019	0.12	0.04	0.05
Hospital	0.015	0.27	0.15	0.15
Other utilities	0.007	0.15	0.08	0.10
Bus & train	0.005	0.08	0.03	0.03
Parking	0.003	0.09	0.05	0.05
Taxi	0.003	0.06	0.03	0.03

A2.2 Description of the Consumer Expenditure Survey Sample

We employ a sample derived from the Consumer Expenditure Surveys (CE) to augment our evidence from the PSID that low-asset houshold concentrate their spending on a narrower set of categories. We make use of the CE data on income, assets, and expenditure from survey years 1996 to 2016.

The CE surveys households on their expenditures for up to four consecutive quarters. We only include households that were surveyed in the fourth interview. In this interview they are asked about asset and debt holdings and about their income over the previous 12 months. The CE does not provide information on households pensions, and is more limited than the PSID in collecting information on some other forms of illiquid assets. Therefore, we stratify households by assets only with respect to their liquid assets, using the definition in Kaplan et al. (2014) for households that are hand-to-mouth. The asset information for liquid assets parallels that in the PSID. It includes the household's balances in checking or savings accounts, money market funds, certificates of deposit, holdings of treasury bills and other government savings bonds, the value of stocks outside of pension funds. Debts include credit card and store credit debt, student loans, and medical or personal loans.

We express a household's assets relative to its annual income. That income sums household earnings, farm and business income, retirement payments including from social security, government transfers, and alimony receipts. Our income measure is before taxes. (The corresponding CE variable for after-tax income was eliminated after 2015.)

Each household's quarterly expenditures are divided into many distinct categories. To examine the share of categories purchased, we exclude durable categories as well as utilities (e.g., water, gas, electricity, trash collection) that we view as tied to the choice of housing. The resulting 27 nondurable categories are listed in Table A6. The table reports the fraction of households that spend on the category in a quarter, as well as the average fraction adding or dropping the category in a quarter.

A3 Additional Empirical Results

A3.1 More on Persistence of Hand-to-Mouth Status

Section 4.2 reports the tendency for households to transit across the three $H2M$ statuses (not $H2M$, $H2M_{NW}$, $H2M_{LIQ}$) over two or four years. In this section we report transition rates over four years after first stratifying households by their long-run earnings or their average rate of growth in earnings. Earnings are measured after subtracting payroll taxes and adding transfer payments. Long-term earnings are measured in two steps. In the first, $ln(earnings_t)$

Table A6: Nondurable Expenditure Categories, CE

Category	Share	Positive	Add	Drop
Food at home	0.289	1.00	0.00	0.00
Motor fuel	0.113	0.92	0.01	0.01
Food away from home	0.097	0.86	0.06	0.06
Telephone services	0.072	0.96	0.02	0.02
Health insurance	0.067	0.61	0.04	0.03
Motor vehicle insurance	0.052	0.61	0.12	0.12
Professional services	0.035	0.52	0.14	0.13
Video and audio – services	0.034	0.74	0.04	0.04
Tuition, other school fees, and childcare	0.034	0.19	0.06	0.06
Tobacco and smoking products	0.026	0.28	0.04	0.04
Public transportation	0.020	0.24	0.11	0.11
Tenants' and household insurance	0.016	0.33	0.08	0.08
Personal care services	0.015	0.68	0.10	0.10
Club memberships, fees for sports, lessons or instructions	0.014	0.33	0.10	0.10
Prescription drugs	0.014	0.44	0.12	0.11
Information processing other than telephone services	0.013	0.52	0.07	0.06
Alcoholic beverages at home	0.012	0.40	0.09	0.09
Admission tickets	0.012	0.45	0.14	0.14
Motor vehicle fees	0.012	0.49	0.19	0.18
Lodging away from home – hotel	0.011	0.19	0.12	0.12
Household operations – nondurables	0.010	0.24	0.09	0.09
Laundry and other apparel services	0.009	0.40	0.10	0.11
Financial and legal services	0.009	0.29	0.12	0.13
Alcoholic beverages away from home	0.008	0.32	0.10	0.10
Hospital and related services	0.005	0.06	0.05	0.05
Elderly care, funeral and dating services	0.002	0.02	0.02	0.02
Medical supplies	0.001	0.02	0.01	0.01

is regressed on a cubic in head's age and a full set of year dummies for all households with heads ages 25-64. Secondly, residuals from that regression are averaged across years for each household. A household's average rate of growth in earnings is similarly measured in two steps. In the first, $\Delta ln(earnings_t)$ is regressed on a quadratic in head's age and a full set of year dummies for all households with heads who are within ages 25-64 in both t and $t + 2$. Residuals from that regression are then averaged for each household.

