Who Are the Hand-to-Mouth?*

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August 4, 2021

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 fact, we see from the PSID that such "hand-to-mouth" households do *not* display higher growth in spending. These households do display much higher average propensities to consume (APCs) than anticipated by the standard savings model. 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 the propensity to be hand-to-mouth, not current assets, that predicts low consumption growth, high APC, and other spending differences for the hand-to-mouth. 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 fairly high inter-temporal elasticity of substitution (IES). The model shows that preferences play a dominant role in differences in MPCs across consumers and, in particular, mostly explain the higher MPCs for low-asset households.

1 Introduction

Many households hold little wealth. These ostensibly "hand-to-mouth" households are often estimated to exhibit larger marginal propensities to consume (MPCs). To that point,

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

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. Given their perceived higher MPCs, these households feature prominently in discussions of tax and transfer schemes to boost aggregate output.[1] 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.

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.[2] 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 consumption behavior of households in the Panel Study of Income Dynamics (PSID). Following Zeldes (1989a), we treat households with little net worth 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 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 hand-to-mouth (or $H2M$ for short) households. The first is that expected consumption growth is, if anything, lower for $H2M$ households. Our PSID panel follows households' income, assets, and spending for up to twenty-one years. That allows us to relate a household's behavior to the frequency it appears hand-to-mouth in other waves as well as its current $H2M$ status. We see it is those households frequently hand-to-mouth that exhibit much lower spending growth. 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. This leaves a choice: Dispute the extensive evidence for higher MPCs for $H2M$ households or entertain alternatives to the standard

[1]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)).

[2]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).

model that generate heterogeneity in targeted assets.

Our second fact is that households that enter the period with low wealth relative to income display much higher average propensities to consume (APCs), where APC is consumption over total income. This contradicts the standard savings model where $H2M$ households rebuild assets on average, implying an APC less than one. Again it is those households frequently observed as hand-to-mouth, either based on low net worth or a lack of liquid assets, that display much higher APCs, consistent with these households targeting lower assets-to-income.

One reason $H2M$ 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 frequently 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 those frequently hand-to-mouth spend differently than other households. Controlling for total spending, they allocate spending to fewer expenditure categories. Assuming time-separable preferences, that behavior cannot 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 for $H2M$ households 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 or a high IES target lower assets, we explore a quantitative model that allows households to differ in these two key parameters. When we refer to a household's low discount factor 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 in the form of βR. We should also note that a low household β could be motivated from behavioral models, rather than taken as a primitive. For instance, Lian (2021) shows that consumers who anticipate optimizing mistakes will act as though they have a lower discount factor.[3]

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 the shares of $H2M$ households in the PSID, due to low wealth or lack of liquid assets, as well as average net worth by $H2M$ status.

We find that modest preference heterogeneity plays a major role in dispersion in MPCs Differences in preferences, independent of shocks, capture a full half of the model's variance across agents' MPCs despite 83% of households having standard "macro" preferences, being patient and inter-temporally inelastic. Consistent with the empirical literature, our model produces higher MPCs for agents classified hand-to-mouth, especially those classified $H2M$ due to low wealth. We find that preference heterogeneity is crucial for the higher MPCs for $H2M$ agents. In particular, preferences explain 86% of the higher MPCs for the poor $H2M$. Finally, we find that the average effective IES for the poor hand-to-mouth is as high as for others. While they are disproportionately at a borrowing constraint, muting their inter-temporal response, those not literally constrained are especially responsive given they tend to exhibit high-IES preferences.

Our model results are relevant for the design of transfer payments, particularly those designed to stimulate spending. The standard model implies $H2M$ households are sensitive to the timing of transfers because their marginal utility from a transfer is highest when pushed below targeted assets. For example, social security benefits, while providing some insurance against adverse lifetime shocks, do not provide that intertemporal insurance. But, if being hand-to-mouth reflects a high IES, the timing of transfers may be less of a concern. Related, the standard model implies MPCs are higher after negative income shocks, suggesting greater spending impact for stimulus payments timed at the trough of a recession or targeted to those experiencing larger income declines. But this argument is weakened to the extent MPCs reflect preferences rather than bad shocks. Finally, our results on the effective IES of $H2M$ agents suggest they will respond to policies that alter the inter-temporal terms of trade, not only though monetary policy, but also such policies as sales-tax holidays.

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

[3]Lian further shows that this result holds regardless of whether the underlying behavioral cause of mistakes reflects inattention, mental accounting, rules of thumb, or hyperbolic discounting.

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, e.g., Kaplan and Violante (2014) and Kaplan et al. (2018), the literature has focused on assessing the implications for fiscal and monetary policies. 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 a large literature identifying preference heterogeneity. Recent examples include Parker (2017), Gelman (2019), Athreya, Mustre-del-Río and Sánchez (2019), and Calvet, Campbell, Gomes and Sodini (2019a). Our work is especially complementary to Calvet et al. (2019a), who also find support for heterogenity in both the IES and discount factors across a sample of Swedish households.[4]

The paper proceeds as follows. To guide our empirical work, we begin in Section 2 by reviewing predictions of the standard buffer-stock savings model of consumption smoothing. In Section 3 we describe the PSID panel we employ as our primary data source. We present our empirical results in Section 4. There we first describe how we identify $H2M$ households and our strategy to highlight persistent versus transitory factors in their spending. We then 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 dispersion in MPCs, especially those of the $H2M$. We conclude in Section 6.

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

[4]They draw this conclusion from the heterogeneity in how households reduce savings as the need for precautionary savings declines.

present the standard single-asset environment.

Specifically, suppose agents live for $T = 80$ years, receiving a stochastic endowment y_t from age 22 to age 60, living in retirement until age 80. The endowment y_t follows a first-order Markov chain on support $\{y_1, ..., y_N\}$, with $0 < y_1 < ... < y_N < \infty$. Preferences over consumption streams as of age τ are given by:

$$\mathbb{E} \sum_{t=\tau}^{T} \beta^{t-\tau} u(c_t),$$

where $\beta \in (0,1)$ and the expectation is conditional on some initial state. We assume u takes the CRRA form:

$$u(c) = \begin{cases} \frac{c^{1-\gamma}}{1-\gamma} \text{ if } \gamma \neq 1 \\ \ln c \text{ if } \gamma = 1. \end{cases}$$

The parameter $\sigma \equiv 1/\gamma$ is the inter-temporal elasticity of substitution (IES).

The agent has access to a non-contingent savings vehicle that has gross return $R = 1+r < \beta^{-1}$. The environment is partial equilibrium and we take R to be a primitive of the model. The level of assets is restricted to be above some threshold $\underline{a} \leq 0$. At the start of age t, the agent has resources ("cash on hand") $x_t \equiv Ra_t + y_t$ to allocate to consumption and next period's assets a_{t+1}. Let $\mathcal{C}(x, y)$ denote the associated optimal consumption function, where a subscript indexing age is implicit. Letting $c_t = \mathcal{C}(x_t, y_t)$, consumption satisfies the usual Euler equation:

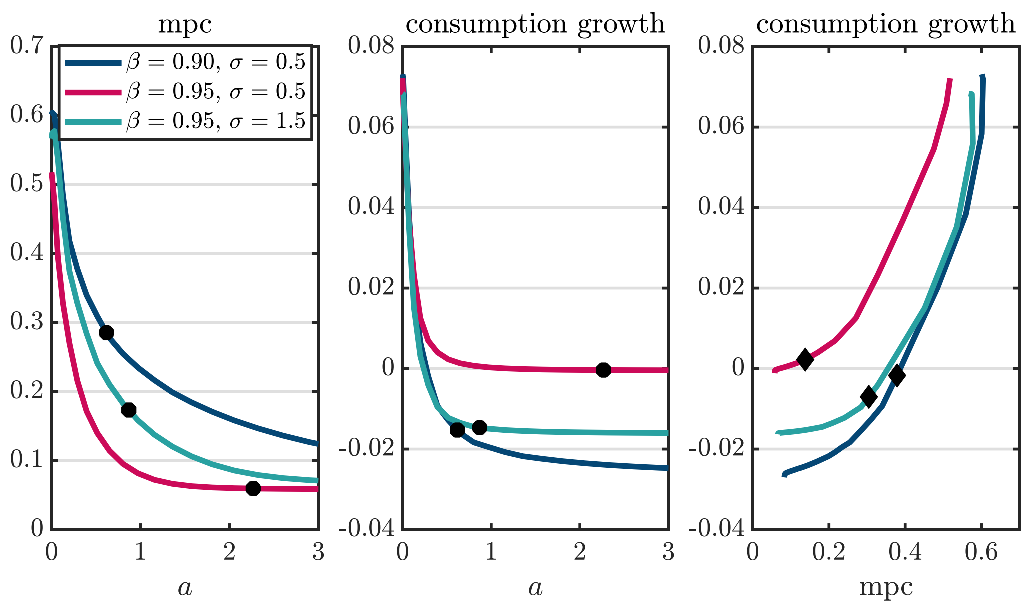
$$\mathbb{E}_t \left[\beta R \left(\frac{c_{t+1}}{c_t} \right)^{-\frac{1}{\sigma}} \right] \leq 1, \tag{1}$$

with equality when $a_{t+1} > \underline{a}$.

We define the *marginal propensity to consume* (MPC) as $\partial \mathcal{C}/\partial x$. As is well known (see Carroll and Kimball, 1996), in this environment $\mathcal{C}_t$ is a strictly increasing and concave function of x. Hence, the MPC is well-defined almost everywhere and decreasing in the level of assets. A voluminous literature uses this fact to proxy MPC with some measure of wealth or liquid wealth. But the consumption function is defined for a particular utility function, borrowing constraint, and process for income. It is not generally the case that the MPC is monotonic in assets when comparing across people potentially with distinct preferences or distinct processes for changes in income. Consider an individual with relatively low assets. That asset position may reflect a string of low income realizations. Alternatively, the individual may have a low target level of assets to long-run income.

We solve the model numerically for a calibrated income process to show how the MPC varies with assets under three alternative preference specifications. Details are provided in Appendix A1. Preferences for the first agent type exhibit an annual discount factor of 0.95 and an IES of 0.5, values fairly standard to the literature. The other cases differ either by giving agents a lower β of 0.9 or a higher IES of 1.5.

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.

The left panel of Figure 1 plots the average MPC at age 40 and at each level of assets, a_t, separately for each preference type. 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. Given a set of preferences, and the assumed income process, low-wealth households exhibit higher MPCs. Furthermore, the relation of MPC to assets is non-linear–MPC is especially high at low-levels of assets. This is consistent with the empirical literature's focus on low-asset households (e.g., Zeldes, 1989b). But these predictions are sensitive to preference heterogeneity. Assets, independent of shocks, are lower for agents that are less patient or that have a lower demand for precautionary savings, say due to a high IES. Thus the relationship of MPCs across a population may reflect, not only movements along a curve such as in Figure 1 for a given type, but also the responses of assets versus MPCs across the curves for differing types. From the figure we see that either a low β or high IES is associated with a higher MPC even conditional on assets. Therefore, it is apparent that assets are not a sufficient statistic for an agent's MPC.

To help assess the role of heterogeneity, in Section 4.4 we examine whether low-asset households exhibit faster consumption growth. Given preferences, there is a tight connection between MPC and expected consumption growth. If an agent receives an increase in endowment today, the optimal spending response is to try to equate marginal utility today to the expectation of βR times next period's marginal utility. For unconstrained agents that implies a low MPC since they begin at or near that equality. But for constrained agents MPCs are high precisely because marginal utility is high relative to its expectation in the future. Absent preference heterogeneity, that requires that high-MPC agents anticipate high future consumption. Conversely, if expected consumption growth were not high, there is no cause to disproportionately apply any added endowment to current consumption.

