Mental Accounts and Consumption Sensitivity Across the Distribution of Liquid Assets

By James Graham and Robert A. McDowall*

We study consumption spending responses to predictable income using household-level data from a U.S. financial institution. Even for households with large liquid asset balances, we find no spending in anticipation of income receipt, substantial spending following receipt, and significant front-loading with respect to date of receipt. To rationalize these findings, we develop a tractable model of mental accounts where consumption choices are partitioned across current income and current assets. Our model reproduces the timing, magnitude, and cross-section of consumption responses observed in the data. Finally, we use the model to study the effectiveness of targeted and untargeted fiscal stimulus policies.
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The sensitivity of household spending to income fluctuations is central to our understanding of micro- and macroeconomic consumption dynamics. A long empirical literature extensively documents excess consumption sensitivity relative to the benchmark permanent income hypothesis model of consumer behavior (Hall, 1978; Zeldes, 1989; Campbell and Mankiw, 1990; Johnson, Parker and Souleles, 2006; Parker et al., 2013). In response, the theoretical literature has emphasized the role of liquidity constraints in explaining a lack of consumption smoothing among low-wealth households (Deaton, 1991; Carroll, 1997; Mankiw, 2000; Kaplan and Violante, 2014). But recent empirical work shows that even households with large liquid wealth balances exhibit excess consumption sensitivity, thereby challenging the explanatory power of the liquidity constraint mechanism (Kueng, 2018; Baugh et al., 2021; Gelman, 2021).[1]

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[1]A recent literature following Kaplan, Violante and Weidner (2014); Kaplan and Violante (2014) studies excess consumption sensitivity among high networth households with low liquid balances: the

In this paper we revisit the empirical evidence on excess consumption sensitivity and rationalize our findings with a simple behavioral model of household consumption expenditure. First, we use a large administrative dataset from a U.S. financial institution to study high-frequency household expenditure responses to anticipated income receipts. We find that households do not spend in advance of anticipated receipts, concentrate most of their spending in the first month following income receipt, and that these patterns of expenditure are observed across the distribution of liquid asset holdings. Second, we study consumption responses in a simple and analytically tractable model of mental accounts following Shefrin and Thaler (1988). Third, we embed the mental accounts framework in a quantitative model estimated to match both spending responses across the distribution of liquid wealth and the life-cycle profile of liquid asset holdings. Finally, we revisit the effectiveness of targeted and untargeted fiscal stimulus policies under the mental accounts model.

Our empirical analysis utilizes novel administrative data on de-identified bank accounts and transactions for millions of customers at a large U.S. financial institution. We observe account-level inflows, outflows, and (liquid) balance sheet items at the daily frequency. We use this information to estimate household-level expenditure responses to predictable income receipts such as tax refunds, bonus checks, and regular paychecks. Additionally, our high-quality balance sheet data enables us to estimate spending responses across the distribution of liquid wealth.[2] Following the recent literature, we adopt a straightforward estimation strategy that regresses daily consumption expenditures on leads and lags of identified income receipts conditional on date- and household-level fixed effects (see, for example, Baugh et al., 2021). Acknowledging that we only observe spending rather than consumption itself, we refer to our estimated response coefficients as marginal propensities to consume (MPC).

In line with the results of a large prior literature, we estimate an average 3-month, non-durables, cumulative MPC out of tax refunds of 0.25 (Gelman, 2021; Baugh et al., 2021; Kueng, 2018; Parker et al., 2013; Johnson, Parker and Souleles, 2006). We also find that households do not spend in anticipation of tax refunds and heavily concentrate their spending response around the date of refund receipt. The first result is reflected in precisely estimated near-zero spending responses in the 30 days prior to tax refund arrival. We refer to the second result as *front-loading* of expenditure, as we find that around 70 percent of the total response over a 5 month period is concentrated in the first month following refund receipt. We then estimate household spending responses across the distribution of liquid asset balances. Across all levels of liquid wealth, we again find no anticipated spending response and substantial front-loading of expenditures. Additionally, while estimated MPCs are declining with household liquidity, even very wealthy

wealthy hand-to-mouth. In contrast, we focus on the puzzle of excess sensitivity among households with large liquid balances.

[2]Illiquid asset positions are largely absent from our dataset and so we are unable to investigate spending responses across the illiquid or total wealth distributions.

households spend a significant fraction of their income receipts.

We show that these spending patterns – lack of anticipation, front-loading, and excess sensitivity across the liquid wealth distribution – are robust to different categories and measures of household expenditure, multiple tax refund events, conditioning on tax filing dates, stratifying by liquid wealth within income groups, and to the receipt of different forms of anticipated income such as bonus checks and regular paychecks. Overall, our empirical results are inconsistent with the predictions of standard models of consumption smoothing behavior as well as models in which liquidity constraints alone explain excess consumption sensitivity.

In order to rationalize these consumption expenditure patterns, we first develop a tractable model of mental accounts following Thaler (1985); Shefrin and Thaler (1988). In a departure from standard assumptions on preferences, households treat current income and current assets as non-fungible. In particular, households exhibit both a static and dynamic aversion to dissaving. Statically, households spend less out of future income to avoid drawing down asset balances now. Dynamically, households spend more out of current income to avoid building asset balances that will need to be drawn down later. We embed these preferences in a simple life-cycle model and derive analytical expressions for MPCs out of anticipated income receipts. We show that the model nests standard consumption smoothing and hand-to-mouth behavior as limit cases. Moreover, the model can reproduce the lack of anticipated spending and front-loading of expenditure observed in the data.

We then build and estimate a heterogeneous household life-cycle model with mental accounts to quantitatively capture observed spending patterns across the distribution of liquid wealth. The model is calibrated to a monthly frequency and features earnings risk, liquid assets, a borrowing constraint, and announcements about one-off future income inflows (e.g. tax refunds or a bonus check). We also allow for ex-ante heterogeneity with a fraction of mental accounts households and the remainder holding standard preferences. We estimate the parameters of the model to target: contemporaneous MPCs out of anticipated income receipts across the distribution of liquid wealth; and the life-cycle profile of liquid asset holdings. The model provides a close fit to both targeted statistics as well as untargeted statistics concerning: the lack of anticipated spending responses to future income inflows; and the front-loading of spending responses with respect to the date of income receipt.

We show that the estimated prevalence and strength of mental accounts preferences are crucial for explaining observed consumption responses and patterns of wealth accumulation. In the absence of mental accounts spending prior to, contemporaneous with, and following income receipt is far too low. And when all households have mental accounts, consumption is too sensitive to income across the distribution of liquid wealth. We show that an estimated model with standard preferences cannot simultaneously match the cross-sectional profiles of spending responses and liquid wealth accumulation. Finally, we show that while an otherwise standard model augmented with heterogeneous discount factors can match these statistics, it fails to reproduce the observed lack of anticipation and front-loading of expenditure.

Finally, we consider the implications of our model for the design of fiscal stimulus payments. In recent decades the U.S. government has implemented various untargeted transfers, such as tax rebates in 2001 and 2008 and COVID-era stimulus checks in 2020 and 2021, and other more targeted transfers, such as the unemployment payment supplements paid out under the CARES Act of 2020.[3] We study pre-announced fiscal stimulus policies in partial equilibrium that are: paid to all households; targeted to the poorest quintile of households by income; and targeted to the poorest quintile of households by liquid wealth-to-income. Our results provide two illustrative lessons for the design of fiscal stimulus payments. First, stimulus policies have little impact on aggregate spending at announcement, so payments should be disbursed quickly. Second, targeting payments to low-income or -wealth households makes little difference to aggregate consumption responses and so stimulus policies need not be especially concerned about the targeting of payments.

I. Related Literature

Our paper follows a large empirical literature that exploits household-level micro-data and quasi-exogenous variation in individual income receipts to study consumption expenditure fluctuations. These studies have variously drawn on individual tax refunds (Souleles, 1999; Baugh et al., 2021; Gelman, 2021), government stimulus payments (Johnson, Parker and Souleles, 2006; Parker et al., 2013; Parker, 2017; Kueng, 2018), regular paychecks (Olafsson and Pagel, 2018), and payments from unemployment and social insurance schemes (Hastings and Shapiro, 2018; Ganong and Noel, 2019).

We make several contributions to this empirical literature. First, we leverage an exceptionally rich household-level bank transaction dataset to study consumption responses to several forms of income receipt. Our final sample for analysis contains 1.7 million households with observations at the daily frequency, which is large even in comparison with the high quality micro-data used in recent studies (Parker, 2017; Gelman, 2021; Baugh et al., 2021). Our bank transaction data also draws on a broader cross-section of U.S. households than, for example, data derived from households self-enrolled in personal finance applications (Gelman, 2021; Baugh et al., 2021).