Transition rates separately for the bottom versus top four quintiles of long-run earnings are given in Table A7. Results splitting by the bottom, middle, and top three quintiles for average growth rate in earnings are given in Table A8. Both sets of results are discussed in Section 4.2.

A3.2 Results Controlling for Long-term Earnings

Table A9 reports the impact of $H2M$ status on spending growth, volatility of spending growth, and number of categories consumed controlling for being in the bottom quintile in

Table A7: $H2M$ Transition Rates by Bottom vs. Top Quintiles of Long-run Earnings

	Not $H2M_t$	$H2M_{NW,t}$	$H2M_{LIQ,t}$
	Bottom Quintile of Long-run Earnings		
Not $H2M_{t+4}$	.619	.149	.307
$H2M_{NW,t+4}$	.151	.660	.261
$H2M_{LIQ,t+4}$	.231	.192	.431
	Top Four Quintiles of Long-run Earnings		
Not $H2M_{t+4}$	.829	.292	.532
$H2M_{NW,t+4}$	.056	.537	.150
$H2M_{LIQ,t+4}$	.115	.171	.318

Note: Sample is PSID 1999-2019.

Table A8: $H2M$ Transition Rates by Growth in Long-run Earnings

	Not $H2M_t$	$H2M_{NW,t}$	$H2M_{LIQ,t}$
	Bottom Third, Growth Rate of Long-run Earnings		
Not $H2M_{t+4}$	.802	.226	.455
$H2M_{NW,t+4}$	.076	.585	.187
$H2M_{LIQ,t+4}$	.122	.189	.358
	Middle Third, Growth Rate of Long-run Earnings		
Not $H2M_{t+4}$	.813	.262	.509
$H2M_{NW,t+4}$	.059	.562	.157
$H2M_{LIQ,t+4}$	.128	.176	.334
	Top Third, Growth Rate of Long-run Earnings		
Not $H2M_{t+4}$	.804	.241	.426
$H2M_{NW,t+4}$	.063	.593	.208
$H2M_{LIQ,t+4}$	.134	.165	.367

Note: Sample is PSID 1999-2019.

terms of long-term household earnings. The construction of long-term earnings is described in Appendix A3.1. The results for Column (1) are discussed in Section 4.3, Column (2) in Section 4.4, and Column (3) in Section 4.5.

Table A9: Controlling for Long-term Earnings rather than Fixed Effects

	$\Delta \ln c$ (1)	$\|\Delta \ln c_{res}\|$ (2)	$\ln N$ (3)
$\ln c$			.196
			(.005)
$H2M_{NW}$	.006	.012	$-.035$
	(.004)	(.003)	(.006)
$H2M_{LIQ}$	$-.006$	.002	$-.025$
	(.004)	(.003)	(.005)
Bottom quintile of long-term earnings	$-.014$ (.003)	.023 (.004)	-.103 (.009)
R^2	.08	.20	.01

Note: Sample size is 24,214 in Columns (1) to (4); it is 30,626 in Column (5). Growth rates are annualized. N_t in Column (5) denotes the number of categories with positive spending. Not-$H2M$ group is omitted in all regressions. Regressions include the controls described in Section 4.1.

A3.3 Results Excluding Durable Categories

Table A10 reports the impact of $H2M$ status on spending growth and spending volatility excluding the durable categories of vehicles and vehicle repairs. Spending volatility, as in the text table, is the absolute value of residual spending growth after removing predicted growth from the fixed-effects regression in Column (2). These results are discussed in Section 4.6.