We can use the Euler equation (1) to develop this intuition further and guide our empirical analysis. If consumption growth is approximately log-normally distributed, we can log-linearize the Euler equation (1) as:

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

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 $1/\sigma$). Consistent with (2), the middle panel of Figure 1 displays average consumption growth against assets from the calibrated model for each preference type at age 40. Conditional on preferences, low assets predicts higher consumption growth. But our empirical results show that low-asset households do not subsequently display that higher growth. From Figure 1, a low β or a high IES imply fewer targeted assets, while also predicting lower consumption growth. So if low-assets indicates a low discount factor or high IES, that could justify the failure to observe higher consumption growth for those observed as hand-to-mouth.

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. Consider preferences $\beta = 0.95, \sigma = 0.5$. At mean assets the MPC averages 0.06 and average consumption growth is zero. But for assets that generate MPCs of 0.2 consumption growth averages about 1% per year, while to generate an average MPC of 0.4 requires about 4% consumption growth. Similar remarks apply to the other preference types. 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. In Section 5, we gauge the importance of that heterogeneity for dispersion in MPCs.

Another empirical moment that can help identify heterogeneity in targeted assets is the *average propensity to consume* (APC) out of income:

$$APC(x, y) \equiv \frac{\mathcal{C}(x, y)}{ra + y},$$

which is well defined whenever $ra + y > 0$. To understand the mapping between APC and resources, we can rewrite the flow budget constraint as:

$$\frac{a' - a}{ra + y} = 1 - APC,$$

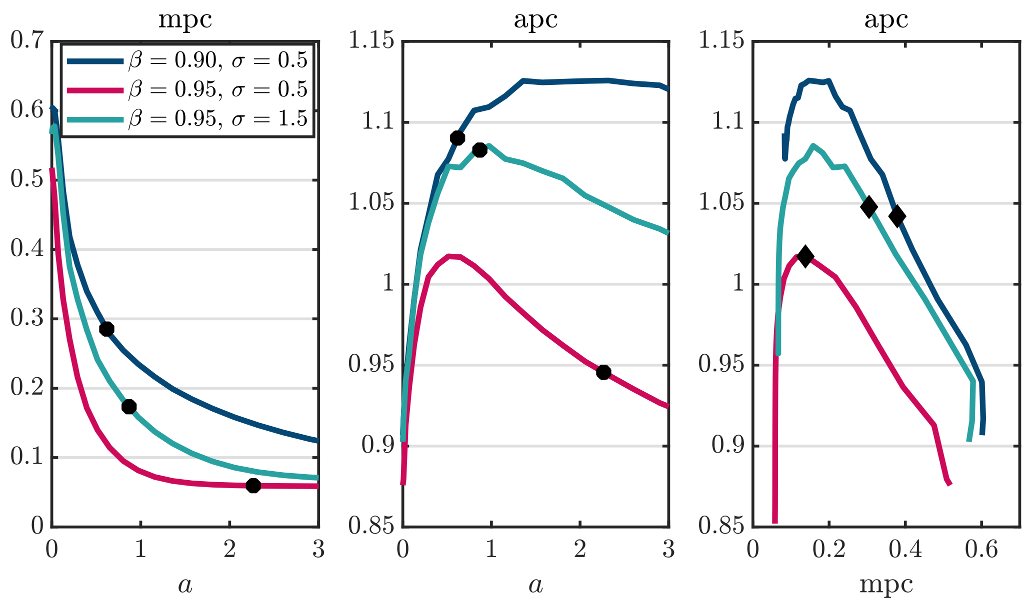
where a is start-of-period assets and a' is next period's asset position. Hence, assets are accumulating when $APC < 1$. That is, $APC \gtrless 1$ signals whether the agent's asset position is above or below their target.

The right two panels of Figure 2 present average APCs from the model at age 40, first plotted against average assets then against average MPC. (The first panel repeats the pattern in MPCs versus assets from Figure 1.) For a given preference type, we see that the relation of APC to assets or to MPCs is not monotonic. There are two distinct forces at play. Agents hit by a negative income shock will exhibit high APCs, together with a fall in assets, as they try to smooth consumption relative to the future. That acts to make APCs and MPCs positively covary. On the other hand, agents have a desire to build up assets if they are low relative to income, or conversely spend them down if relatively high. For this reason, given an agent's income, the APC is increasing in a.[5] Related to this, conditional on income, the APC is monotonically *negatively* related to an agent's MPC. Thus the slopes of the curves in Figure 2 reflect these offsetting forces. From the middle panel, we see that at low assets the desire to rebuild assets dominates. As a result, APCs are actually lowest near the borrowing

[5]More exactly, if asset dynamics are monotone (that is, $a' - a$ is decreasing in a given y) and $r \approx 0$, then APC is increasing in a for a given level of income.

constraint. By sharp contrast, the data in Section 4 show that households observed as hand-to-mouth exhibit much higher APCs. We further note, from the right-most panel, that lower APCs are quite consistent with either very low or very high MPCs.

Figure 2: MPC and APC



Note: The left panel depicts $\partial \mathcal{C}(x, y)/\partial x$ as a function of a. The middle depicts $APC(x, y)$ as a function of a. The right depicts $\partial \mathcal{C}(x, y)/\partial x$ on the x-axis and $APC(x, y)$ 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.

By contrast, looking across the preference types in Figure 2 reveals a clear relationship between preferences and APCs. An agent with either a low β or high IES will typically hold fewer assets and exhibit both higher APCs and MPCs during the working life. In Section 4 we find that low-asset households do have notably higher APCs. Most striking, we find it those households frequently observed hand-to-mouth, not necessary currently so, that display particularly high APCs. These results, like that for expected consumption growth, suggest differences in targeted assets play an important role in determining who is observed as hand-to-mouth and in determining their MPCs.[6]

The literature typically 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, which is perhaps less familiar, is that the agent has a high elasticity of inter-temporal substitution (assuming that $\beta R < 1$). The third possibility

[6] In a recent paper Lewis, Melcangi and Pilossoph (2021) find that MPC's for the 2008 Economic Stimulus Act, estimated from the Consumer Expenditure Survey, are higher for households with higher APCs. From Figure 2, that finding also suggests that differences in APCs reflect differences in targeted assets.

is differences in the income process, a high anticipated growth rate or low volatility, which reduces the demand for precautionary savings. 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

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 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.

In the next section we identify households as hand-to-mouth, following Zeldes (1989a) 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, for instance for calculating a household's APC. After-tax income is the sum of earnings and transfer income, 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 for our sample. Unless stated otherwise, our results reflect spending on all these categories. But our results are robust if we exclude spending on the durable categories of vehicle purchases and repair. (See Section 4.8.1.)

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.

4 Empirical Results

In this section we examine the canonical model's predictions for the consumption growth and APCs of $H2M$ households. Contrary to those predictions, $H2M$ households exhibit lower consumption growth and a higher APC. We show that these patterns are driven by permanent differences between households. In a sequence of empirical exercises, 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 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 (1989a) 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,[7] 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.

[7] 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.

In our PSID sample, 40.6% of the households (pooling across waves) 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, which we assign to the low-net-worth $H2M_{NW}$ category; that is, 73% of the $H2M_{NW}$ group would also satisfy the KVW liquidity-constrained definition.[8] 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.

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

4.2 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 hand-to-mouth based on net worth ($H2M_{NW}$) in column (2) to those not hand-to-mouth in column (1). These hand-to-mouth are 7 years younger on average;

[8] 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.

their earnings and incomes are only half as much; and of course their wealth, both liquid and illiquid, is much lower. Turning to the wealthy hand-to-mouth ($H2M_{LIQ}$), we see they are not really so wealthy. In particular their median net worth is only 30 percent that of households not classified hand-to-mouth. By other measures, they are intermediate to the groups in columns 1 and 2. They more closely resemble those not hand-to-mouth in age, but better resemble the poor hand-to-mouth in earnings and income.

Recall from the Euler equation (1), a potential source of differences in consumption growth rates is heterogeneity in expected rates of return:[9] 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 hand-to-mouth do face a high marginal return to saving.[10]

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.

[9] See Fagereng, Guiso, Malacrino and Pistaferri (2020), Calvet, Bach and Sodini (2019b), Fagereng, Holm, Moll and Natvik (2019).

[10] PSID surveys for 2011 and later allow us to separately identify credit card debt. Households categorized as hand-to-mouth 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 by net worth or liquid wealth.

4.3 Empirical Strategy

In Sections 4.4 to 4.7 we document four facts about the behavior of the hand-to-mouth. For each fact, we follow a three-step empirical strategy, with additional robustness checks described in Section 4.8.

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:

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

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. $H2M_{t,k}$, for $k = NW, LIQ$, takes value one if household i is $H2M_{t,k}$ 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, namely: a quadratic in age, two change-in-marital-status dummies (marriage and separation), and two change in family size dummies (increase and decrease). 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 the level dependent variable is APC, we report the results of regressing APC at time t on lagged $t-2$ measures of hand-to-mouth status.

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 permanent differences. To this end, our second specification adds household fixed effects to equation (3). When adding fixed effects, we drop the race dummies.

As we shall see, in many cases adding the fixed effects changes the estimated β significantly, and typically brings the predictions closer to the standard model. This raises the question of what the fixed effects capture. Our third specification strives to answer this by including observables in the benchmark specification equation (3) that stand in for the household's fixed effect. The observables we add are the frequencies that a household is coded as hand-to-mouth by each measure over the entire sample:

$$\Delta \ln c_{i,t+2} = \sum_{k \in \{NW,LIQ\}} \beta_k H2M_{t,k} + \sum_{k \in \{NW,LIQ\}} \alpha_k \mathrm{Fr}H2M_k + \boldsymbol{\delta}' \boldsymbol{D}_t + \boldsymbol{\gamma}' \boldsymbol{X}_{i,t} + \varepsilon_{i,t+2}, \qquad (4)$$

where $\mathrm{Fr}H2M_{i,k} \in [0,1]$ is the fraction of household-i observations they are classified as $H2M_k$, $k = NW, LIQ$.

The coefficients β_k capture the role of current wealth and liquidity, while the α_k reveal whether a persistent tendency to be hand-to-mouth is also informative. A household may be hand-to-mouth due to bad luck or because they have a low asset-to-income target. Those more frequently hand-to-mouth are interpreted as having a low target for net worth or liquidity. However, given the time sample of up to 21 years, some of that average frequency undoubtedly reflects shocks as well as ex ante targets. The specification establishes whether two households with similar assets and demographics behave differently, and if this difference is correlated with whether those asset positions are typical for the households.

4.4 Fact 1: 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.) In this subsection, we document that the hand-to-mouth do not display higher growth in consumption. In fact, those frequently hand-to-mouth have lower average consumption growth. Adding this control brings the impact of *current* hand-to-mouth status more in line with the standard model.

Table 3 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 4.3. Starting with column (1), which omits household fixed effects and the frequency controls, 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

Table 3: Consumption and Income Growth for the Hand-to-Mouth

	Consumption Growth			Income Growth		
	(1)	(2)	(3)	(1)	(2)	(3)
$H2M_{NW}$	.002	.020	.023	.010	.028	.033
	(.004)	(.005)	(.006)	(.004)	(.006)	(.007)
$H2M_{LIQ}$	-.008	.002	.002	.009	.025	.027
	(.003)	(.005)	(.005)	(.004)	(.005)	(.005)
Fraction			-.037			-.041
time $H2M_{NW}$			(.008)			(.008)
Fraction			-.021			-.043
time $H2M_{LIQ}$			(.007)			(.007)
Fixed Effects	No	Yes	No	No	Yes	No

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 4.3. Standard errors are clustered at household level.

effects, low-net-worth households have a significantly higher rate of consumption growth – 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.