Second, we confirm and refine several results from the recent literature. We report an average, 3-month, non-durables MPC of 0.25, in the middle of the range of previous estimates (Gelman, 2021; Baugh et al., 2021; Kueng, 2018; Parker et al., 2013; Johnson, Parker and Souleles, 2006). We find that households

[3]For economic analyses of the spending response to these policies, see Johnson, Parker and Souleles (2006); Parker et al. (2013, 2022); Carroll et al. (2020); Ganong, Noel and Vavra (2020).

are essentially unresponsive to anticipated income in the 30 days prior to receipt. Additionally, households front-load their spending, with around 70 percent of total spending taking place in the first 30 days after income receipt. Similar results are reported in Kueng (2018), Gelman (2021), and Baugh et al. (2021). However, we further document that the lack of anticipation and front-loading of expenditure is associated with tax refunds, bonus checks, and regular paychecks, and also holds for households across the distribution of liquid wealth. Finally, we find that although MPCs are declining with household liquidity, even very wealthy households spend a significant fraction of their income receipts. These results are consistent with Parker (2017); Gelman (2021); Baugh et al. (2021), but contrast with the rising MPC profile reported by Kueng (2018).

In light of these empirical findings, the theoretical literature has moved on from the strict consumption smoothing behavior embedded in the permanent income hypothesis of Friedman (1957). Following Deaton (1991), Carroll (1997), and Mankiw (2000), much of the literature turned to the role of liquidity constraints in explaining excess consumption sensitivity. In order to capture constrained consumption behavior among high networth households Kaplan and Violante (2014), and Kaplan, Violante and Weidner (2014) introduced wealthy hand-to-mouth households, those with few liquid assets but large illiquid asset balances. However, the empirical findings of this paper along with those in the recent literature demonstrate that even households with very high liquid asset balances exhibit strong consumption responses to income receipts. A further literature drawing on behavioral economics proposes that households exhibit rational inattention (Reis, 2006; Gabaix, 2014), face temptations to spend out of available resources (Laibson, 1997; Gul and Pesendorfer, 2001), have reference-dependent preferences (Kőszegi and Rabin, 2006), or simply make mistakes in their consumption choices (Lian, 2023).

Our paper contributes to both the theoretical and quantitative literatures by extending the mental accounts framework of Thaler (1985) and Shefrin and Thaler (1988). Several empirical papers propose mental accounting as an explanation for excess consumption sensitivity, but do not explicitly model this behavior (Hastings and Shapiro, 2012; Feldman, 2010; Hastings and Shapiro, 2018; Baugh et al., 2021). Koszegi and Matejka (2018) provide formal microeconomic foundations for mental accounts by way of costly attention allocation across balance sheet items. In contemporaneous work Gimeno-Ribes (2023) studies mental accounts preferences in a heterogeneous household incomplete markets model and compares MPCs out of various forms of income receipt: anticipated versus unanticipated income, and labor market versus investment income. Our contribution is to explicitly link the mental accounts framework to our empirical findings that households do not spend out of anticipated income receipts, front-load spending to the date of income receipt, and exhibit these spending patterns even when holding large liquid asset balances.

Table 1—: Household Summary Statistics

	Mean	25^{th}	Median	75^{th}
Panel (a): Sample of all active account holders				
Age	42.2	32.0	41.0	52.0
Account users	1.4	1.0	1.0	2.0
Total income	5935	2273	3923	6782
Labor income	4022	1835	2957	4754
Total liquid assets	8673	473	1835	6442
Checking accounts	4955	341	1255	3691
Savings accounts	2302	0	0	263
Revolving credit balances	920	0	0	0
Panel (b): Sample of tax refund recipients				
Total income	5259	2425	3868	6245
Total liquid assets	7279	581	1828	5699
Expenditure	4949	2323	3677	5882
Tax refund	2072	360	1120	2993

Source: Authors' calculations using financial institution data.

II. Data

A. Data Source

We utilize an administrative dataset of de-identified household bank accounts and transactions obtained from a large, American financial institution. The complete dataset consists of a panel of 17.2 million U.S. households with active checking accounts over the period 2012 to 2019. We aggregate individual accounts to the primary account holder level and restrict our analysis to primary account holders of working age, 24 to 64.

To ensure that we observe the main checking account of a household, we restrict our sample to those with at least five deposit account outflows in each month of a given calendar year. Households with very few observed transactions are likely to hold additional checking accounts at other financial institutions, and may spread their spending across multiple banks. Since we cannot observe these transactions, including these households in the sample would distort our analysis of financial activity and spending decisions in the face of income shocks. See Online Appendix A.1 for further details.

For each account holder, we observe individual transactions, checking account, savings account, and credit card balances, as well as non-transaction accounts such as money market accounts, brokerage accounts, and certificates of deposit held at the bank. We do not observe comprehensive measures of illiquid assets such as houses, mortgages, or retirement accounts, so we ignore those assets in this paper.

One novel feature of our analysis stems from our observation of flows in and out of deposit accounts, debit cards, and credit cards at the daily frequency. In contrast with much of the prior literature, this data provides an extremely high-frequency picture of spending across a very large number of households in response to income receipts.[4]

Panel (a) of Table 1 reports summary statistics for the subsample of households satisfying our account restriction criteria.

B. *Income Receipts*

We study the response of household spending to anticipated income receipts including tax refunds, bonus paychecks, and regular paychecks.

We first briefly describe tax refund receipts, while Online Appendices A.3 and A.4 provide further details. In the U.S. approximately 80 percent of individual tax filers receive refunds, while many of the remainder make tax payments.[5] The size of an individual tax refund is determined by income received from all sources, the IRS income tax withholding tables, and any withholding allowances adopted by employees. Individuals can adjust tax withholdings at any time by claiming allowances for changes in personal circumstances such as marital status or number of dependents. The size of a tax return can be calculated after withholdings are chosen, annual income has been earned, and the result of previous tax returns is known. Any remaining uncertainty over the size of refund is essentially resolved at the date of filing but for unexpected complications or mistakes in an individual's return. While the precise date of refund arrival is unknown when filing, the IRS reports that 90 percent of individual tax refunds are processed within 21 days of their respective filing dates.[6]

Due to the size of our dataset, we restrict our analysis to the subsample of households receiving tax refunds in 2014 and 2015. We further restrict the subsample to households receiving just one tax refund in a given calendar year. Around 30 percent of households receive two refunds in a given year, so our restriction ensures that our analysis does not confound the response of spending out of lagged refunds with the receipt of subsequent refunds. Our final sample consists of 1.7 million unique households with a total of 882.3 million household-day observations across the two years.

[4]Both Baugh et al. (2021) and Gelman (2021) observe high frequency transaction data provided by financial services applications. However, their sample sizes are markedly smaller at around 200,000 and 46,000 households, respectively.

[5]In 2018, the IRS received 153 million individual tax returns and issued 120 million individual income tax refunds. See Table 2 and Table 7 of the IRS Data Book (Internal Revenue Service, 2017).

[6]See various IRS publications such as `https://www.irs.gov/pub/irs-pdf/p2043.pdf` and `https://www.irs.gov/pub/irs-prior/i1040--2013.pdf`.

Table 2—: Comparison of Expenditures Across Data Sources

	Total	Non-Durables	Durables	Services	Food Services	Groceries
CEX	4776	981	634	2316	303	337
BANK	5348	1059	168	1252	306	220

Note: All comparisons using monthly averages from data in 2016. Total expenditure in the financial institution data includes all unclassified spending. Non-durables: food at home, laundry and cleaning, postage/stationery, apparel, motor oil/gasoline, entertainment, smoking supplies, and drugs. Durables: housekeeping and other household supplies, furnishings, and equipment; reading; medical supplies; auto repairs; and vehicle purchases. Services: food services, transportation, insurance, education, housing services, personal services, telecommunications, and other bills. Food services: food away from home and alcoholic beverages. Groceries: food at home.
Source: Authors' calculations using financial institution data and the Consumer Expenditure Survey.