A3.4 Spending Growth and Volatility by Age and Earnings

Table A11 reports spending growth and volatility of that growth $|\Delta \ln c_{res}|$ by age group. The first age group includes households with heads ages 25 to 39. The second age group includes households with heads ages 40 to 64. Table A12 similarly reports estimates dividing the sample instead by a household's long-term earnings. Long-term earnings are defined as a household's average natural log of earnings after removing a cubic function of the head's age and year dummies. Households are divided between those in the lower two quintiles versus upper three. Section 4.6.4 discusses the estimates under these sample splits.

Table A10: Consumption Growth and Volatility for the Hand-to-Mouth, excluding Durables

	Cons Growth		$\lvert\Delta \ln(c)_{res}\rvert$	
	(1)	(2)	(1)	(2)
$H2M_{NW}$	-.002	.015	.026	.003
	(.004)	(.008)	(.003)	(.004)
$H2M_{LIQ}$	-.008	.001	.014	-.004
	(.004)	(.006)	(.003)	(.003)
R^2	.07	.19	.02	.39
Fixed Effects	No	Yes	No	Yes

Note: Sample size is 24,214. Growth rates are annualized. Not-$H2M$ group is omitted in all regressions. Regressions include the controls described in Section 4.1. Standard errors are robust; for Columns (1) and (3) they are clustered by household.

A3.5 More on the Extensive Category Margin

The results of Tables 6 and 7 indicate that the hand-to-mouth consume fewer distinct categories, but move into and out of categories more elastically. To explore this further, we decompose the growth in nondurable consumption between $t-1$ and t into three components: the change in spending on goods consumed in both periods (the "intensive" margin); the addition of new goods; and the dropping of old goods. In particular, suppose individual i consumes N_k categories of goods in period $k = t-1, t$. Let I denote the set of categories consumed in both $t-1$ and t. Let A denote the set of categories added in period t, and D the set of categories dropped between $t-1$ and t. Hence, $N_{t-1} = I \cup D$ and $N_t = I \cup A$. Let $x_{n,k}$ denote expenditure on good n in period $k = t-1, t$, always expressed in period t prices. We decompose growth in expenditure between $t-1$ and t as follows:

$$\begin{aligned} \frac{c_t - c_{t-1}}{0.5(c_t + c_{t-1})} &= \frac{\sum_{n \in N_t} x_{n,t} - \sum_{n \in N_{t-1}} x_{n,t-1}}{0.5(c_t + c_{t-1})} \\ &= \underbrace{\frac{\sum_{n \in I} (x_{n,t} - x_{n,t-1})}{0.5(c_t + c_{t-1})}}_{\text{Intensive}} + \underbrace{\frac{\sum_{n \in A} x_{n,t}}{0.5(c_t + c_{t-1})}}_{\text{Add}} + \underbrace{\frac{-\sum_{n \in D} x_{n,t-1}}{0.5(c_t + c_{t-1})}}_{\text{Drop}}. \end{aligned}$$

To obtain the contribution of the sub-components, we individually regress the three measures on the right-hand side of this decomposition on the total growth rate of nondurable expenditure defined on the left-hand side. Mechanically, the coefficients from the three regressions will add up to one. We run this decomposition for the pooled group of individuals in the PSID, as well as stratifying households by non-$H2M$, $H2M_{NW}$, and $H2M_{LIQ}$.

Table A11: Consumption Growth and Volatility by Age

	Consumption Growth				$\lvert\Delta \ln(c)_{res}\rvert$			
	Ages 25 to 39		Ages 40 to 64		Ages 25 to 39		Ages 40 to 64	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$H2M_{NW}$	$-.0004$	.009	.005	.033	.014	$-.005$	.022	.007
	(.005)	(.010)	(.005)	(.011)	(.004)	(.005)	(.004)	(.006)
$H2M_{LIQ}$	-.007	.003	-.009	.002	.003	$-.006$	.007	$-.004$
	(.006)	(.009)	(.004)	(.007)	(.004)	(.005)	(.004)	(.004)
R^2	.08	.28	.07	.19	.02	.50	.01	.38
Fixed effects	No	Yes	No	Yes	No	Yes	No	Yes

Note: Sample size is 10,588 for ages 25-39, 13,626 for 40-64. Growth rates are annualized. Not-$H2M$ group is omitted in all regressions. Regressions include the controls described in Section 4.1. Standard errors are robust; for Columns (1), (3), (5), and (7) they are clustered by household.