The third column in Table (3) provides a sense of why including fixed effects has a large impact. Here we replace the fixed effects with controls for how frequently a household is denoted hand-to-mouth over the sample, thereby capturing a household's tendency to have low net worth or liquidity. Including the frequency of $H2M$ status brings the baseline coefficients in line with the fixed-effects estimates. Moreover, conditional on current $H2M$ status, household frequently $H2M_{NW}$ or $H2M_{LIQ}$ have significantly *lower* consumption growth. This predictably low growth is consistent with $H2M$ households having lower targets for net worth or liquidity relative to income, as would obtain if they exhibit a lower discount factor (relative to return on savings), a higher IES, or less anticipated consumption volatility.[11]

[11] The fixed effects and frequencies in specifications (2) and (3) could be correlated with future income draws that also affect consumption growth. But we find similar results when controlling for a household's income and income growth over its entire sample.

The right panel of Table 3 repeats the three specifications of equation (3) but with log growth in income (earnings plus financial income) as the outcome variable. Standard consumption smoothing arguments suggest that a household that anticipates higher future income should draw down assets or increase debt today. Hence, low-wealth individuals may anticipate relative faster income growth compared to their higher wealth counterparts. For income growth, the specification without fixed effects suggests that both the $H2M_{NW}$ and the $H2M_{LIQ}$ each have about a one percentage point higher growth rate than the non-$H2M$. Adding the fixed effect increases the differences by a factor of two to three. Conditional on current hand-to-mouth status, an individual that frequently finds itself designated as $H2M_{NW}$ or $H2M_{LIQ}$ tends to have significantly *lower* income growth. Interestingly, households that tend (on average) to have low net worth or liquidity do not have a steeper income profile, as suggested by consumption smoothing logic; in fact, the opposite is true.

To sum up Fact 1, being hand-to-mouth does not predict higher consumption growth. However, this fact conflates two underlying outcomes: (i) Households frequently observed as hand-to-mouth display significantly less consumption growth, while (ii) controlling for that hand-to-mouth tendency, currently being $H2M_{NW}$ does predict significantly faster consumption growth. If we interpret households frequently $H2M$ 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 higher MPCs and lower expected consumption growth.[12] We consider several robustness checks in Section 4.8 with respect to measures of expenditures and controls as well as presenting results stratifying households by age or permanent income. In all cases, these summary statements continue to apply.

4.5 Fact 2: H2M Have Higher APCs

As illustrated in Section 2 (middle panel Figure 2), conditional on assets, a high average propensity to consume is an excellent proxy for preferences that yield a low target wealth and a high MPC. In Table 4 we report the results of regressing APC at time t on lagged $t-2$ measures of $H2M$ status and controls for specifications in levels as described in Section 4.3.[13] We see in Column (1) that subsequent average propensity to consume is *higher* for $H2M$ households. That is, the hand-to-mouth continue to draw down, rather than build,

[12] In Appendix A3.1 we also project the growth in household spending on all measured changes in total household income, both transitory and permanent. We refer to this data moment as a marginal propensity to consume out of income – MPCY for short. We highlight there why the MPCY can speak qualitatively to the marginal propensity to consume out of cash on hand. We find that it is a household's propensity to be seen as hand-to-mouth, not its recent status, that predicts a higher MPCY.

[13] We measure household APC by its expenditures relative to after-tax income, including asset income. But in Section 4.8.1 we show findings are robust to excluding durable categories.

their buffer stock of savings relative to their wealthier or more liquid counterparts.

Table 4: The Average Propensity to Consume

	(1)	(2)	(3)
$H2M_{NW}$	.073	.003	-.006
	(.012)	(.010)	(.017)
$H2M_{LIQ}$	.075	.004	.006
	(.010)	(.008)	(.010)
Fraction			.146
time $H2M_{NW}$			(.022)
Fraction			.189
time $H2M_{LIQ}$			(.025)
Fixed effects	No	Yes	No

Note: Sample size is 24,213. Not-$H2M$ group is omitted in all regressions. Regressions include the controls described in Section 4.3. Standard errors are clustered at household level.

Controlling for fixed effects, reported in Column (2), essentially eliminates any differences in APCs between the groups. That is, a given household's APC does not depend on whether it was most recently hand-to-mouth. Column (3) documents that it is those households frequently hand-to-mouth that exhibit relatively high APCs. As with fixed effects, the most recent $H2M$ status is then no longer significant in predicting a household's APC. These results are consistent with the hypothesis that households frequently hand-to-mouth have significantly lower targets for assets or liquidity relative to income.

We discuss robustness checks and alternative specifications in Section 4.8. In particular, we examine APCs by hand-to-mouth status dividing households by age and by long-term earnings. The conclusions from Table 4 continue to apply, namely that it is frequently being hand-to-mouth, not the most recent status, that predicts household APC; though magnitudes are somewhat smaller when households are separated by long-term income.

Our results show that households frequently hand-to-mouth exhibit much lower consumption growth as well as much higher APCs. From Section 2, that is consistent with these households targeting lower assets to income. A natural follow-up question is whether a household's APC can itself serve as a proxy for that heterogeneity. A number of data sources that are neither long panels nor have reliable asset information nevertheless allow households to be stratified by their APC.[14] Table 3 related consumption growth to both current and frequency of $H2M$ status. The first column of Table 5 repeats that specification, while column (2) adds household APC as an added control. Because measurement errors in spending cause a spurious correlation between measured APC at t and consumption growth from t to $t+2$, we instrument for household APC at t with its $t-2$ value. APC is a strong negative predictor of subsequent consumption growth. Furthermore its inclusion eliminates $H2M_{LIQ}$'s role as a proxy for heterogeneity and cuts the importance of frequency $H2M_{NW}$ by more than half. The final column drops those variables, employing only APC as a control for heterogeneity. Controlling only for APC replicates a good deal of the impact of fixed effects or controlling for frequency of hand-to-mouth. In particular, low-net-worth households have a 1.3 log point higher rate of consumption growth, as anticipated by the standard savings model, while $H2M_{LIQ}$ has a point estimate of essentially zero.[15]

Table 5: APC and Consumption Growth

	(1)	(2)	(3)
$H2M_{NW}$	.023	.022	.013
	(.006)	(.007)	(.004)
$H2M_{LIQ}$	.002	$-.001$	$-.002$
	(.005)	(.005)	(.004)
Fraction time $H2M_{NW}$	-.037	-.017	
	(.008)	(.009)	
Fraction time $H2M_{LIQ}$	-.021	.001	
	(.007)	(.008)	
APC		$-.075$	$-.076$
		(.016)	(.015)

Note: Column (1) repeated from Table 3. Sample size in (2) and (3) equals 19,386. APC at t instrumented by APC at $t-2$ Growth rates are annualized. Not-$H2M$ group is omitted in all regressions. Regressions include the controls described in Section 4.3. Standard errors are clustered at household level.

[14] The Consumer Expenditure Survey is one important example–see Lewis et al. (2021) as an application.

[15] An advantage of this final specification, compared to those including fixed effects or long-run frequencies, is that it employs only information at time t or before in predicting consumption growth from t to $t+2$.

4.6 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.[16] 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 frequently 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 absolute value of consumption growth, $|\Delta \ln c|$, and income growth, $|\Delta \ln (y + ra)|$, on lagged hand-to-mouth status as well as the controls outlined in Section 4.3. Specifically, if the growth rate is calculated between waves t and $t+2$ of the survey, the hand-to-mouth indicators are computed on period t data. This specification is designed to capture whether a hand-to-mouth household today faces greater or lesser uncertainty about the future than a non-$H2M$ household.

The results are reported in Table 6, first for consumption growth, then income. From Column (1), we see that the hand-to-mouth, especially the poor hand-to-mouth, face more variable future consumption growth. For context, the means of the dependent variables $|\Delta \ln c|$ and $|\Delta \ln (y + ra)|$ are both about 0.14. Thus the coefficients on $H2M_{NW}$ and $H2M_{NW}$ of 2.4% and 0.8% represent increases respectively of about 17% and 6% of that mean. But these effects are dramatically reduced for $H2M_{NW}$ status and eliminated for $H2M_{LIQ}$ once we either include individual fixed effects, Column (2), or control for fraction of surveys a household is $H2M_{NW}$ or $H2M_{LIQ}$, Column (3). From the specification in Column (3), we see it is households that are frequently hand-to-mouth, by either measure, that have notably more volatile consumption growth.

Results for volatility in income growth are presented in Columns (4) to (6) of the table. These largely parallel those for consumption: (i) Hand-to-mouth households exhibit greater income uncertainty over the subsequent two years; (ii) those effects are sharply reduced by controlling for a household's fixed effect or its tendencies to be hand-to-mouth; and (iii) being frequently hand-to-mouth by either net worth or liquid assets is associated with considerably more volatile income growth.[17]

[16] They would also display higher APCs and lower consumption growth and MPCs, as shown in Figure 2.

[17] If a household faces a hard constraint in consecutive periods then its consumption must necessarily track income; that is, if a household is literally hand-to-mouth, then $c = y+ra$. In an earlier working paper (Aguiar, Bils and Boar (2019)) we regress the absolute value of the difference $|\Delta \ln c - \Delta \ln (y + ra)|$ on lagged $H2M$ status. The hand-to-mouth, especially those frequently so, also exhibit more volatile consumption-income ratios. This suggests that many households measured hand-to-mouth are not literally so.

Table 6: Consumption and Income Volatility for the Hand-to-Mouth

	$\lvert\Delta \ln(c)\rvert$			$\lvert\Delta \ln(y+ra)\rvert$		
	(1)	(2)	(3)	(4)	(5)	(6)
$H2M_{NW}$	.024	.005	.006	.022	.007	.007
	(.003)	(.003)	(.004)	(.004)	(.004)	(.005)
$H2M_{LIQ}$	.008	-.003	-.003	.022	.011	.009
	(.003)	(.003)	(.003)	(.004)	(.003)	(.004)
Fraction time $H2M_{NW}$			.033			.026
			(.006)			(.008)
Fraction time $H2M_{LIQ}$			.026			.032
			(.007)			(.010)
Fixed Effects	No	Yes	No	No	Yes	No

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 4.3. Standard errors are clustered at household level.

In Section 4.8 we consider robustness of these results to alternative measures of volatility, alternative measures of spending, and to the impact of measurement error in expenditure and income. But we continue to see that the households who are frequently hand-to-mouth predictably exhibit more uncertain income and consumption.

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 frequently 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 particularly compelling explanation for why certain households are frequently hand-to-mouth.

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

The savings problem of Section 2 illustrates low wealth relative 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. Sections 4.4 to 4.5 imply differences in asset targets, not just luck, are important for explaining the hand-to-mouth, while Section 4.6 suggests differences in income processes do not align with the implied target differences. In this section, we look at detailed consumption behavior of low-wealth individuals to shed further light on household heterogeneity. More specifically, we examine households "extensive" margin for various consumption categories; that is, whether a broad category is consumed at all.[18]

We first show that households who are frequently hand-to-mouth allocate their spending differently, spreading it over fewer categories than other households exhibiting the same total spending. These differences for a static choice problem not only imply that hand-to-mouth 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 frequently hand-to-mouth, with spending per category (the intensive margin) comprising less. Those close to adjustment on an extensive margin may exhibit a highly elastic response of total spending to changes in inter-temporal prices. The fact that adjustment on the extensive margin may alter the price elasticity is a familiar concept in economics. This idea has been applied to macro-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. In Appendix A4, we provide a simple example of 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.

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 the categories listed in Table 7.[19] 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. We can have a finer decomposition of expenditure into distinct categories using the Consumer Expenditure Survey (CE). In Appendix A2 we

[18] See Michelacci, Paciello and Pozzi (2019) for an analysis of the extensive margin of expenditure in the Kilts-Nielsen Consumer Panel.

[19] We exclude basic utilities like water, heat, and electricity as these may be included in rental contracts.

report the CE counterpart of Table 7.