Panel (b) of Table 1 reports summary statistics for our subsample of refund recipients. The median tax refund of $1120 represents nearly 30 percent of median monthly income. Note, however, that this is the median refund among all first refunds, which covers both federal and state refunds. The average size of refunds in our data is fairly representative of the broader population. For example, the IRS reports that the average federal refund was $2899 in 2018, compared to $2844 in our transaction data.[7]

In Online Appendix A.5 we describe our identification and measurement of bonus checks in our dataset. In brief, we select a subsample of households whose paychecks arrive at regular frequency but who also receive a large off-pay cycle payment from their usual employer. Table A.3 reports summary statistics for this subsample of 163,000 households. As might be expected, households receiving bonus checks earn more and are wealthier than our broader sample of tax refund recipients.

C. Expenditures

To construct household expenditures in our data, we categorize transactions according to Merchant Category Codes (MCCs) in close accordance with the National Income and Product Accounts Handbook (U.S. Bureau of Economic Analysis, 2023). MCCs are four digit codes used by retail financial services firms to classify firms' sales according to the kinds of goods and services they provide. After identifying consumption expenditures, we trim the top $1 \cdot 10^{-5}$ expenditure days to control for extreme outliers in household spending. See Online Appendix A.2 for further details.

In this paper we primarily study non-durable expenditures, but in the data

[7]See the 2018 IRS filing season tax statistics at https://www.irs.gov/newsroom/filing-season-statistics-by-year. For comparisons with our data, see Table A.2 in Online Appendix A.4.

we also observe spending in several other categories. Table 2 compares average monthly spending across these categories in our data with spending in the Consumer Expenditure Survey (CEX) micro-data for the year 2016 (U.S. Bureau of Labor Statistics, 2023). Average household spending in our data is reasonably close to the CEX for total spending, non-durables spending, and food services. However, our data does not accurately capture spending on durables and broader services spending. Durable goods in our data can be difficult to identify due to the importance of the extensive margin over purchase decisions and the use of (unobserved) installment payment plans. And because services are frequently paid for with cash, they are often missed in our transactions data.

Figure 1 reports monthly shares of household outflows into both identified expenditures and non-identified categories. Note the significant share of outflows associated with cash withdrawals, paper checks, and unobserved credit card payments. In sum, these unclassified expenditures represent roughly a third of average total monthly outflows. Rather than discard this information, we use an imputation procedure to allocate these expenditures across categories.

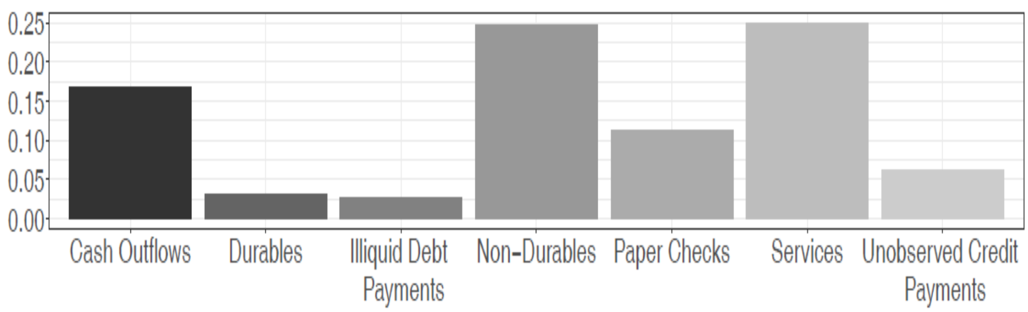

Figure 1. : Monthly Shares of Household Outflows

Source: Authors' calculations using financial institution data.

We restrict attention to non-durables since it is the main spending category of interest in this paper. Our imputation procedure is as follows. For an individual household i define: e_i as total identified and unidentified expenditures; e_i^{nd} as identified non-durable spending; and e_i^{uc} as unidentified spending due to cash withdrawals, unclassified checks, and payments to unobserved credit cards. Then for individuals i in a population q (e.g. the set of all households, or the subset of those in a particular quantile of the liquid wealth distribution), $\xi_q \equiv \frac{1}{N_q}\sum_{i=1}^{N_q} e_{i,q}^{nd}/(e_{i,q} - e_{i,q}^{uc})$ is the average non-durable expenditure share among identified expenditures. Following the empirical strategy in Section III.A below, we estimate spending responses to income receipts separately for e_i^{nd} and e_i^{uc}. We then construct the total non-durable response to an income receipt by allocating a fraction ξ_q of the unidentified expenditure response to the total non-durable response. The average expenditure shares ξ_q are computed for the relevant populations q using data from the month prior to income receipt.

Our imputation procedure relies on two plausible assumptions. First, the true non-durables share of unidentified spending should be similar to the identified non-durables share ξ_q. Similar to the spending shares in Figure 1, the 2018 Survey of Consumer Payment Choice (SCPC) reports that around 40 percent of cash and paper check transactions and 36 percent of payment card transactions are allocated towards retail goods, respectively.[8] Second, the composition of unclassified spending should not change around the date of income receipt. In Online Appendix B.3 we show that these composition changes are indeed very small.

Finally, in Online Appendix B.2 we show that estimated spending responses with and without imputation are very similar (see Section III.D for further discussion).

D. Liquid Assets

Next, we measure household liquid asset balances in our data set. To do this, we aggregate checking accounts, savings accounts, and non-transaction account balances all measured at the end of each calendar month.[9] Note that we measure gross, rather than net, liquid asset balances. We exclude credit card balances because: first, we do not know the size or share of credit card balances held outside of our financial institution; second, observable credit card balances at any given time are held by a small fraction of the population (see Panel (a) of Table 1); and third, we do not know the size of household credit card limits which would enable us to measure available liquidity via credit.

Table 3 compares annual total after-tax incomes, checking account balances, and total liquid balances in our data, the Survey of Consumer Finances (SCF), and the SCPC for the year 2016 (Board of Governors of the Federal Reserve System, 2016; Federal Reserve Bank of Atlanta and Federal Reserve Bank of Boston, 2016). The median household in our data holds around 3 weeks of monthly income in its liquid accounts, two thirds of which is in highly liquid checking accounts. We find that: household incomes are very similar to those in the SCF and the SCPC; checking account balances are similar to those in the SCPC but somewhat lower than reported in the SCF; but total liquid balances are less than half of those reported in the SCF. This suggests that our data understates total liquidity available to observed households.

Additionally, we likely fail to capture households in the upper and lower tails of the wealth distribution altogether. Very wealthy individuals employ various forms of wealth management that are not well-captured by our single source of

[8]See Table D in Foster, Greene and Stavins (2019).

[9]Note that while checking and savings accounts are perfectly liquid (money can be transferred immediately between accounts within the bank), transfers from non-transaction accounts such as money market and brokerage accounts operate with a short delay, usually one or two days. Additionally, liquidation and transfer of certificates of deposit may incur some cost.

Table 3—: Comparison of Liquid Assets Across Data Sources

	Annual Income			Checking Accounts			Total Liquid Balances		
	25^{th}	Median	75^{th}	25^{th}	Median	75^{th}	25^{th}	Median	75^{th}
SCF	33956	61541	102568	308	1850	6167	987	4687	19734
SCPC	29445	55417	92362	150	817	2864	–	–	–
BANK	31754	50568	82484	338	1251	3687	459	1796	6182

Note: All comparisons made using data from 2016. Income statistics for the SCPC are computed as percentiles from the middle values of each income interval reported by individuals in the sample. Incomes in both the SCF and SCPC are adjusted for income tax using information from Congressional Budget Office (2019).
Source: Authors' calculations using data from our financial institution, the Survey of Consumer Finances, the Survey of Consumer Payment Choice, and the Congressional Budget Office.

banking data, and 6.5 percent of U.S. households, likely the very poorest, are unbanked (Federal Deposit Insurance Corporation, 2017).

In Section III.C we estimate the response of household expenditures to tax refunds across our observed distribution of household liquidity. We measure liquidity as the ratio of month-end liquid asset balances to monthly income. We then take the average of the assets-to-income ratio across the 9 months prior to tax refund receipt. Using average liquidity prior to receipt ensures that spending responses conditional on liquidity are not confounded by changes in portfolio holdings as households approach the date of tax refund.[10] And restricting to just 9 months prior to tax refund avoids confounding due to changes in liquid assets around the date of the previous year's refund. Finally, to avoid small denominator problems in our liquidity ratio we further restrict the sample of households to those with average monthly income greater than \$500, which removes around 2 percent of the sample of tax refund recipients.