Table A12: Consumption Growth and Volatility by Long-term Earnings

	Consumption Growth				$\lvert\Delta \ln(c)_{res}\rvert$			
	Lower 2 quint.		Upper 3 quint.		Lower 2 quint.		Upper 3 quint.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)
$H2M_{NW}$	.007	.022	.007	.019	.008	$-.001$	.012	.003
	(.006)	(.013)	(.004)	(.008)	(.004)	(.007)	(.004)	(.004)
$H2M_{LIQ}$	-.003	.010	-.007	-.003	.006	-.004	$-.003$	-.005
	(.007)	(.010)	(.004)	(.005)	(.005)	(.006)	(.003)	(.003)
R^2	.07	.21	.08	.19	.01	.40	.01	.35
Fixed effects	No	Yes	No	Yes	No	Yes	No	Yes

Note: Sample size is 8,081 for lower quintiles, 16,133 for upper. Growth rates are annualized. Not-$H2M$ group is omitted in all regressions. Regressions include the controls described in Section 4.1. Standard errors are robust; for Columns (1), (3), (5), and (7).

Table A13 reports the results. The estimates indicate that the $H2M$ households are relatively prone to adding and dropping goods as they adjust expenditure while those with higher wealth tend to operate more on the intensive margin. (The p-value of the tests that the elasticities are the same across the two groups are all well below one percent.)

Table A13: Decomposition of Spending Growth by Hand-to-Mouth status

Status	Not $H2M$	$H2M_{NW}$	$H2M_{LIQ}$
Intensive	0.722	0.673	0.722
Add	0.124	0.147	0.129
Drop	0.154	0.180	0.149

Note: Regressions include the controls described in Section 4.1.

A4 The Extensive Margin and the IES: A Simple Two-Good Example

In this appendix we provide a simple model that links the extensive margin analysis of Section 4.5 and the inter-temporal elasticity of substitution. The example is designed to deliver a transparent and plausible explanation about why certain consumers are prone to be highly elastic at the margin in terms of total expenditure's response to relative price (including interest rate) movements.

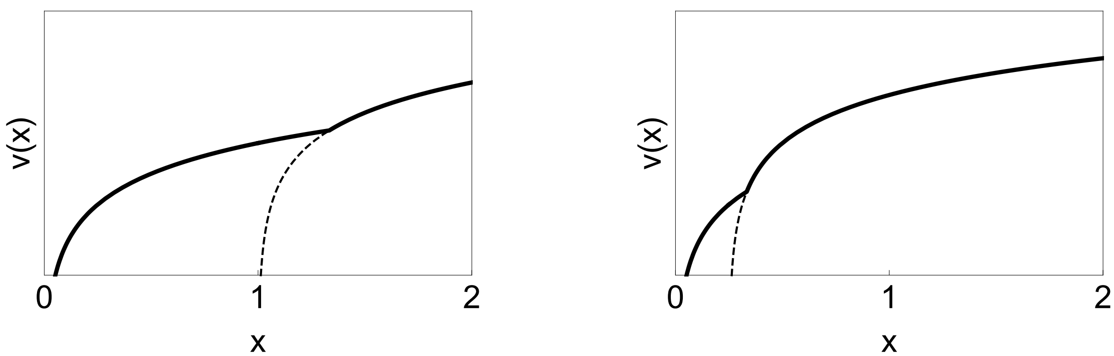
Suppose there are two goods, c_1 and c_2 and utility is given by $u(c_1, c_2 - \underline{c}y)$, where y is average income and $\underline{c}$ is a parameter that captures a minimum consumption level as a fraction of income. To make things simple, suppose both goods trade at price 1 and period income is $y = 1$. We shall contrast two individuals with differing $\underline{c}$.