Table 7: 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

Our first exercise explores whether the hand-to-mouth consume a different number of distinct categories conditional on total nondurable expenditure. That is, do the hand-to-mouth allocate a given level of expenditure differently between the number of goods versus spending per good? To explore this, we regress the log number of categories with positive expenditure on log total expenditure as well as our $H2M$ dummies, adding year dummies and the demographic controls. The presence of total expenditure as a regressor controls for the Engel curve for variety of categories with respect to total spending. Note that under time-separability, the number of goods is a static decision conditional on total expenditure, and is therefore independent of time preference and borrowing constraints.

The results are reported in Table 8. 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).) The final column estimates the impact of $H2M_{KVW}$ on the log number of categories in our CE sample. For comparison we construct $H2M_{KVW}$ in the PSID sample, reporting PSID results for that measure in the third column to compare to those from the CE.

Table 8: Number of Categories Consumed

Dependent variable is $\ln N_t$

	PSID (1)	PSID (2)	PSID (3)	CE (4)
$\ln c$	.220	.216	.221	.456
	(.005)	(.005)	(.005)	(.002)
$H2M_{NW}$	-.048	-.026		
	(.007)	(.006)		
$H2M_{LIQ}$	-.036	-.008		
	(.006)	(.005)		
Fraction time $H2M_{NW}$		-.041		
		(.013)		
Fraction time $H2M_{LIQ}$		-.084		
		(.016)		
$H2M_{KVW}$			-.043	-.115
			(.005)	(.002)
Observ.	30,626	30,626	30,626	192,299

Note: Categories 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 4.3. Standard errors clustered at household level for PSID.

The estimates show a clear pattern that low-wealth and low-liquidity households consume fewer categories of goods conditional on a given level of total expenditure. This pattern is established for both measures of $H2M$ status, as well as for $H2M_{KVW}$ status in the PSID and in the CE. The effect is also economically significant. For instance, comparing the coefficients for total expenditure and for being hand-to-mouth based on net worth, 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.

The table's second column includes how frequently a household is hand-to-mouth in the PSID. Households frequently hand-to-mouth, by either measure, are those who consume fewer categories, conditional on total expenditure. Once we include a household's fraction of time as hand-to-mouth, current $H2M$ status is much less relevant, with being hand-to-mouth based only on liquidity statistically insignificant. Thus, as our results for consumption growth, consumption volatility, and APCs, it is a household's propensity to be hand-to-mouth, not its current $H2M$ status, that is key to predicting spending behavior.

Our next set of results concern the elasticity of the number of goods to a change in total expenditure. To explore this, we regress $\Delta \ln N_t$ on $\Delta \ln c_t$, interacting the growth of total expenditure with our $H2M$ indicators.[20] This specification tests whether *at the margin* of changing total nondurable expenditure, the hand-to-mouth allocate added spending differently than the non-$H2M$ along the extensive versus intensive margins.

Results are reported in Table 9. We see from Column (1) that the category elasticity is higher for the $H2M_{NW}$.[21] The second column interacts expenditure growth with how frequently a household is hand-to-mouth. This clearly shows that it is actually those who are regularly hand-to-mouth, especially frequently $H2M_{NW}$, that are much more likely to adjust on the extensive margin in changing their total spending. Once we include the fractions of time $H2M_{NW}$ and $H2M_{LIQ}$, the current $H2M$ indicators are no longer relevant.

The results of Tables 8 and 9 document heterogeneity across consumers in the relevance of their extensive margin of consumption. That heterogeneity correlates with the tendency to have low assets or liquidity. As noted above, responsiveness of total spending 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. After reviewing some robustness checks on our empirical results, in Section 5 we will allow for such differences as one candidate in calibrating preference heterogeneity.

4.8 Robustness Checks

In this section we examine robustness of our results to several measurement issues: (i) the type of goods in expenditures; (ii) measurement error in income and expenditure; (iii) the measure of volatility in 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 frequently hand-to-mouth display lower consumption growth, higher APCs, and more volatile spending.

[20] 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. The coefficients are all annualized.

[21] In Appendix A3.4 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.

Table 9: Regression of $\Delta \ln N_t$ on $\Delta \ln c_t$

Dependent variable is $\Delta \ln N_t$

	(1)	(2)
$\Delta \ln c$	.138	.123
	(.006)	(.006)
$\Delta \ln c \times H2M_{NW}$	.038	-.021
	(.011)	(.016)
$\Delta \ln c \times H2M_{LIQ}$	.015	-.013
	(.012)	(.014)
$\Delta \ln c \times$ Fraction time $H2M_{NW}$		.099
		(.022)
$\Delta \ln c \times$ Fraction time $H2M_{LIQ}$		.055
		(.028)

Note: Sample size is 24,214. Regressions include controls for $H2M$ status, in addition to the controls described in Section 4.3. Column (2) also controls for fraction time in each $H2M$ status. Standard errors clustered at household level.

4.8.1 Excluding Durables

Our empirical results in Sections 4.4 to 4.6 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 A3.2 we explore robustness of the results to excluding these two categories. Table A7 gives results for consumption growth, $\Delta \ln c$, and volatility of that growth, $|\Delta \ln c|$. These align with the results above – households frequently $H2M_{NW}$ or $H2M_{LIQ}$ show both significantly lower and more volatile consumption growth. However, the effects for nondurable consumption volatility are actually larger. The coefficients on $H2M_{NW}$ and $H2M_{LIQ}$ increase to 0.050 and 0.047, both equalling about a third of the mean nondurable $|\Delta \ln c|$. Excluding durable categories has little impact on the estimates for APCs. Households frequently $H2M_{NW}$ or $H2M_{LIQ}$ continue to show higher APCs (see Table A8), though these effects are slightly stronger excluding durables.

4.8.2 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 hand-to-mouth 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 hand-to-mouth status, then the observed autocorrelation will be lower for the group with the greater mis-measurement.

Table 10 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 $t-2$ hand-to-mouth status. Looking across the rows, there is little evidence that the hand-to-mouth 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.

Table 10: Autocorrelation of Income and Spending Growth

	Not $H2M$	$H2M_{NW}$	$H2M_{LIQ}$
$\rho(\Delta \ln y_t^d, \Delta \ln y_{t-1}^d)$	-.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 4.3. Standard errors are clustered at household level. For brevity of exposition, we denote $y^d \equiv y + ra$.

4.8.3 Consumption Volatility in Levels, rather than Growth Rates

We find in Section 4.6 that households who are frequently $H2M$ show more volatile spending as measured by the absolute value of growth rates in their spending. Here we ask if they also exhibit more volatility in the level of consumption as measured by the standard deviation in their expenditures. We first compute the standard deviation of each households log expenditure over the sample. We then regress the household-level standard deviation on its frequency of hand-to-mouth status.[22] The coefficients for fraction of time $H2M_{NW}$ and $H2M_{NW}$ are 0.060 (standard error 0.007) and 0.037 (standard error 0.010), respectively.

[22]More exactly, we first regress log expenditure on our set of controls, which include age effects and year dummies. We then compute the standard deviation of the residuals for each household. Each of 4,421 households constitutes one observation in the regression. We weight households by the number of surveys underlying their standard deviation as well as their PSID sampling weight.

There coefficients represent respectively 23% and 14% of the mean standard deviation across households of 0.264. Thus, using this alternative measure of volatility, we continue to see that frequently hand-to-mouth households display more volatile spending.

4.8.4 Dividing the Sample by Age and Income

From Table 2, households that are frequently hand-to-mouth are younger on average and have lower earnings. In Appendix A3.3 we examine rates of spending growth, volatility of spending, and APCs 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 earnings.[23] Of course, there is no presumption that differences in preferences are orthogonal to earnings.[24] 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, and largely quantitatively, continue to hold when dividing households by age or long-term income. We point to appendix tables A9 to A12 for the detailed results. Here we highlight the takeaways, especially any discrepancies from the results for the full sample.

As above, consumption growth is predictably lower for households that are frequently hand-to-mouth. Frequently being $H2M_{NW}$ strongly predicts lower consumption growth within all groups, whereas for $H2M_{LIQ}$ this effect is absent for higher-earnings households. Being frequently hand-to-mouth, by either measure, continues to predict a higher APC even within age or earnings group. But these effects are about half as large estimated within earnings groups. Finally, while frequently being hand-to-mouth is, in general, associated with more volatile growth in expenditures, frequent $H2M_{LIQ}$ status does not predict higher volatility for higher-earnings households.

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 will mask or reverse behavior for

[23]Long-term earnings is defined by a household's average natural log of earnings after removing year dummies and a cubic function of the head's age.

[24]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. (2019a) that the behavior of hand-to-mouth households is consistent with a high IES.

$H2M$-households as predicted by the standard model of homogeneous agents facing income shocks. A logical candidate to model such differences is through heterogeneity in the stochastic process generating income draws; however, the results of Sections 4.6 and 4.8.3 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.[25] The extensive margin analysis of Section 4.7 suggests a role for IES differences across individuals, as does prior empirical work.[26]

In this section, we explore a quantitative model in which household's differ in these two key parameters. The purpose is threefold: (i) explore whether and to what extent key moments of the wealth distribution, filtered through a state-of-the-art model, suggest heterogeneity in discount factors or IES; (ii) examine whether a degree of preference heterogeneity can bring our empirical results from Section 4 to better align with predictions of precautionary savings models; and (iii) study the implications of that calibrated heterogeneity for describing behavior that is key to macroeconomic policy, such as the MPC distribution.

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.[27] To do so, we move to a two-asset model, using portfolio choices to distinguish IES effects from the discount factor's. 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.[28]

[25]This includes evidence from surveys eliciting respondent preferences, e.g., Barsky, Juster, Kimball and Shapiro (1997), Parker (2017), and also from structural estimates, with Calvet et al. (2019a) being a recent example.

[26]Both Barsky et al. (1997) and Calvet et al. (2019a) 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.

[27]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 in households classified hand-to-mouth in the data disproportionately hold debt charging high rates (see Section 4.2), providing a high marginal return to saving.

[28]An alternative approach to disentangle the two parameters would be to introduce interest rate "shocks" to the standard model of Section 2 and try to match its responses to the corresponding empirical moments. As is well known, such an exercise is difficult empirically, particularly when consumers are not necessarily on their Euler equations.

5.1 Model Environment

In this section, we recap the key elements of the KV model, which we take directly from their paper, but augment by allowing for preference heterogeneity.[29]

Agents live $J = 232$ quarters (58 years), spending $J^w = 152$ at work and $J^r = 80$ retired. Consumer i 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 intertemporal elasticity of substitution. Note that we allow the time-preference parameter β and σ to vary by individual. 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:

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

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. KV estimate a fourth-order polynomial for χ_j using the PSID. The variance of the fixed effect is set to 0.18 and the variance of the (mean-zero) quarterly innovations to random walk z_{ij} is set at 0.003 to match the age profile of the cross-sectional variance in earnings. 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.[30] Illiquid asset $a \geq 0$ has a higher return, but consumers must pay a fixed cost κ to alter their stock of a. Again following KV, we set the illiquid after-tax return to 2.21% and κ to $\$1,000$. In addition to a financial return, illiquid assets generate a significant service flow.[31]

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

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

[31] KV calibrate the fixed cost to match that one-third of households in the Survey of Consumer Finance are hand-to-mouth. We keep their value of κ, but will calibrate preference parameters to match the shares of hand-to-mouth observed in our PSID sample. The service flow is given by: $s_{ij} = \zeta a_{ij} + h_{ij}$, where

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: $\mathcal{T}(y_{ij}, m_{ij}, a_{ij})$. 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.

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 with homogeneous preferences. We therefore take a conservative approach and consider three preference specifications. We have explored calibrations with four types, but typically find that two of the groups are nearly identical with no significant improvement in fit.