In Table 4 we divide households into deciles of the observed liquidity distribution and report averages of liquid assets-to-income, checking account balances-to-income, total income, and the size of tax refund within each decile. Across the distribution, liquid asset holdings vary in size from around one week of total income to more than 5 months of total income. There is similar variation in checking account balances. Total income is increasing with household liquidity until around the sixth decile, at which point it flattens out and falls slightly over the upper deciles. Importantly, the size of tax refund does not systematically vary with household liquidity. This suggests that our results in Section III.C are not simply explained by differences in magnitude of tax receipt across the distribution of liquid assets.

[10]Both Baugh et al. (2021) and our results in Section IV.D suggest that households do not, in fact, adjust their portfolios in anticipation of tax refunds.

Table 4—: Liquidity, Income, and Tax Refunds Among Refund Recipients

	Liquid Assets-to-Income Decile									
	1	2	3	4	5	6	7	8	9	10
Liquid/Income	0.21	0.36	0.49	0.64	0.80	1.00	1.35	1.91	3.09	5.11
Checking/Income	0.11	0.20	0.28	0.38	0.50	0.65	0.96	1.45	2.55	4.91
Total Income	4348	4860	5163	5420	5680	5909	6026	6088	6017	5840
Tax Refund	2049	1999	2020	2029	2096	2132	2161	2154	2110	2097

Source: Authors' calculations using financial institution data.

See Online Appendix A.6 for further discussion and comparisons to external data sources.

III. Empirical Analysis

A. Empirical Strategy

We estimate dynamic household spending responses to anticipated income receipts at the daily frequency. To do this we employ a distributed lags regression specification

$$Y_{i,t} = \alpha_i + \lambda_t + \sum_{j=-30}^{150} \delta_j Receipt_{i,t+j} + \epsilon_{i,t} \tag{1}$$

where i and t are household and date identifiers, $Y_{i,t}$ is an outcome variable of interest such as total or non-durable expenditure, α_i is a household-specific fixed effect, λ_t is a day-specific fixed effect, and $Receipt_{i,t+j}$ is the size of income inflow received at the j^{th} lead or lag relative to date t. The coefficients δ_j estimate the leading, contemporaneous, and lagged responses of the dependent variable $Y_{i,t}$ to a payment received at date t. The responses δ_j are measured as shares of the payment $Receipt_{i,t+j}$. In other words, Equation (1) estimates the marginal propensity to consume (MPC), or expend, out of an anticipated income receipt.

Identification of the spending responses δ_j is due to variation in event time, which is measured relative to the day of income receipt. Day fixed effects λ_t control for average spending patterns on a particular calendar day, so that typical expenditures due to particular weekdays, holidays, or seasons (e.g. tax seasons) do not influence estimated spending responses. Household fixed effects α_i control for any correlation between average household-specific expenditures and income receipts. Such correlations may be due to differences in economic circumstances across households, for example.

We report cumulative MPCs from Equation (1), which are simply the sum of response coefficients δ_j over $j \in [-30, K]$ for some K. In all of the figures that follow, we illustrate 95 percent confidence intervals around the estimated cumulative MPCs as shaded regions surrounding the coefficient estimates.[11]

B. *Expenditure Responses to Tax Refund Receipts*

We first consider household responses to anticipated tax refunds. Our first exercise reports the responses of total expenditure and each component of the household balance sheet. Figure 2 illustrates our estimates from Equation (1). Panels (a) to (e) show that households do not spend, make payments, or transfer funds across their balance sheet in the 30 days prior to receipt of their tax refunds.[12] On the day of receipt, tax refunds are first deposited into household transaction accounts (see Panel (a)). However, households begin spending and making transfers immediately (see Panels (b) to (f)). The bulk of transactions and transfers take place within 30 days of refund receipt. For example, Panel (b) shows that two thirds of the expenditure response over a 150-day period occurs within the first month. Over the entire 150 days, households allocate around 60 percent of their tax refunds to consumption expenditure, 20 percent to non-transaction accounts, 6 percent to credit card payments, and leave around 12 percent in their primary transaction accounts.

Figure 3 shows the response of (imputed) non-durable expenditure to anticipated tax refunds. Again, we find that households do not spend out of refunds in the 30 days prior to refund receipt. On the day of refund arrival, households spend 4 cents on non-durables out of every dollar received. Over the first 30 days post-refund households spend 19 cents, and they spend 25 cents in the first 90 days. As is the case for total expenditures, non-durable spending is extremely front-loaded with respect to date of receipt with 67 percent of all spending taking place in the first 30 days. Non-durable spending responses are around half the size of the total expenditure responses reported in Panel (b) of Figure 2.

Finally, note that our MPCs are consistent with estimates from the recent literature. Our 3-month MPC for non-durables is 0.25, which compares to previous estimates of: 0.14 (Gelman, 2021), 0.15 (Baugh et al., 2021), 0.22 (Kueng, 2018), 0.201 (Parker et al., 2013), 0.386 (Johnson, Parker and Souleles, 2006).

C. *Expenditure Responses by Household Liquidity*

We now consider differences in spending responses to tax refunds across the distribution of household liquidity. As detailed in Section II.D, we measure liquidity as the average ratio of month-end liquid asset balances relative to monthly

[11] That our confidence intervals are not so easily discerned in our figures is a result of the very small coefficient standard errors estimated under our large sample size.

[12] Baugh et al. (2021) also estimate zero responses in advance of tax refunds but show that households do transfer funds across the balance sheet in advance of tax payments.

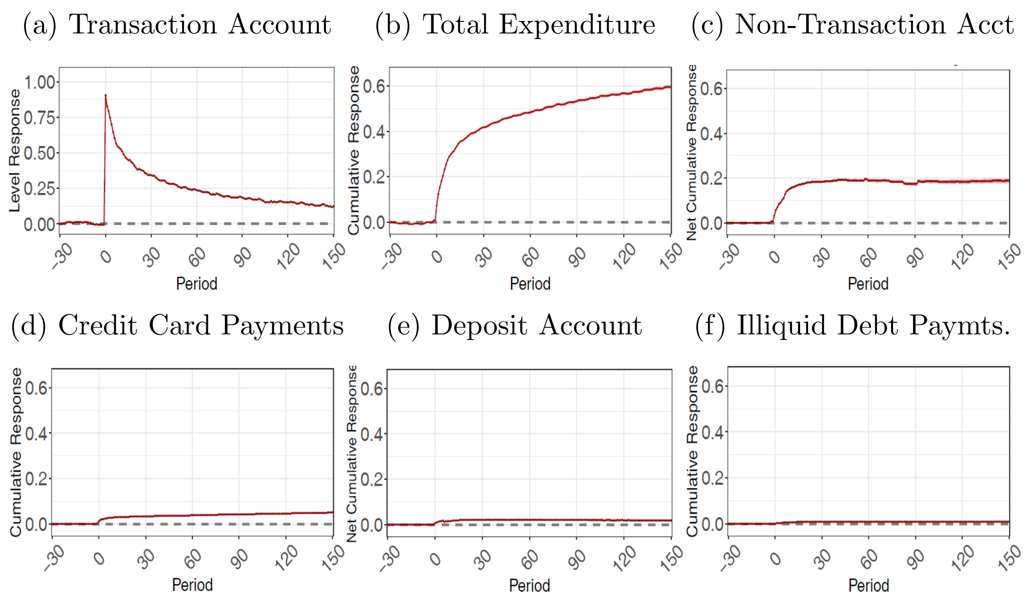

Figure 2. : Expenditure and Balance Sheet Responses to Tax Refunds

Note: Transaction accounts: checking and savings accounts. Non-transaction accounts: brokerage accounts, money market funds, retirement funds, and certificates of deposit. Credit card payments: excess payments toward credit card balances. Note that these credit card payments include some double counting since observable expenditures on credit cards at the time of purchase are assigned to the total expenditure measure.
Source: Authors' calculations using financial institution data.

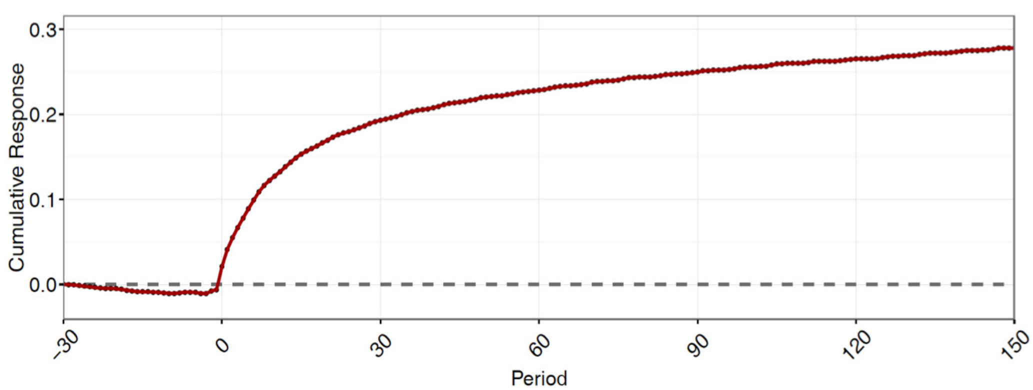

Figure 3. : Non-Durable Expenditure Response to Tax Refunds

Note: Spending responses for partially imputed non-durables (see Section II.C).