To make things concrete, let the indirect utility function over expenditure be given by:

$$v(x) = \max_{c_1, c_2} c_1^{\rho} + \mathbb{1}_{[c_2 > \underline{c}y]}(c_2 - \underline{c}y)^{\rho}$$
$$\text{subject to } c_1 + c_2 \leq x,$$

where $\mathbb{1}_x$ is an indicator function that takes value if x is true and zero otherwise, and ρ is a parameter. The key static decision is to consume both goods versus only good 1. Figure A1 plots $v(x)$ for $\underline{c} = 1$ (left panel) and $\underline{c} = 0.25$ (right panel). The decision between one versus two goods is to choose the max of the two alternatives (where the two-good option is depicted by the dashed line). Of course, the switch from one good to two occurs at much lower expenditures levels for low $\underline{c}$. That is, conditional on spending, the agent with low $\underline{c}$ is likely to consume fewer categories, just like the hand-to-mouth in the data. The key is whether the point at which the agent switches is far or close to the typical level of expenditure. Keep in mind that the decision in the static problem is invariant to monotonic transformations. Hence, one can make the convex kink as dramatic or negligible as one wishes without altering the decision of whether to consume the second good.

Figure A1: $v(x)$ as a function of x



(a) $\underline{c} = 1$ (b) $\underline{c} = 0.25$

To see how this affects the inter-temporal problem, suppose the individual has the following time-separable utility over two periods, $t = 1, 2$:

$$V(x_1) + \beta V(x_2), \tag{5}$$

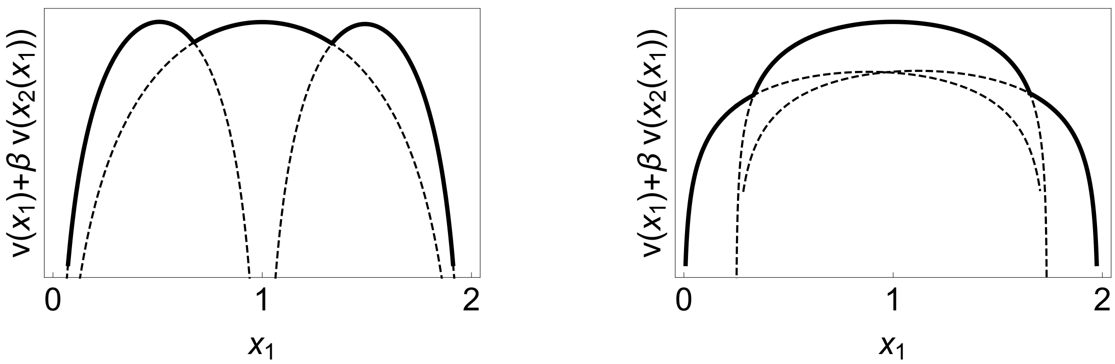
where

$$V(x) = \frac{v(x)^{\frac{1-\gamma}{\rho}}}{1-\gamma}.$$

Given a deterministic income process, y_t, and an interest rate R, the consumer's problem is to maximize (5) subject to $x_1 + R^{-1}x_2 = y_1 + R^{-1}y_2$. Setting $\beta = R^{-1} = 0.98$ and $y_1 = y_2 = y = 1$, Figure A2 plots the value of the objective as we vary x_1 and letting $x_2(x_1) = (2 + r)y - Rx_1$. (We also set $\rho = 1/3$, $\gamma = 1.01$.)

From left to right in Panel A of Figure A2, the dashed lines denote the value from (i) consuming one good in period 1 and two goods in period 2; (ii) consuming one good in both periods; and (iii) consuming two goods in period one and one good in period two. As drawn, the individual is indifferent over the three choices. The important point is that small movements in inter-temporal prices may lead to large shifts in first-period expenditure. In