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. With three types, the potential parameter space is the positive orthant of $\mathbb{R}^8$. In addition to the preference parameters, we also calibrate each type's share of the population. To minimize the computational burden, we restrict attention to a finite grid for both β and σ. Specifically, the annualized β takes values on an equally spaced 16-point grid ranging between 0.85 and 1.00. This interval captures a wide range of discount factors considered in the literature. The IES takes values in $\{0.5, 1.0, 1.5\}$. This is a sparse grid, but again includes common parameter choices.[32] In particular, 0.5 and 1.0 are standard in the macroeconomics literature.[33] The higher number of 1.5, used by KV, is more common in the finance literature employing Epstein-Zin preferences. For reference, KV set all agents to $\beta = 0.941, \sigma = 1.5$. We search for the three population weights that best match five moments:[34] the shares of the pooled sample that are $H2M_{NW}$ and $H2M_{LIQ}$ and the mean ratio of net-worth to income conditional on being observed in each of the three $H2M$ statuses. These empirical targets are reported in the first row of Table 11. We heavily weight the $H2M$ shares to ensure hitting those moments.

The second row of Table 11 describes the population in the calibrated model. This

$h_{ij} \geq -\zeta a_{ij}$ represents housing services obtained from a rental market. KV set $\zeta = 1\%$, quarterly. The units of rental housing h are normalized such that the relative price of c to h is one.

[32]This allows us to collapse the parameter space to one dimension spanning forty-eight preference combinations. Given the partial equilibrium nature of the model, we can solve and simulate life cycles separately for each agent type. To obtain an ergodic distribution, we simulate each preference type 50,000 times. Model moments are annualized from the quarterly simulations so as to be comparable to PSID moments.

[33]Havrnek (2015), in a meta-study of the literature's IES estimates, report a median estimate of 0.5.

[34]Specifically, for each possible triplet from the 48 possible preference combinations, we search over the 3-dimensional probability simplex for the relative shares that minimize the distance between model and empirical moments. We then select the triplet and associated shares that has the smallest distance.

population is comprised of three types of agents. Each type's respective share, together with its preference parameters, are detailed in rows 3-5. These rows are discussed below. From the second row, we see that the population moments for shares of agents $H2M_{NW}$ and $H2M_{LIQ}$ replicate the empirical moments nearly exactly. The calibrated wealth-to-income moments track their empirical counterparts, but less precisely. One one hand, the average wealth-to-income ratio of the non-$H2M$ is 2.7 in the calibration, roughly half that of the data. On the other, average wealth conditional on $H2M$ status is higher than in the data. The $H2M_{NW}$ in the data are fairly indebted (averaging -0.39), while in the model the ratio is only -0.05. The $H2M_{LIQ}$ are richer in the model as well. Appendix A5 presents the simulated moments for each element of the full grid of 48 preference types. Any set of preferences that generates a significant share of $H2M_{LIQ}$ overstates the ratio of net worth to income for that group, typically by a substantial amount.[35]

The middle three rows of Table 11 indicate the preference types comprising the overall population and their type-specific ergodic moments. Row three reports that most agents, 83.4% of the model population, have $\beta = 0.94$ and $\sigma = 0.5$. These preferences are typical of those employed in macroeconomics – a low IES combined with slight impatience relative to the market return on illiquid savings. The second type listed is both highly impatient and fairly elastic ($\beta = 0.85, \sigma = 1.0$). These comprise 12.2% of the population. The remaining 4.4% of agents are fairly patient, but highly elastic, exhibiting $\beta = 0.93, \sigma = 1.5$, preferences close to the original KV specification.

The simulated moments by preference type show that the relatively patient agents ($\beta = 0.94$) that constitute most of the population are infrequently $H2M_{NW}$, and, when not $H2M$, hold wealth equal to 2.7 times their income, close to the population average. On the other hand, the impatient types (row 4) nearly always exhibit low-net worth. In fact, they are net debtors on average. The third group holds moderate levels of assets, but frequently find themselves in one of the $H2M$ groups.

For comparison, the final row of Table 11 reports results restricting to a single preference type. The preferences that minimize the distance between simulated and empirical moments have $\beta = 0.92$ and $\sigma = 0.5$. To capture the shares that are hand-to-mouth, the single-agent preferences are relatively impatient. But, as a result, the wealth of the non-$H2M$ is far too low and so is the aggregate wealth-to-income ratio, even though the single-agent model

[35] In Appendix A5 we also present an alternative calibration that targets median, rather than mean, wealth-to-income ratios for each of the not-$H2M$, $H2M_{NW}$, and $H2M_{LIQ}$. The dominant group, 67.2%, is patient and inelastic with $\beta = 0.94$, $\sigma = 0.5$. Most of the balance, 29%, are moderately patient and elastic with $\beta = 0.92$ and $\sigma = 1.5$. A small remainder of 3.8% is impatient and moderately elastic, $\beta = 0.88$ and $\sigma = 1.0$. This calibration, while precisely hitting the share of each group by $H2M$-status, misses to the same extent or more in terms of wealth: it understates median net worth-to-income by about half for the not-$H2M$ while overstating it by double for the $H2M_{LIQ}$.

Table 11: Type-Specific Moments

Type	Share	Frequency $H2M_{NW}$	Frequency $H2M_{LIQ}$	Net Worth to Income: not $H2M$	Net Worth to Income: $H2M_{NW}$	Net Worth to Income: $H2M_{LIQ}$
Data (PSID)		23.3%	17.3%	5.01	-0.39	2.54
Calibration		23.4%	17.4%	2.67	-0.05	3.44
$\beta = 0.94, \sigma = 0.5$	83.4%	11.8%	19.1%	2.72	-0.01	3.62
$\beta = 0.85, \sigma = 1.0$	12.2%	98.6%	0.10%	0.37	-0.08	0.44
$\beta = 0.93, \sigma = 1.5$	4.4%	26.3%	33.5%	1.26	0.02	1.61
Single agent model:						
$\beta = 0.92, \sigma = 0.5$		26.5%	20.3%	1.71	0.01	2.05

implies, counterfactually, that the average $H2M_{NW}$ agent is not indebted.

Table 12: Calibrated Preference Heterogeneity

	Calibrated Share	Share of Not $H2M$	Share of $H2M_{NW}$	Share of $H2M_{LIQ}$
$\beta = 0.94, \sigma = 0.5$	83.4%	96.9%	43.2%	91.7%
$\beta = 0.85, \sigma = 1.0$	12.2%	0.28%	51.5%	0.07%
$\beta = 0.93, \sigma = 1.5$	4.4%	2.85%	5.28%	8.27%

Table 12 displays the preference mix *within* each $H2M$ status. The first column repeats the preference shares for the overall simulated population, with rows corresponding to types. The remaining three columns report each type's share of those observed, respectively, non-$H2M$, $H2M_{NW}$, and $H2M_{LIQ}$ in the pooled simulation. For example, the "standard" patient-inelastic type comprises nearly all, 97%, of those observed non-$H2M$, a group holding much of the wealth in the economy. Despite rarely being poor hand-to-mouth, the patient-inelastic still constitute 43% of $H2M_{NW}$ by virtue of their dominant share of the population. They constitute most, 92%, of the $H2M_{LIQ}$. By contrast, those who are impatient and fairly elastic make up half of the poor hand-to-mouth, more than four times their 12.2% share of the overall population. Finally, those patient and elastic skew toward being $H2M_{LIQ}$. Their importance in this group is nearly double that of their population share.

Tables 11 and 12 provide a sense of the relative importance of bad luck versus preferences in determining who are the hand-to-mouth. Roughly half of the poor hand-to-mouth are in that state nearly all of the time. The combination of impatience and high IES result in a low level of target savings. The remaining half of the $H2M_{NW}$ cycle in and out of that status due to income realizations. For the wealthy hand-to-mouth, a significant fraction are illiquid due to their relative willingness to substitute inter-temporally. However, the vast majority of the wealthy hand-to-mouth are low IES agents that hold significant assets on average, and occasionally find themselves short of liquidity due to the path of income realizations.

5.3 Revisiting Consumption Behavior: Model versus Data

Table 3 documented that, absent controls for type (either fixed effects or frequency of hand-to-mouth status), being hand-to-mouth does not predict faster consumption growth. This runs counter to the standard model without preference heterogeneity. However, once we control for fixed effects or the frequency of $H2M$ status, the data do show being currently $H2M_{NW}$ predicts faster growth, while being prone to be hand-to-mouth predicts lower consumption growth. In the model simulation, despite differences in initial wealth and permanent income shocks, the fraction of time spent $H2M$ largely reflects differences in preferences. Specifically, 74% of the variation in frequency of time $H2M_{NW}$ and 36% of the variation in frequency of time $H2M_{LIQ}$ is accounted for, in terms of R^2, by preferences alone. Differences in initial wealth and in realized contemporaneous income shocks only account for an added 7% and 16%, respectively, of variations in how frequently $H2M_{NW}$ and $H2M_{LIQ}$.

In Table 13, we replicate the empirical exercise examining consumption growth by $H2M$ status. The first three columns reproduce the empirical results from Table 3, while the final three report their counterparts estimated on our model-simulated data.[36] The first model column indicates that current $H2M$ status predicts modestly lower consumption growth. By including a fixed effect in the column (2), the predicted growth rate for the $H2M_{NW}$ increases by 0.8 percentage points per year, while that for $H2M_{LIQ}$ remains nearly unchanged. Column (3), while dropping the fixed effect, adds fractions of time spent in each $H2M$ status. We see that agents frequently $H2M_{NW}$ exhibit lower consumption growth, consistent with the data. Including these controls increases the coefficient on being currently $H2M_{NW}$, similarly to adding fixed effects. While those frequently $H2M_{LIQ}$ do have lower consumption growth, consistent with the data, including this control does not affect the coefficient for being currently $H2M_{LIQ}$. This reflects that those frequently $H2M_{LIQ}$ are relatively likely to be preference type $\beta = 0.93, \sigma = 1.5$, but that type is only a small share of the total population.

In Table 14, we revisit how the average propensity to consume varies with $H2M$ status.

[36] More exactly, in this subsection we estimate equations (3) and (4) with the model generated data. The table reports results using the full working life-cycle, but results are quite similar if we restrict to individual histories of 21 years, as in the PSID. These statements also apply to the APC results reported in Table 14.

Table 13: Consumption Growth: Data vs. Model

	Data			Model		
	(1)	(2)	(3)	(1)	(2)	(3)
$H2M_{NW}$	.002 (.004)	.020 (.005)	.023 (.006)	-.004	.004	.005
$H2M_{LIQ}$	-.008 (.003)	.002 (.005)	.002 (.005)	-.007	-.006	-.006
Fraction time $H2M_{NW}$			-.037 (.008)			-.017
Fraction time $H2M_{LIQ}$			-.021 (.007)			-.019
Fixed effects	No	Yes	No	No	Yes	No

Note: Columns labeled "Data" reproduce the empirical estimates in Table 3; those labeled "Model" are corresponding estimates from model-generated data.

Table 14: Average Propensity to Consume: Data vs. Model

	Data			Model		
	(1)	(2)	(3)	(1)	(2)	(3)
$H2M_{NW}$	.073 (.012)	.003 (.010)	-.006 (.017)	.085	.001	-.002
$H2M_{LIQ}$	.075 (.010)	.004 (.008)	.006 (.010)	.004	-.004	-.003
Fraction time $H2M_{NW}$			.146 (.022)			.163
Fraction time $H2M_{LIQ}$			.189 (.025)			.174
Fixed effects	No	Yes	No	No	Yes	No

Note: Columns labeled "Data" reproduce the empirical estimates in Table 4; those labeled "Model" are corresponding estimates from model-generated data.