Source: Authors' calculations using financial institution data.

(a) Quintile 1 (b) Quintile 2 (c) Quintile 3 (d) Quintile 4 (e) Quintile 5

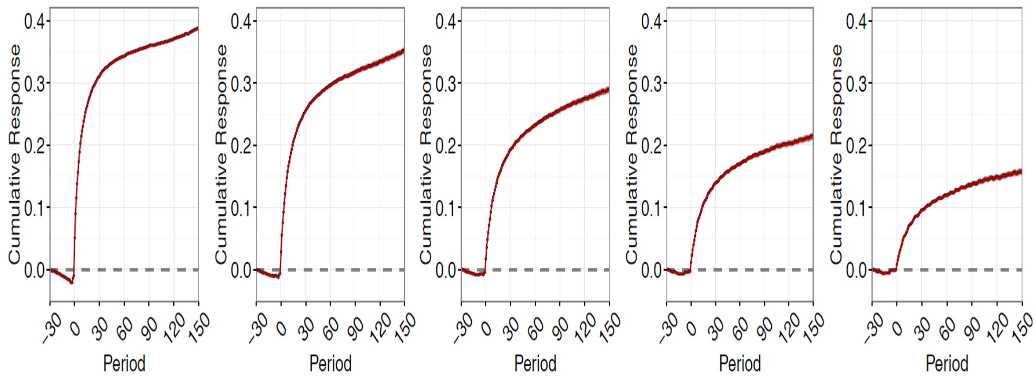

Figure 4. : Non-Durable Expenditure Responses by Household Liquidity

Note: Spending responses to tax refunds. Expenditure measured as partially imputed non-durables, as described in Section II.C. Households split by quantiles of liquid assets-to-income, averaged across the 9 months prior to tax refund.
Source: Authors' calculations using financial institution data.

income in the 9 months prior to refund receipt. Figure 4 illustrates spending responses estimated from Equation (1) separately for each quintile of the liquid asset distribution.

The shape of spending responses is remarkably similar for households with very different liquid asset holdings. Across all quintiles there is no spending response in anticipation of tax refund and significant front-loading of expenditures. For households in the first quintile of liquid assets 84 percent of spending takes place in the first 30 days, while that number is 66 percent for the wealthiest quintile of households. Nevertheless, the size of spending response following refund receipt is declining with liquidity. The cumulative MPCs at 30 days are 0.32, 0.19, and 0.10 for the lowest, middle, and highest quintiles of liquid wealth, respectively.

These estimates are consistent with the recent literature. Parker (2017) estimates that MPCs for the poorest tercile of liquid asset households are 3 times larger than MPCs for wealthier households. Gelman (2021) estimates MPCs for the poorest cash-on-hand quintile of households that are 5 times larger than the wealthiest quintile. And Baugh et al. (2021) estimates that MPCs for the lowest tercile of households by liquid asset balances are 1.5 times larger than MPCs for the average household.

D. *Robustness Checks*

Finally, we conduct a series of extensions and robustness tests of our main results. These results are collected and reported in Online Appendix B.

First, we show that our results are not driven by our categorization or particular measure of non-durables expenditure (see Section B.1). Figure B.1 illustrates the responses of total spending, durables expenditure, food services expenditure, grocery expenditure, and retail and entertainment expenditure to tax refunds. In each of these categories, we find no anticipated spending response and significant front-loading of expenditure to the date of refund receipt.

Second, we consider the influence of our imputation procedure on our estimated responses of non-durables expenditure (see Section B.2). Figure B.2 compares spending responses with and without imputation, where the latter only includes spending on items that can be clearly identified in the transactions data. We find that the pattern of spending is the same whether imputation is used or not: households do not spend in advance of refund and expenditure is front-loaded with respect to date of receipt. While the magnitude of our estimates is around 30 percent smaller for our spending measure without imputation, this simply reflects the exclusion of unclassified spending categories (see Figure 1).

Third, we show that our expenditure patterns are robust to the receipt of multiple tax refunds (see Section B.4). For this exercise we restrict attention to households receiving both a state and federal tax refund in the same calendar year, which yields a subsample of around 700,000 households. Figure B.5 reports estimated non-durables spending responses to first and second tax refunds. Panel (a) shows that the non-durable spending response to first refunds is very similar to the response of households receiving just one refund (see Figure 3). Panel (b) shows that the response to the second tax refund is around 30 percent smaller than the response to the first refund, but otherwise shows the same lack of anticipated spending and front-loading of expenditure patterns.

Fourth, we conduct a similar exercise to Baugh et al. (2021) by re-estimating Equation (1) while conditioning on individual tax filing dates (see Section B.5). This allows us to control for the date at which households actually receive information about their coming tax refund. We identify tax filing dates in our transactions data by selecting the first payment of the calendar year that a household makes to a tax services provider (for further details, see Section A.4). We can identify tax filing dates for 17.3 percent of all households receiving a tax refund. Figures B.6 and B.7 show the estimated non-durables and total expenditure responses to tax filing date and tax refund(s). Consistent with the results in Baugh et al. (2021), we find that household spending is unresponsive to tax filing date. Moreover, spending patterns in response to tax refunds are largely unaffected by conditioning on the tax filing date. We then test whether the lack of response to tax filing date is due to liquidity constraints that prevent households from spending out of expected tax refunds. Figures B.8 and B.9 compare total expenditure responses across households in the bottom and top quintiles of liquid wealth. We find no response to tax filing for either household group, suggesting that available liquidity is not an explanation for the lack of anticipated spending response.

Fifth, we consider whether spending responses vary by household liquidity after conditioning on total income (see Section B.6). We first divide the sample population into low income (less than \$40,000; 34.5 percent of the population), middle income (\$40,000 to \$120,000; 56 percent), and high income (greater than \$120,000; 9.5 percent) groups by annual earnings in the year prior to tax refund. We then stratify by liquid assets-to-income within each income group as: below median, median to 75^{th} percentile, and above 75^{th} percentile. Figure B.10 reports total expenditure responses to tax refunds within each subsample. Once again we find the same patterns of spending response across the population. At all income and wealth levels, households do not spend in anticipation of tax refund and households front-load their spending to the date of receipt. Furthermore, confirming and extending our results in Section III.C, we find that even within income groups high-liquidity households spend a significant fraction of their tax refund but that low-liquidity households spend significantly more than high-liquidity households.

Finally, we study household spending responses to the receipt of two other forms of predictable income: bonus checks and regular paychecks.

We first estimate the response of non-durable expenditures to bonus check receipts (see Section B.7). As in our previous analysis, Figure B.11 shows that there is no anticipated spending response and significant front-loading of spending with respect to date of receipt. However, the spending response to bonus checks is relatively small, with 30-day and 90-day MPCs of 0.14 and 0.20, respectively. In comparison, for tax refunds we estimated 30-day and 90-day MPCs of 0.19 and 0.25, respectively.

We then estimate spending responses to the receipt of regular paychecks following Gelman et al. (2014); Olafsson and Pagel (2018) (see Section B.8). In contrast with tax refunds and bonus checks, regular paychecks are received at regular intervals and the particular day or date of receipt is fully known in advance. We restrict our estimation to a period of one week either side of paycheck receipt to reduce the overlap in spending responses to consecutive paychecks. Figure B.12 compares responses to regular paychecks and tax refunds for different spending categories. Spending responses are remarkably similar in shape and magnitude across income sources. For both types of income, households: exhibit no anticipated spending response; spend rapidly in the days immediately after receipt; and spend similar amounts in the first week after receipt (with the exception of spending on durable goods). Figure B.13 shows spending responses to regular paychecks by liquid wealth. Across the wealth distribution we find: no anticipated spending responses; a sharp increase in spending in the days immediately following receipt; spending responses that are large but declining with liquid wealth.