Figure A2: $V(x_1) + \beta V(x_2(x_1))$ as a function of x_1

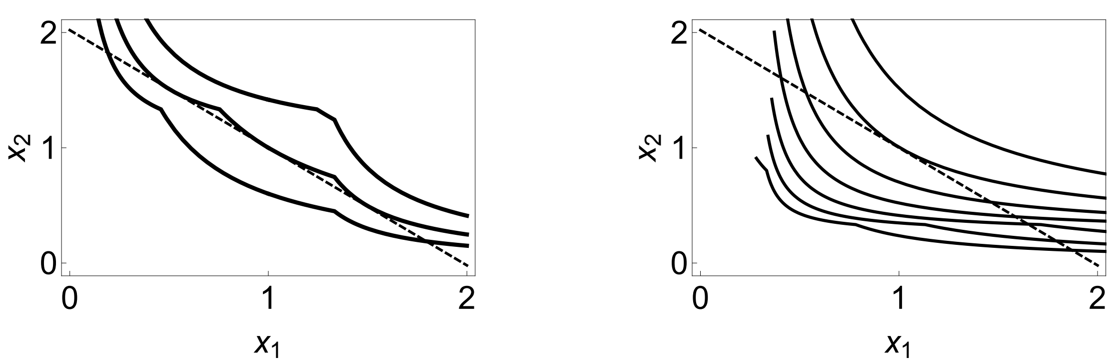


(a) $\underline{c} = 1$ (b) $\underline{c} = 0.25$

the right panel, the dashed lines denote the value from (i) consuming one good in period 1 and two goods in period 2; (ii) consuming two goods in both periods; and (iii) consuming two goods in period one and one good in period two. Here, consuming both goods in both periods is clearly optimal, and doing so is robust to small movements in the interest rate. The bottom line is that the agent with high $\underline{c}$ not only consumes fewer categories, but is also more likely to adjust at the extensive margin, similarly to the hand-to-mouth in the data.

Figure A3 plots the indifference curves for the two period problem. That is, it depicts points (x_1, x_2) for constant $V(x_1) + \beta V(x_2) = \bar{V}$ for various values of $\bar{V}$. It also includes the budget line. Again, the non-convex portion is relevant for the left-hand $\underline{c}$, but not the right. Small changes in R (the slope of the budget line), can have a big effect on the inter-temporal spending of the agent with low $\underline{c}$, who willingly shifts spending over time via adding or dropping the second good. Note that this is akin to this agent having a higher IES.

Figure A3: Indifference Curves



(a) $\underline{c} = 1$ (b) $\underline{c} = 0.25$

A5 Additional Results from Quantitative Model

A5.1 Model with Discount Factor Heterogeneity

A5.1.1 Responsiveness to Fiscal Transfers

Table A14 reports the predictions of the model with β-only heterogeneity for the aggregate MPC from the two fiscal transfers described in Section 5.4. The table also reproduces the consumption responses to targeted and untargeted fiscal transfers implied by our baseline model with heterogeneity in both β and σ. The two fiscal policies have similar implications on consumption in the two models, even when transfers are targeted to those in the bottom on the net-worth distribution. In the benchmark model, these are predominantly the impatient, elastic Type III agents. In the model with discount factor heterogeneity, they are predominantly the impatient type. But the model with discount factor heterogeneity also requires a high IES to match the data, of 1.84, rendering the households in the bottom of the net-worth distribution similar to the Type III agents in the benchmark model.

Table A14: Aggregate MPC out of Fiscal Transfers

	Untargeted	Targeted
	Not financed	
Baseline	0.316	0.738
Only β heterogeneity	0.343	0.729
	Financed	
Baseline	0.053	0.579
Only β heterogeneity	0.086	0.580

Note: The proportional tax rates required to finance the transfers in the two economies are 2.58% and 2.59%, respectively.

A5.1.2 Responsiveness to the Interest Rate

Table A15 reports the percentage change in consumption on impact from a a one-period, unanticipated decline in the interest rate. Similar to the models without heterogeneity, the model with β-only heterogeneity predicts a larger consumption response than the baseline.

Table A15: Consumption Response to a Temporary Interest Rate Cut

	All	not $H2M$	$H2M_{NW}$	$H2M_{LIQ}$
Baseline	0.080	0.088	0.151	0.031
Only β heterogeneity	0.125	0.117	0.205	0.095