As with consumption growth, the model's $H2M_{NW}$ behavior tracks that of their empirical counterparts. In particular, $H2M_{NW}$ exhibit higher APCs with no controls for preference heterogeneity. However, including fixed effects or controlling for frequency $H2M_{NW}$ eliminates this effect. This reflects that those frequently $H2M_{NW}$ show considerably higher APCs, very much like seen in the data. Those frequently $H2M_{LIQ}$ also show much higher APCs, with this effect similar in magnitude to what we estimate from the PSID.

Taking stock, the two-asset KV quantitative model, re-calibrated only to allow a limited set of plausible patience and inter-temporal elasticity parameters, does surprisingly well in matching the behavior of those frequently $H2M_{NW}$, a group that empirically shows especially low expected consumption growth as well as high APCs and high MPCY's. The model allows us to pinpoint a willingness to substitute inter-temporally as well as impatience as crucial characteristics behind the observed behavior of these households. The model is a more limited success in matching behavior of those $H2M_{LIQ}$; but it does capture the tendencies of those frequently $H2M_{LIQ}$ to display lower consumption growth and higher APCs.

5.4 Implications of Preference Heterogeneity

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

The first row of Table 15 computes the marginal propensity to consume out of a \$500 transfer for the simulated sample. This is a pure transfer, not offset by taxes.[37] The table reports the average MPC, then MPCs conditional on being not hand-to-mouth, $H2M_{NW}$ or $H2M_{LIQ}$. The average MPC is 9%. This is a little smaller than Havranek and Sokolova find from their meta analysis of 144 studies; controlling for publication bias, they report an excess spending response, excessive relative to permanent income, of 11%. For the non-$H2M$ the average MPC from our simulated model is only 2%. This low MPC is actually quite consistent with Havranek and Sokolova's meta analysis. Again, controlling for publication bias, they find estimates imply no excess sensitivity of spending for households not constrained by low wealth or liquidity. The low MPC for the non-$H2M$ in the model reflects that they are relatively wealthy and liquid, and therefore close to the boundary to adjust their portfolios.[38]

[37] Using the policy functions, we subtract consumption conditional on a liquid asset position of m from that for position m plus 500, dividing this difference by \$500. This is equivalent to randomly giving a fraction of the simulated population \$500, then regressing the change in consumption on the amount received (either zero or \$500). The coefficient is therefore the percentage consumed by the recipients.

[38] For 12 percent of the non-$H2M$ the transfer actually leads to *reduced* consumption by inducing the agent to deposit in the illiquid asset. Given that requires a fixed cost, the agent cuts consumption to increase the amount deposited.

The MPCs for the hand-to-mouth, especially poor hand-to-mouth, are larger – the $H2M_{NW}$ and $H2M_{LIQ}$ respectively have average MPCs of 27% and 7%. Thus the results clearly reinforce the conventional view of a relatively high MPC for those with low-wealth, while attaching less importance to being $H2M$ based solely on low liquidity.

Table 15: Breakdown of Aggregate MPC

	Population Share	MPC out of \$500	MPC if not $H2M$	MPC if $H2M_{NW}$	MPC if $H2M_{LIQ}$
All preference groups	100%	.089	.021	.272	.072
$\beta = 0.94, \sigma = 0.5$	83.4%	.031	.018	.087	.044
$\beta = 0.85, \sigma = 1.0$	12.2%	.429	.067	.434	-.114
$\beta = 0.93, \sigma = 1.5$	4.4%	.227	.111	.213	.378

The remaining rows of Table 15 show the role played by preference heterogeneity in the MPCs. Recall from Section 2 that, conditional on assets, MPCs are higher if consumers are less patient or more elastic (high σ). Each row reflects a distinct preference type, with Column 1 repeating its population share. Row 2 gives MPCs for the dominant preference type: patient and inelastic. For these standard macro preferences, not only is the MPC close to zero for those not hand-to-mouth, it is even small for those having low net-worth (9%) or low liquid liquidity (4%). As a result, the average MPC for this group is only 3%. The third row reports much higher MPCs for the impatient, medium-elastic type. These consumers have an average MPC of 43%, reflecting both that they are nearly always $H2M_{NW}$ and that they have high MPCs conditional on being so. The fourth row represents patient-elastic types, agents similar to those in the original KV paper. These consumers display an average MPC of 23%.[39] They have high MPCs, averaging 11%, even when not hand-to-mouth. When $H2M_{NW}$, MPCs for these agents are intermediate to MPCs for the other types when observed $H2M_{NW}$. Most notably, when $H2M_{LIQ}$, these fairly patient, but elastic consumers display MPCs nearly an order of magnitude higher, 38%, than the patient, less elastic $H2M_{LIQ}$. Having a high IES makes them more likely to consume their rebate, rather than adjust their

[39]The benchmark rebate coefficient in KV is 0.15, somewhat lower than the MPC here of 0.23. The difference largely stems from the KV agents being more patient ($\beta = 0.94$ vs. $\beta = 0.93$). It also reflects that the KV rebate coefficient captures a slightly different experiment. Specifically, they randomly assign a rebate to half the population in quarter t and to the remaining half in period $t + 1$. Thus, everyone is eventually treated, and the control group in the first quarter increases consumption in anticipation of the transfer. This lowers the rebate coefficient. Performing our experiment using the KV calibration generates an unanticipated transfer MPC of 0.16 out of \$500.

asset portfolio. Table 15 thus reveals that asset positions alone give only a partial picture of MPCs. Heterogeneity in preferences, either in discount factors or inter-temporal elasticities, generates much more dispersion in MPCs.

To get a better sense of what drives the higher MPC of the $H2M$, we can decompose the difference in MPC 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 12); and let s_k denote the share of the population in $H2M$ status k. Note that this implies that s_{jk}/s_k is that share of status k that is of type j, corresponding to the last three columns of Table 12. We then have for each $H2M$ status k:

$$\begin{aligned} \mathbb{E}[MPC_i|k] - \mathbb{E}[MPC_i] = & \sum_j \frac{s_{jk}}{s_k} \left(\mathbb{E}[MPC_i|j,k] - \mathbb{E}[MPC_i|j] \right) \\ & + \sum_j \left(\frac{s_{jk}}{s_k} - s_j \right) \mathbb{E}[MPC_i|j]. \end{aligned} \tag{5}$$

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 15 exceeds the overall average by 0.18 ($= 0.27 - 0.09$).

This is broken into the two terms on the right-hand side of (5). The first captures the importance of $H2M$ status given a preference type. In particular, 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 by each types representation in $H2M$ status k. This term is zero if MPCs do not vary by $H2M$ status. From the shares reported in Table 12 and the MPC's in Table 15, we find that this first term is 0.026 for $k = H2M_{NW}$, or only 14 percent 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 that type. This term then multiplies the average MPC for type j. The summation therefore reflects the extent high-MPC types are disproportionately in $H2M$ status k. This term is zero absent preference heterogeneity, but in the simulation accounts for 86% 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. The variance of MPCs across individuals in the simulated population is 0.039. We can decompose this number 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. For the simulation, the average within-type variance is 0.021, or 54% of the total.[40] The remaining 46% reflects the differences in means across types, which total 0.018. Hence, nearly half of all variation in MPCs is accounted for purely by preference heterogeneity. Even for within-type dispersion in MPCs, the distribution of preferences plays an important role. In particular, the within-type variance for the patient/inelastic agents is only 0.015, while it is 0.039 and 0.082 for the impatient and patient elastic types, respectively. That is, a high inter-temporal elasticity is crucial to generate dispersed MPCs within a preference type.

We provide a breakdown of average IES by preference type and $H2M$ status, similar to that for MPCs in Table 15, in Appendix A5. Because the consumer's problem is solved for a fixed set of interest rates, we do not have a policy function with respect to interest rate changes. This would require solving the model with a specific stochastic process for interest rates. We therefore consider the thought experiment of a one-time unanticipated small change in the one-period liquid interest rate (for both borrowing and saving). For consumers at an interior solution to their Euler equation, this response is governed by σ. Those with zero liquid assets, who face a discontinuity in the interest rate schedule, and those at their borrowing constraint are assumed to be insensitive to small changes in interest rates and are assigned an IES of zero.[41]

This experiment yields an effective IES of 0.45 for the overall population. That value, close to the σ for the predominant preference type, is in line with the standard one-agent macroeconomic calibration. The effective IES of the poor hand-to-mouth is also 0.45. This reflects that the majority of this group has $\sigma = 1.0$, combined with the fact that only 35 percent of the $H2M_{NW}$ are at the constraint. The $H2M_{LIQ}$ agents are more bunched at the

[40] For the single-type calibration, the variance of MPC is 0.024, close to the within-type variance in the heterogenous population.

[41] This implies that those optimized at zero liquidity or at the negative constraint are strictly constrained. We abstract from the fact that in a richer model, with interest rate shocks, a change in the rate may induce portfolio rebalancing, altering the response of consumption to the interest rate change. We also abstract from any impact of capital gains or losses due to interest rate policy shifts (as in Auclert, 2019).

discontinuity in the interest rate schedule at zero liquid assets – 52 percent are at the zero kink or the borrowing constraint. As a result, their average effective IES is only 0.25.

These results suggest that the poor hand-to-mouth are not less sensitive to interest rates, despite their proximity to borrowing constraints, and so may be effective targets of policies that alter the inter-temporal terms of trade such as the Car Allowance Rebate System (aka cash-for-clunkers) of 2009 or sales-tax holidays. These results are also relevant for the optimal timing of insurance. For example, progressivity in social security benefits provides some insurance against adverse lifetime income shocks, but are only paid out after the eligibility age. The lack of precautionary savings of the poor hand-to-mouth suggests they would find that delay costly. But, if these households are relatively elastic inter-temporally, then the policy's impact on their welfare may hinge primarily on its generosity, not its timing.

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 $H2M$ households display higher APCs and no faster spending growth than households with more assets, consistent with a role for preference heterogeneity. These statements apply to households we label hand-to-mouth based on their low net worth, or only on their lack of liquid assets (the wealthier hand-to-mouth). 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 finding 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, all the "puzzles" we see in spending by $H2M$ households project on a household's tendency to be hand-to-mouth, not on its current asset position. That is, it is households that typically hold few assets that display lower spending growth, higher APCs, more volatile spending, and more volatility in terms of categories of spending. We view these findings as consistent with important, relatively stable, differences in preferences for hand-to-mouth 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 most of the model population, 84%, must exhibit quite standard preferences with a high discount factor and a low IES. But to explain the significant shares of $H2M$ households requires much of the remaining population be impatient and fairly elastic, while a small share is patient but highly elastic. Notably, half of the poor hand-to-mouth are impatient, with fairly high IES, despite those preferences comprising only 12% of the calibrated population. We find from the model that preference heterogeneity is key for dispersion in MPCs across consumers, with preferences explaining 86% of the higher MPCs for the poor $H2M$.

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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 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 two alternative values for $\beta \in \{0.90, 0.95\}$ and $\sigma \in \{0.5, 1.5\}$.[42] 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

[42] 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, the preceding analysis indicates that the frequently 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. The frequently hand-to-mouth have a slightly shallower age profile, in line with Table 3, but the difference is small relative to the standard errors.

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

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

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.[43] The results are reported in Table A2, along with bootstrapped 95% confidence intervals.

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

Table A1: First-Stage Income Process Parameters

	Rarely $H2M$	Frequently $H2M$
Age-25	.053	.049
	(.005)	(.004)
$(\text{Age-25})^2$	-.002	-.002
	(<.001)	(<.001)
$(\text{Age-25})^3$	(<.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.

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 infrequently hand-to-mouth and that estimated for those frequently so, separately for each of our four preference specifications. This reveals whether frequent $H2M$ status reflects the differential income process for these 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 for frequency of $H2M$ status is opposite the data. That is, the empirical income process for the frequently hand-to-mouth predicts less frequent hand-to-mouth 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.