IV. A Simple Model of Mental Accounts

We now develop a tractable model of mental accounts that can rationalize the observed timing and magnitude of consumption responses to income receipt. The novelty of the model is due to a departure from standard assumptions on preferences regarding the fungibility between current income and current assets (Thaler, 1985; Shefrin and Thaler, 1988). We embed mental accounts preferences in a simple life-cycle model, derive analytical expressions for MPCs out of anticipated income receipts, and demonstrate both a lack of anticipated responses and front-loading of expenditure to the date of income receipt.

Note that in order to provide analytical results our simple model abstracts from income uncertainty and borrowing constraints. We extend the analysis to study MPCs across the distribution of liquid wealth in our quantitative, heterogeneous household model in Section V.

A. *The Mental Accounts Utility Function*

We posit a mental accounts utility function of the form

$$U(c) \equiv u(c) - d(c, c^d) \tag{2}$$

Where $u(\cdot)$ denotes a standard utility function with $u' > 0$ and $u'' < 0$, and $d(\cdot)$ is a penalty function over the consumption choice c and a default consumption level c^d. The penalty function is

$$d(c, c^d) = \begin{cases} 0 & \text{if } c \leq c^d \\ \psi\left(u(c) - u(c^d)\right) & \text{if } c > c^d \end{cases} \tag{3}$$

where ψ governs the strength of the penalty when consumption deviates from the default, and the size of the penalty is the difference between the utility from consuming c and the utility from consuming c^d. Because $u' > 0$, the penalty is increasing in consumption deviations from default. Finally, we assume that default consumption is equal to current income: $c^d = y$.

Our assumptions characterize mental accounts as a partition of consumption choices across the types of resources that are available. Households treat spending out of current income differently from spending out of current assets, as illustrated by the kinked utility function in Figure 5. When $\psi = 0$ households face the standard utility function, which is smoothly differentiable across all values of consumption. But consider the extreme case $\psi = 1$. For consumption less than current income, households incur no penalty and the utility functions under $\psi = 0$ and $\psi = 1$ are the same. When consuming out of current assets, the penalty is incurred and the mental accounts utility function lies strictly below the standard utility function.

Finally, notice that under mental accounts households exhibit dissavings aversion as consumption approaches current income. To see this, note that

$$U'(c) = \begin{cases} u'(c) & \text{if } c \leq c^d \\ (1-\psi)u'(c) & \text{if } c > c^d \end{cases} \tag{4}$$

A household consuming $c = c^d$ faces marginal utility $u'(c)$, the same as in the

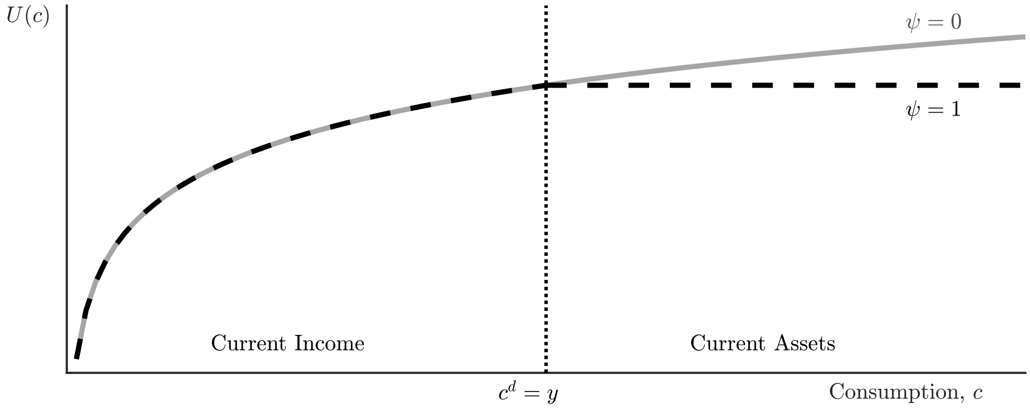

Figure 5. : Utility Function in the Mental Accounts Model

standard model. But an infinitesimal increase in consumption entails consumption out of current assets and marginal utility falls to $(1-\psi)u'(c)$. This penalty discourages consumption out of current assets, a form of dissavings aversion.

B. Mental Accounts in a Life-Cycle Model of Consumption and Savings

We now embed the mental accounts utility function in an otherwise standard life-cycle model of consumption and savings behavior. Note that we restrict our model to household choices about the use of income and liquid assets. We consider a monthly model frequency, and thus think of liquid assets as similar to checking or savings account balances at the beginning of the month after consumption spending out of income received during the past month. We abstract from decisions associated with illiquid assets such as financial investments, housing, or retirement accounts (see Kaplan, Violante and Weidner, 2014; Kaplan and Violante, 2014).

Households live for T months, face no income uncertainty or borrowing constraint, and are endowed with initial assets a_0 and a deterministic stream of income $\{y_t\}_{t=0}^{T-1}$. The decision problem is:

$$\begin{aligned} \max_{c_t, a_{t+1}} \sum_{t=0}^{T-1} \beta^t & \left[\frac{c_t^{1-1/\gamma}}{1-1/\gamma} - d(c_t, c_t^d) \right] \\ & c_t + a_{t+1} = y_t + a_t(1+r) \\ & c_t^d = y_t \\ & a_T = 0 \end{aligned}$$

where c_t is consumption, a_{t+1} are asset choices, a_t are assets available at the beginning of the period, r is the net interest rate, β is the discount factor, the penalty function $d(\cdot)$ is from Equation (3), and flow utility is due to the CRRA function with intertemporal elasticity of substitution γ.

An analytical solution to the problem is complicated by the kinks induced by the penalty function in Equation (3). To proceed, we take first order conditions assuming that optimal consumption choices are interior to the kinks. Then the Euler equations are:

$$(1-\psi \mathbb{1}_{c_t>y_t})c_t^{-1/\gamma} = \beta(1+r)(1-\psi \mathbb{1}_{c_{t+1}>y_{t+1}})c_{t+1}^{-1/\gamma} \tag{5}$$

where $\mathbb{1}_{c_t>y_t}$ is an indicator function equal to zero if the household consumes out of current income and equal to one if the household consumes out of current assets.

Equation (5) shows that mental accounts introduce both static and dynamic distortions in household consumption behavior. On the margin at time t, households prefer to consume out of current income rather than current assets. This encourages saving over dissaving at time t, which leads to larger asset balances at time $t+1$. But this may induce future consumption out of assets, reducing marginal utility at time $t+1$. Households must balance these static and dynamic considerations.

In Online Appendix C.1 we show that combining the Euler Equation (5) with the intertemporal budget constraint yields the consumption function:

$$c_t = \frac{(\beta(1+r))^{\gamma t}(1-\psi \mathbb{1}_{c_t>y_t})^{\gamma}}{\sum_{s=0}^{T-1}\beta^{\gamma s}(1+r)^{(\gamma-1)s}(1-\psi \mathbb{1}_{c_s>y_s})^{\gamma}}\left(a_0(1+r)+\sum_{s=0}^{T-1}\frac{y_s}{(1+r)^s}\right) \tag{6}$$

where the final term is the present discounted value of life-time wealth. Note that the consumption function is not everywhere continuously differentiable with respect to income. This is because changes in income may lead households to consume out of current assets thereby triggering the dissaving aversion penalty.

C. *MPCs from Anticipated Income Receipts*

We now study MPCs out of anticipated income receipts (e.g. tax refunds). In order to provide analytical expressions for MPCs, we need to make assumptions about model parameters and the path of income. In Online Appendices C.2 and C.3 we derive consumption responses under two special cases. First, we assume that absent the increase in income $c_t = y_t$ for all t. Second, we assume that income follows a hump-shaped life-cycle profile. For ease of intuition, we consider the first special case here.

We assume that but for the income inflow, model parameters and the path of income $\{y_t\}_{t=0}^{T}$ are such that $c_t = y_t$ for all t. At time $t=0$ the household learns they will receive a one-time increase in income in period h: $y_h + \Delta$. Following this income announcement, the consumption smoothing motive induces households to increase consumption a little in all periods so that $c_t > y_t$ for all $t \neq h$. But at date h consumption increases by less than income so that $c_h < y_h + \Delta$. Thus, dissavings aversion is triggered in all periods $t \neq h$ and we can rewrite Equation (6) as:

$$c_t = \frac{(1-\theta)(\beta(1+r))^{\gamma t}(1-\psi \mathbb{1}_{t\neq h})^{\gamma}}{(1-(1-\psi)^{\gamma})(1-\theta)\theta^h + (1-\psi)^{\gamma}(1-\theta^T)} \times W_0$$

where $\theta = \beta^{\gamma}(1+r)^{\gamma-1}$, $W_0 = \left[a_0(1+r) + \sum_{s=0}^{T-1}(y_s + \mathbb{1}_{s=h}\Delta)/(1+r)^s\right]$ is lifetime wealth, and $\mathbb{1}_{s=h}\Delta$ denotes additional income received in period h.