Table A2: Residual Income Process Parameters

	Rarely $H2M$	Frequently $H2M$
ρ	.891	.902
	[.852 .936]	[.837 .925]
σ_η^2	.057	.044
	[.025 .075]	[.029 .062]
σ_ν^2	.019	.091
	[.000 .126]	[.061 .132]
σ_α^2	.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.

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
$\beta = 0.90, \sigma = 1.5$	.900	.759	.117	.201

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, $y/6$.

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 hand-to-mouth, hand-to-mouth by net worth, and hand-to-mouth by liquid wealth are based on these measures of assets relative to our broad measure of earnings, as discussed at the beginning of Section 4.

Our base measure for expenditures includes 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 measure of nondurable and services spending excludes spending on vehicles or their repair from the base measure. Beginning with the 2005 survey, the PSID added categories for home repairs, home furnishings, clothing, vacations, recreation, and telecommunications. We consider robustness to this broader measure in judging households spending relative to income (APC). Our base measure of expenditures relative to after-tax income averages 58.3 percent. For the broader measure available beginning with the 2005 survey, this average is 72.7 percent.

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.

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.

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 A5. 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 H2M status and MPCYs

Conditional preferences and income process, the model of Section 2 clearly predicts the MPC is declining in cash-on-hand. Identifying sizeable, purely transitory income shocks to estimate MPCs is a well-recognized challenge, especially for data sufficiently rich to stratify by wealth. Here we examine household responses to all measured changes in income, transitory and permanent. We refer to this data moment as a marginal propensity to consume out of income – MPCY for short. We first highlight why the MPCY can speak qualitatively to the marginal propensity to consume out of cash on hand. That reasoning is an analog to its by use by Blundell, Pistaferri and Preston (2008) as a key moment to identify propensities to spend out of transitory versus permanent income. We then take advantage of the panel attribute of the PSID to show that, while hand-to-mouth households do exhibit higher MPCYs, it is a household's propensity to be seen as hand-to-mouth, not its recent status, that predicts a higher MPCY.

Suppose we observe $\Delta c_t \equiv c_t - c_{t-1}$. From the consumption function, $\Delta c_t = \mathcal{C}(x_t, y_t) -$

Table A5: 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

$\mathcal{C}(x_{t-1}, y_{t-1})$. Approximating the consumption function around (x_{t-1}, y_{t-1}), we have

$$\begin{aligned} \mathcal{C}(x_t, y_t) - \mathcal{C}(x_{t-1}, y_{t-1}) &\approx \mathcal{C}_x \Delta x_t + \mathcal{C}_y \Delta y_t \\ &= MPC * R\Delta a_t + MPCY \Delta y_t, \end{aligned} \tag{6}$$

where C_x and C_y are evaluated at (x_{t-1}, y_{t-1}), the second line uses $x_t = Ra_t + y_t$, and we define $MPCY \equiv MPC + \mathcal{C}_y$ as the marginal propensity to consume out of a change in income. Recall that holding x constant, $\mathcal{C}_y$ captures consumption's response to anticipated future income following today's y realization. If y is iid, $\mathcal{C}_y = 0$, while if y is persistent and the individual is not constrained, then $\mathcal{C}_y > 0$. Hence, we expect $MPCY \geq MPC$ to hold in the data.

To scale the responses, divide (6) through by $y_{t-1} + ra_{t-1}$ to obtain:

$$\frac{\Delta c_t}{y_{t-1} + ra_{t-1}} \approx MPC \frac{R\Delta a_t}{y_{t-1} + ra_{t-1}} + MPCY \frac{\Delta y_t}{y_{t-1} + ra_{t-1}}, \tag{7}$$

where MPC and MPCY are evaluated at (x_{t-1}, y_{t-1}). a_t denotes start of period t assets, we have $\Delta a_t = ra_{t-1} + y_{t-1} - c_{t-1}$. Hence, Δa_t is in the individual's $t-1$ information set. If the growth rate of income is *iid* (that is, log income is a random walk), then the first term on the right of (7) is orthogonal to $\Delta y_t/(y_{t-1} + ra_{t-1})$. In that case, a regression of consumption growth on income growth, within a sample of individuals of similar (x_{t-1}, y_{t-1}) and consumption functions, provides an estimate of MPCY. In the model of Section 2 the MPCY monotonically decreases in assets a for a given set of parameters.

Table A6: Marginal Propensity to Consume out of Income

Dependent variable is $\Delta c/(y + ra)$

	OLS		IV	
	(1)	(2)	(3)	(4)
$\Delta y/(y + ra)$	.039	.018	.089	.048
	(.008)	(.009)	(.018)	(.020)
$\Delta y/(y + ra) \times H2M_{NW}$	.025	-.033	.001	-.113
	(.023)	(.034)	(.038)	(.060)
$\Delta y/(y + ra) \times H2M_{LIQ}$	.025	-.021	.067	-.027
	(.019)	(.024)	(.039)	(.049)
$\Delta y/(y + ra)$ $\times$Fraction time $H2M_{NW}$		.103		.188
		(.040)		(.073)
$\Delta y/(y + ra)$ $\times$Fraction time $H2M_{LIQ}$		.116		.241
		(.046)		(.106)

Note: Sample size is 24,214. $H2M$ indicators are lagged values. Instruments for IV estimates are changes in weeks worked and annual hours for each of head and spouse. Regressions also include $H2M$ dummies, in addition to the controls described in Section 4.3. Regressions include fractions of time $H2M_{NW}$ and $H2M_{LIQ}$.

In Table A6 we regress the (normalized) change in consumption on the (normalized) change in household earnings, dummies for $H2M_{NW}$ and $H2M_{LIQ}$ status at $t-2$, as well as interactions for the change in earnings with each of those dummies. Earnings include transfer income. All regressions include year, age and demographic controls as described in Section 4.3. The normalization factor is the average of household earnings in period t and $t-2$. To be clear, the coefficient on $\Delta y/(y+ra)$ gives the MPCY for non-$H2M$ households, while the coefficients on the interacted terms give the *differential* for each group's MPCY relative to non-$H2M$. Columns (1)-(2) in the table report OLS estimates. Columns (3)-(4) report IV estimates, discussed below.

The point estimates in Column (1) suggest higher MPCY for $H2M$ households, but the differences are modest and not statistically significant. The estimated MPCYs are fairly low for all households, as anticipated by the empirical literature (e.g., Blundell et al., 2008, Straub, 2019, Fisher, Johnson, Smeeding and Thompson, 2019). Column (2) includes our measures for frequency of $H2M$ status. We see it is those households frequently hand-to-mouth, by net worth or liquidity, that have clearly higher MPCYs.

One concern is that the right-hand-side variable Δy is measured with error, generating attenuation bias in the data moment MPCY. To address this, we reestimate each specification instrumenting for changes in earnings using lagged employment status, changes in weeks worked and in annual hours for both the head and the spouse. This will correct for that attenuation bias, assuming measurement error in earnings changes is orthogonal to these instruments.[44] But it should also be kept in mind that this source of variation may have different implications for the persistence of the income change, thus altering the magnitude and interpretation of the MPCY moment. The IV results, reported in Table A6 Columns (3)-(4), tell a similar story to the OLS. The baseline magnitudes are now higher, consistent with attenuation bias in the OLS specification. The IV estimates continue to show that it is those households frequently hand-to-mouth, either measured by net worth or liquid wealth, that display significantly larger MPCYs.

A3.2 Results Excluding Durable Categories

Tables A7 and A8 report the impact of $H2M$ status on spending growth, spending volatility (absolute value of spending growth) and the APC excluding the durable categories of vehicles and vehicle repairs. These robustness results are discussed in Section 4.8.

[44]Note that the instruments are not designed to correct for the endogeneity of labor supply, only measurement error. Our goal is to establish whether and to what extent low-wealth consumers have expenditure changes that are more or less correlated with income changes. This is distinct from separately identifying the simultaneous choices of consumption and labor supply.

Table A7: Consumption Growth and Volatility for the Hand-to-Mouth, excluding Durables

	Consumption Growth			$\lvert\Delta \ln c\rvert$		
	(1)	(2)	(3)	(1)	(2)	(3)
$H2M_{NW}$	-.002	.015	.017	.032	.005	.004
	(.004)	(.006)	(.007)	(.003)	(.003)	(.005)
$H2M_{LIQ}$	-.008	.001	.001	.016	-.003	-.003
	(.004)	(.005)	(.005)	(.003)	(.003)	(.003)
Fraction			-.031			.050
time $H2M_{NW}$			(.008)			(.007)
Fraction			-.020			.047
time $H2M_{LIQ}$			(.007)			(.007)
Fixed Effects	No	Yes	No	No	Yes	No

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 4.3. Standard errors are clustered at household level.

Table A8: The Average Propensity to Consume excluding Durables

	(1)	(2)	(3)
$H2M_{NW}$	.080	.002	-.010
	(.010)	(.010)	(.018)
$H2M_{LIQ}$	.082	.005	.007
	(.010)	(.009)	(.010)
Fraction			.167
time $H2M_{NW}$			(.024)
Fraction			.201
time $H2M_{LIQ}$			(.026)
Fixed effects	No	Yes	No

Note: Sample size is 24,213. Not-$H2M$ group is omitted in all regressions. Regressions include the controls described in Section 4.3. Standard errors are clustered at household level.

Table A9: Consumption Growth and Volatility by Age

	Consumption Growth				$\|\Delta \ln c\|$			
	Ages 25 to 39		Ages 40 to 64		Ages 25 to 39		Ages 40 to 64	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$H2M_{NW}$	.001	.026	.005	.030	.020	.004	.028	.007
	(.005)	(.008)	(.005)	(.010)	(.004)	(.004)	(.005)	(.007)
$H2M_{LIQ}$	-.007	.004	-.009	-.004	.005	-.006	.009	-.002
	(.006)	(.007)	(.004)	(.006)	(.005)	(.005)	(.004)	(.004)
Fraction time $H2M_{NW}$		-.030		-.043		.030		.035
		(.010)		(.012)		(.008)		(.010)
Fraction time $H2M_{LIQ}$		-.026		-.017		.030		.024
		(.012)		(.008)		(.011)		(.009)

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 4.3. Standard errors are clustered at household level.

A3.3 Results Splitting by Age and by Long-term Income

Table A9 reports spending growth and volatility of that growth $|\Delta \ln c|$ 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 A10 conducts the same sample division in estimating the APC. Tables A11 and 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 4.8.4 discusses the estimates under these sample splits.

A3.4 More on the Extensive Category Margin

The results of Tables 8 and 9 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

Table A10: Average Propensity to Consume by Age

	Ages 25 to 39		Ages 40 to 64	
	(1)	(2)	(1)	(2)
$H2M_{NW}$	.054	-.046	.092	.033
	(.012)	(.019)	(.019)	(.027)
$H2M_{LIQ}$	.062	-.012	.083	.016
	(.013)	(.016)	(.013)	(.013)
Fraction time $H2M_{NW}$		.191		.104
		(.027)		(.032)
Fraction time $H2M_{LIQ}$		.191		.193
		(.030)		(.035)

Note: Sample size is 10,588 for ages 25-39, 13,625 for 40-64. Not-$H2M$ group is omitted in all regressions. Regressions include the controls described in Section 4.3. Standard errors are clustered at household level.

Table A11: Volatility by Long-term Earnings

	Consumption Growth				$\lvert\Delta \ln c\rvert$			
	Lower 2 quint.		Upper 3 quint.		Lower 2 quint.		Upper 3 quint.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)
$H2M_{NW}$	.007	.027	.007	.019	.013	.006	.014	.007
	(.006)	(.011)	(.004)	(.007)	(.005)	(.008)	(.004)	(.005)
$H2M_{LIQ}$	-.003	.009	-.007	-.004	.006	-.002	.002	-.003
	(.007)	(.010)	(.004)	(.005)	(.005)	(.006)	(.003)	(.004)
Fraction time $H2M_{NW}$		-.038		-.025		.014		.016
		(.013)		(.009)		(.011)		(.008)
Fraction time $H2M_{LIQ}$		-.028		-.006		.023		.001
		(.013)		(.007)		(.012)		(.008)

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 4.3. Standard errors are clustered at household level.

Table A12: Average Propensity to Consume by Long-term Earnings

	Lower two quintiles		Upper three quintiles	
	(1)	(2)	(1)	(2)
$H2M_{NW}$	.034	.007	.030	-.006
	(.021)	(.034)	(.009)	(.010)
$H2M_{LIQ}$	.074	.025	.020	-.005
	(.021)	(.021)	(.007)	(.009)
Fraction time $H2M_{NW}$		.055		.071
		(.042)		(.016)
Fraction time $H2M_{LIQ}$		.142		.076
		(.049)		(.020)

Note: Sample size is 6,446 for lower quintiles, 12,904 for upper. Not-$H2M$ group is omitted in all regressions. Regressions include the controls described in Section 4.3. Standard errors are clustered at household level.

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 the non-hand-to-mouth and the hand-to-mouth separately.

Table A13 reports the results. The estimates indicate that the hand-to-mouth 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 4.3.

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 4.7 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.

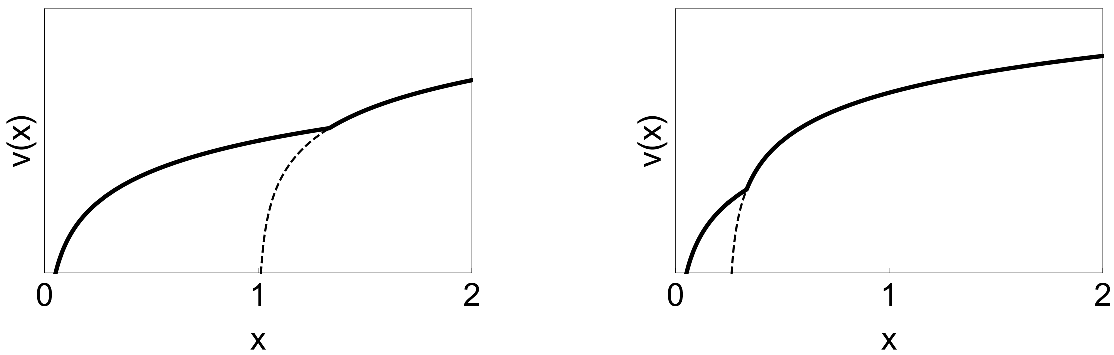
Suppose there are two goods, c_1 and c_2 and utility is given by $u(c_1, c_2 - \underline{c}y)$, where y is average income and $\underline{c}$ is a parameter that captures a minimum consumption level as a fraction of income. To make things simple, suppose both goods trade at price 1 and period income 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, $t = 1, 2$:

$$V(x_1) + \beta V(x_2), \tag{8}$$

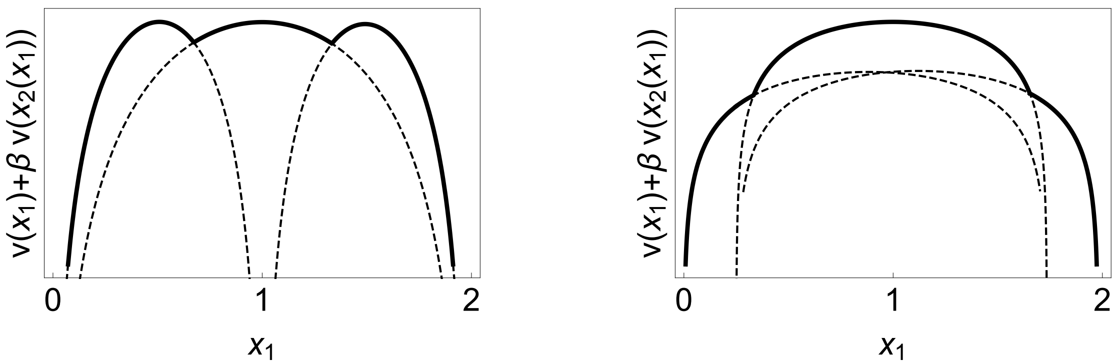
where

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

Given a deterministic income process, y_t, and an interest rate R, the consumer's problem is to maximize (8) 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 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

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

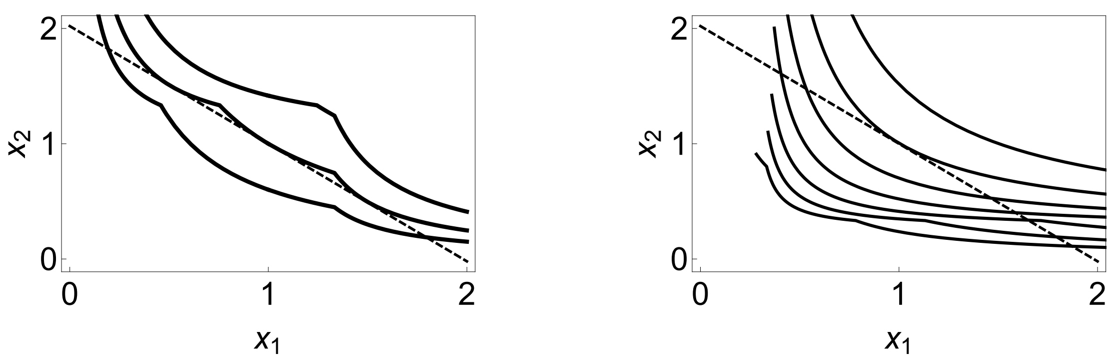


(a) $\underline{c} = 1$ (b) $\underline{c} = 0.25$

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

Table A14 reports the implied moments for the grid of preference types (β, σ) we consider in the calibration.

Table A14: Type-Specific Moments Preference Grid

	Frequency	Frequency	Net Worth to Income		
Type	$H2M_{NW}$	$H2M_{LIQ}$	not $H2M$	$H2M_{NW}$	$H2M_{LIQ}$
			$\sigma = 0.5$		
$\beta = 0.85$	0.93	0.01	0.62	-0.06	0.59
$\beta = 0.86$	0.91	0.01	0.70	-0.06	0.72
$\beta = 0.87$	0.88	0.02	0.82	-0.05	0.87
$\beta = 0.88$	0.85	0.03	0.97	-0.05	1.01
$\beta = 0.89$	0.79	0.05	1.15	-0.04	1.13
$\beta = 0.9$	0.70	0.09	1.34	-0.03	1.33
$\beta = 0.91$	0.51	0.16	1.51	-0.00	1.58
$\beta = 0.92$	0.26	0.20	1.70	0.01	2.04
$\beta = 0.93$	0.16	0.20	2.15	0.00	2.78
$\beta = 0.94$	0.11	0.19	2.72	-0.00	3.61
$\beta = 0.95$	0.08	0.18	3.41	-0.00	4.45
$\beta = 0.96$	0.05	0.19	4.27	-0.00	5.19
$\beta = 0.97$	0.03	0.19	5.16	8.38	6.15
$\beta = 0.98$	0.01	0.19	6.10	0.02	6.92
$\beta = 0.99$	0.00	0.19	7.03	0.04	7.63
$\beta = 1$	0.00	0.20	7.94	0.06	8.21
			$\sigma = 1$		
$\beta = 0.85$	0.98	0.00	0.37	-0.07	0.44
$\beta = 0.86$	0.98	0.00	0.37	-0.07	0.45
$\beta = 0.87$	0.97	0.00	0.39	-0.07	0.41
$\beta = 0.88$	0.96	0.00	0.44	-0.07	0.42
$\beta = 0.89$	0.94	0.01	0.54	-0.07	0.55
$\beta = 0.9$	0.92	0.02	0.70	-0.05	0.78
$\beta = 0.91$	0.83	0.06	0.87	-0.02	1.03
$\beta = 0.92$	0.39	0.19	0.97	0.01	1.33
$\beta = 0.93$	0.27	0.28	1.49	0.01	1.95
$\beta = 0.94$	0.17	0.33	2.35	-0.00	3.11
$\beta = 0.95$	0.08	0.37	3.67	-0.01	5.12
$\beta = 0.96$	0.03	0.34	5.31	-0.00	7.52

	Frequency	Frequency	Net Worth to Income		
Type	$H2M_{NW}$	$H2M_{LIQ}$	not $H2M$	$H2M_{NW}$	$H2M_{LIQ}$
$\beta = 0.97$	0.00	0.32	6.94	0.01	9.41
$\beta = 0.98$	0.00	0.34	8.36	0.08	10.8
$\beta = 0.99$	0	0.33	9.74		11.7
$\beta = 1$	0	0.29	10.4		13.0
			$\sigma = 1.5$		
$\beta = 0.85$	0.99	0	0.56	-0.07	
$\beta = 0.86$	0.99	0	0.46	-0.07	
$\beta = 0.87$	0.99	0.00	0.47	-0.07	0.67
$\beta = 0.88$	0.98	0.00	0.40	-0.07	0.68
$\beta = 0.89$	0.98	0.00	0.41	-0.07	0.42
$\beta = 0.9$	0.96	0.00	0.41	-0.06	0.36
$\beta = 0.91$	0.91	0.03	0.56	-0.04	0.67
$\beta = 0.92$	0.39	0.18	0.78	0.02	1.00
$\beta = 0.93$	0.26	0.33	1.25	0.02	1.60
$\beta = 0.94$	0.16	0.41	2.44	0.01	3.23
$\beta = 0.95$	0.07	0.43	4.62	-0.01	6.46
$\beta = 0.96$	0.01	0.39	7.40	-0.01	9.88
$\beta = 0.97$	0.00	0.36	10.0	0.13	11.8
$\beta = 0.98$	0	0.33	12.1	0	13.0
$\beta = 0.99$	0	0.33	13.5	0	13.1
$\beta = 1$	0	0.34	14.4	0	13.0

In Table A15 we pursue a different calibration strategy by targeting median net worth to median income ratios for hand-to-mouth groups, in addition to the frequency of each $H2M$ status. The top panel reports the fit of the model and the bottom reports the calibrated preference types and their respective shares.

Table A16 provides a breakdown of average IES by preference type and $H2M$ status four our baseline simulated model. Results are discussed in Section 5.4.

Table A15: Alternative Calibration Strategy

Panel A. Moments

	Frequency	Frequency	Median Net Worth to Income		
Type	$H2M_{NW}$	$H2M_{LIQ}$	not $H2M$	$H2M_{NW}$	$H2M_{LIQ}$
Data (PSID)	23.3%	17.3%	2.21	-0.06	0.98
Calibration	23.7%	17.9%	1.18	-0.05	1.82

Panel B. Calibrated Preference Heterogeneity

	Calibrated Share	Share of Not $H2M$	Share of $H2M_{NW}$	Share of $H2M_{LIQ}$
$\beta = 0.94, \sigma = 0.5$	67.2%	79.2%	34.7%	71.3%
$\beta = 0.88, \sigma = 1.0$	3.76%	0.19%	15.3%	0.07%
$\beta = 0.92, \sigma = 1.5$	29.0%	20.6%	50.0%	28.6%

Table A16: Breakdown of Aggregate IES

	Population Share	IES	IES if not $H2M$	IES if $H2M_{NW}$	IES if $H2M_{LIQ}$
All preference groups	100%	0.45	0.51	0.45	0.25
$\beta = 0.94, \sigma = 0.5$	83.4%	0.44	0.49	0.49	0.25
$\beta = 0.85, \sigma = 1.0$	12.2%	0.38	0.99	0.37	0.98
$\beta = 0.93, \sigma = 1.5$	4.4%	0.82	1.31	0.90	0.16