We define the MPC out of anticipated income received at h as the change in consumption as Δ approaches zero from above.[13] The MPC at date t is

$$\begin{aligned} MPC_t^h &\equiv \lim_{\Delta \to 0^+} \frac{c_t(y_h + \Delta) - c_t(y_h)}{\Delta} \\ &= \frac{(1-\theta)\beta^{\gamma t}(1+r)^{\gamma t - h}(1-\psi \mathbb{1}_{t\neq h})^{\gamma}}{(1-(1-\psi)^{\gamma})(1-\theta)\theta^h + (1-\psi)^{\gamma}(1-\theta^T)} \end{aligned} \tag{7}$$

The parameter ψ determines the strength of the consumption response in period h relative to periods $t \neq h$. In the extreme case where $\psi = 1$, the MPC is

$$MPC_t^h = \begin{cases} 1 & \text{if } t = h \\ 0 & \text{if } t \neq h \end{cases}$$

This household acts like a hand-to-mouth consumer at the date of income receipt $t = h$, but is unresponsive to both future ($t < h$) and past ($t > h$) income receipts. When $\psi = 0$ households have standard preferences, experience no aversion to dissaving, and the MPC becomes

$$MPC_t^h = \frac{(1-\theta)\beta^{\gamma t}(1+r)^{\gamma t - h}}{(1-\theta^T)}$$

With log-utility, an infinite horizon $T \to \infty$, and an income receipt announced and received at $h = t = 0$, the MPC becomes

$$MPC = 1 - \beta$$

which is the consumption response under the permanent income model, and is a function of the familiar annuity factor. Thus the mental accounts model nests

[13] This assumption ensures consistency with our argument that the inflow causes households to consume less than current income in period h and more than current income in all periods $t \neq h$.

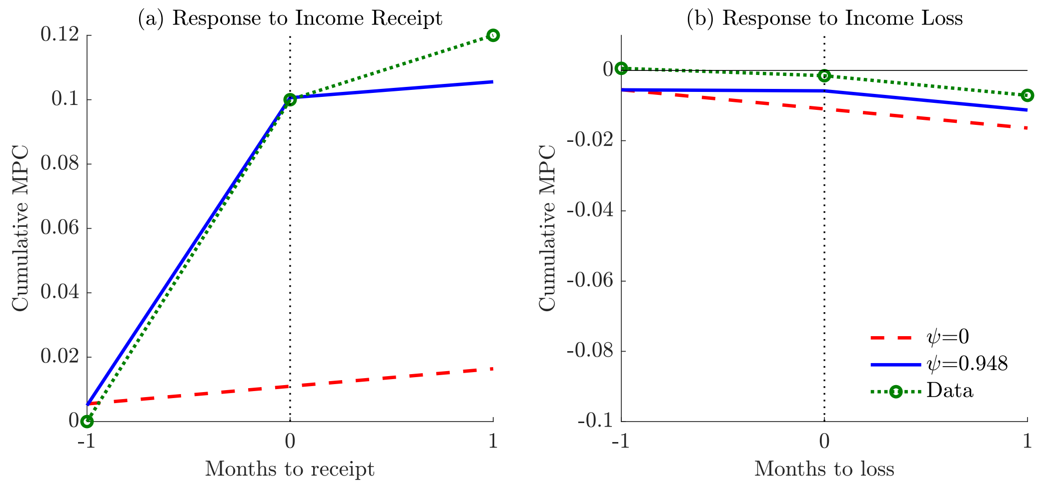

Figure 6. : Consumption Responses to Anticipated Income Changes

Note: Panel (a) reports MPCs computed from Equation (7). Panel (b) reports MPCs computed from Equation (8). Model parameters: $T = 12 \times 40$, $r = 0$, $\gamma = 1$, and $\beta = 0.995$. In Panel (a), the green dotted line illustrates MPCs estimated for households in the top quintile of liquid assets-to-income, as reported in Figure 4. In Panel (b), the green dotted line illustrates the estimated MPCs reported in Table 3 of Baugh et al. (2021).
Source: Authors' calculations, financial institution data, Baugh et al. (2021).

both hand-to-mouth and standard consumption smoothing behavior as edge cases with respect to the dissaving aversion parameter ψ.

To demonstrate that the mental accounts model is capable of reproducing our estimated consumption responses from Section III, consider the following back-of-the envelope calculation. We compute MPCs using Equation (7) and assuming a monthly model, a 40 year time-horizon, log-utility, zero return on monthly savings, and a large discount factor reflecting the monthly frequency. Panel (a) of Figure 6 shows cumulative MPCs in the month prior to, month of, and month following income receipt.

The solid blue line shows MPCs under mental accounts with $\psi = 0.948$, the dashed red line shows MPCs when $\psi = 0$, and for comparison the dotted green line shows estimated MPCs for the highest quintile of liquid assets from Figure 4. Because this group of households hold large liquid asset balances they are least likely to be affected by the presence of income uncertainty and borrowing constraints, and thus closest to the assumptions of our simple model. In the standard model ($\psi = 0$), MPCs are low and smoothly increasing across time. While in the model with mental accounts ($\psi > 0$), MPCs are high in the period of income receipt, but MPCs are low prior to and after income receipt. Thus, a basic life-cycle model with mental accounts can reasonably replicate both the front-loading of consumption and lack of anticipated response to income receipt observed in Section III. The standard model fails to replicate these features of the data as the consumption smoothing motive dominates household spending responses over time.

D. MPCs from Anticipated Income Losses

Although not the focus of this paper, we might also be interested in how households respond to anticipated negative income shocks (e.g. required tax payments). Baugh et al. (2021) estimates household responses to both tax refunds and payments but shows that spending is essentially insensitive to anticipated tax payments. We now show that our mental accounts model is qualitatively consistent with these asymmetric spending responses.

In Online Appendix C.4 we show that MPCs out of anticipated negative income shocks at h are given by:

$$MPC_t^h = \frac{(1-\theta)(\beta(1+r))^{\gamma t}(1-\psi \mathbb{1}_{t=h})^{\gamma}}{(1-\theta^T) - (1-(1-\psi)^{\gamma})\,(1-\theta)\theta^h} \tag{8}$$

Panel (b) of Figure 6 illustrates MPCs to an anticipated decline in income: $\Delta < 0$. Again, the solid blue line shows MPCs under mental accounts and $\psi = 0.94$, the dashed red line shows MPCs when $\psi = 0$. The dotted green line shows estimated MPCs out of tax payments from Table 3 of Baugh et al. (2021). In both the standard model and mental accounts model households effectively smooth consumption with respect to income loss as MPCs are small, negative, and smoothly increasing in absolute value over time. But only the mental accounts model effectively captures the asymmetry of spending responses reported in Baugh et al. (2021). Households spend a lot of out additional income around the date of a receipt but change spending very little in anticipation of and following a negative income shock (e.g. required tax payment).

V. A Quantitative Mental Accounts Model

We now embed the mental accounts framework in a heterogeneous household life-cycle model to rationalize observed consumption responses across the liquid wealth distribution.

A. Model Setup

A model period is one month. We consider working life only, so households live for T periods and enter a terminal retirement state at $T+1$. The idiosyncratic state variables are $\mathbf{s} = [t, a, z, e, h]$, where t is current age, a is liquid assets, z is an idiosyncratic productivity shock, e is employment status, and h determines the date of an anticipated income receipt relative to date t.

Households can save in a one-period liquid asset a paying the risk-free return r. Savings are restricted to be non-negative: $a' \geq 0$. At the beginning of life, a fraction π_a of households receive an endowment of assets equal to a proportion λ_a of their initial income.

We define total income m as labor income plus one-off inflows of funds. Labor income is a function of a deterministic life-cycle component Γ_t and stochastic productivity and employment processes. Productivity z follows a log-AR(1) process with persistence ρ_z and standard deviation of shocks σ_z. Employment status $e \in \{0, 1\}$ follows a two-state Markov chain, where the probability of becoming unemployed (i.e. the separation rate) is π_u, and the probability of finding a job is π_e. Unemployed households receive unemployment insurance given by a simple replacement rate ω_u relative to their usual labor income. Labor income is then given by

$$y(t, z, e) = (e + (1 - e)\omega_u)\, z\Gamma_t \tag{9}$$

Households may receive announcements about a one-off, future income receipt (e.g. a tax refund). For simplicity, we assume that these announcements are zero probability events. At the date of announcement $h < 0$, and the household anticipates an inflow at date $t - h$. When $h = 0$, the household receives the additional income in the current period. And for $h = 1$, the household no longer anticipates any future inflows. The size of the inflow is proportional to household labor income $\Delta \times y(t, z, e)$ at date of receipt. Total income is thus

$$m(t, z, e, h) = (1 + \mathbb{1}_{\{h=0\}}\Delta) y(t, z, e) \tag{10}$$

The household decision problem is described by the value function

$$\begin{aligned} V_t^i(a, z, e, h) = &\max_{c,a'} \left\{ \frac{c^{1-1/\gamma}}{1 - 1/\gamma} - d(c, c^d; \psi_i) + \beta \mathbb{E}\left[V_{t+1}(a', z', e', h')\right] \right\} \\ \text{s.t} \quad & c + a' = m(t, z, e, h) + a(1 + r) \\ & c^d = m(t, z, e, h) \\ & h' = \min\{h + 1, 1\} \\ & a' \geq 0 \end{aligned}$$

where γ is the intertemporal elasticity of substitution, $d(c, c^d; \psi_i)$ is the mental accounts penalty function from Equation (3) allowing for heterogeneity in the penalty parameter ψ_i, c^d is default consumption equal to current total income $m(t, z, e, h)$, and β is the common discount factor. We assume two types of households $i \in \{0, 1\}$ such that $\psi_i \in \{0, \psi\}$ and a fraction π_i exhibits mental accounts behavior $\psi > 0$.

Finally, following Gourinchas and Parker (2002), the terminal value after re-

Table 5—: Externally Calibrated Model Parameters

Parameter	Symbol	Value	Source
Panel (a): Primitives			
Real return on liquid assets (%)	r	0.0072	OECD, 1999–2019
Fraction receiving endowment	π_a	0.8827	SCF, 1998–2019
Endowment as fraction of income	λ_a	1.0538	SCF, 1998–2019
Panel (b): Income			
Deterministic income	$\{\Gamma_t\}_{t=1}^{T}$	·	SCF, 1998–2019
AR(1) income, persistence	ρ_z	0.0960	Gelman (2021)
AR(1) income, std. dev. shocks	σ_z	0.1975	Gelman (2021)
UI replacement rate	ω_u	0.5000	DOL, 2016
Job finding rate	π_e	0.2444	CPS, 1999-2019
Job separation rate	π_u	0.0130	CPS, 1999-2019
Anticipated income receipt size	Δ	0.2896	Bank data

Note: Real return reported at annualized rate. Job finding and separation rates reported as monthly probabilities.

tirement is a function of accumulated assets

$$V_{T+1}(a) = \kappa \frac{a^{1-1/\gamma}}{1-1/\gamma} \tag{11}$$

which is similar to a warm-glow bequest motive (see De Nardi, 2004).

B. *Calibration and Estimation*

We first choose a subset of parameters consistent with information external to the model. We then estimate the parameters $\Theta = \{\beta, \gamma, \kappa, \psi, \pi_i\}$ via Simulated Method of Moments (SMM) to capture household wealth holdings and consumption responses to income receipts.

Table 5 reports our externally calibrated parameters. The model period is one month, households enter the model at age 25, and retire at age 65, so that $T = 480$. The annual return on assets r is taken from the average of real 3-month yields on certificates of deposit from 1999–2019 (Organization for Economic Co-operation and Development, 2023; U.S. Bureau of Labor Statistics, 2021*a*). We compute π_a as the fraction of young households with non-negative liquid wealth, and λ_a as the ratio of liquid wealth to monthly, after-tax, per-capita income conditional on positive wealth. These statistics are computed for 25 year old households in the 1998–2019 waves of the Survey of Consumer Finances (SCF) (Board of Governors of the Federal Reserve System, 2019). Consistent with our empirical work, we take liquid assets to be the sum of checking and savings accounts, money market mutual funds, call accounts, and certificates of deposit.

The deterministic life-cycle income profile Γ_t is computed using real, after-tax income per-capita from the 1998–2019 waves of the SCF. We restrict the sample to working-age households in the labour force earning at least \$500 per year. After-tax income is derived from the 2016 federal income tax thresholds and tax rates for single and married households from the Congressional Budget Office (2019). We then regress log-income on cohort fixed effects and a fourth-order polynomial in household age. We use the fitted values and interpolate across months within years to construct the life-cycle income profile. We illustrate the estimated life-cycle profile Γ_t in Figure D.1 of Online Appendix D.2.

The idiosyncratic productivity parameters ρ_z and σ_z are taken from Gelman (2021) who estimates an AR(1) process for log-income from a monthly panel of 46,000 continuing workers in data provided by a financial services app. The unemployment insurance replacement rate is set to $\omega_u = 0.5$ consistent with the average of state-level rates (U.S. Department of Labor, 2016). We set the monthly job finding rate π_e and separation rate π_u to the averages of monthly rates reported in the Current Population Survey from 1999–2019 (U.S. Bureau of Labor Statistics, 2021*b*). The size of the anticipated income inflow $\Delta = 0.2896$ is set to match the ratio of median tax refund to median income, as reported in Table 1.

Given the fixed parameters above, we estimate the five parameters $\Theta = \{\beta, \gamma, \kappa, \psi, \pi_i\}$ via SMM. The SMM objective function is

$$\min_{\Theta} \; \Omega \times \sum_{l=1}^{5} \left(\mathbf{d}_l^{mpc} - \mathbf{m}_l^{mpc}(\Theta)\right)^2 + (1-\Omega) \times \sum_{s=1}^{5} \left(\mathbf{d}_s^{liq} - \mathbf{m}_s^{liq}(\Theta)\right)^2 \tag{12}$$

where $\mathbf{d}_l^{mpc}$ and $\mathbf{d}_s^{liq}$ are observed statistics on MPCs and household wealth, $\mathbf{m}_l^{mpc}(\Theta)$ and $\mathbf{m}_s^{liq}(\Theta)$ are model-generated statistics, and Ω is a hyper-parameter that governs the relative importance of the MPC and wealth statistics in the estimation. Our baseline estimates are produced under equal weights, $\Omega = 0.5$.

We first target cumulative one-month MPCs out of tax refunds across quintiles $l = [1, \cdots, 5]$ of the liquid assets-to-income distribution (see Figure 4). Model MPCs are computed from a simulated panel of 25,000 households. For each household, we draw one income announcement date $\hat{t}$ from a uniform distribution over $[12, T-12]$ and set $h = -1$ at that date. At date $\hat{t}+1$ the household receives additional income $\Delta \times y(\hat{t}+1, z_{\hat{t}+1}, e_{\hat{t}+1})$, and no further inflows are announced or received. Analogous to our empirical analysis, we construct model MPCs as

$$MPC_t = \frac{c(t, a_t, z_t, e_t, h_t) - c(\hat{t}-1, a_{\hat{t}-1}, z_{\hat{t}-1}, e_{\hat{t}-1}, 1)}{\Delta \times y(\hat{t}+1, z_{\hat{t}+1}, e_{\hat{t}+1})} \tag{13}$$

Table 6—: Estimated Model Parameters

Model	Ω	Parameters					
		β	γ	κ	π_i	ψ	β_L
Mental Accounts	0.5	0.832	0.258	442.329	0.126	0.768	–
Life-Cycle	0.5	0.476	0.164	2859.151	–	–	–
Life-Cycle	1	0.499	0.200	2596.307	–	–	–
Life-Cycle	0	0.882	0.327	68.208	–	–	–
Het. Discount Factor	0.5	0.790	0.199	960.439	0.274	–	0.152

Note: Discount factors β and β_L are reported at annualized rates. Parameters estimated via SMM under the objective function in Equation (12) with weights Ω.

for $t \in \{\hat{t}, \hat{t}+1, \hat{t}+2\}$. Also consistent with our empirical work, we measure the average liquid assets-to-income ratio for each household over the 9 months prior to announcement date $\hat{t}$, and compute average MPCs within each quintile of the liquid wealth distribution. Second, we target median liquid assets-to-monthly income by age group as computed from 1998–2019 waves of the SCF, restricting to the subsample of households that earn at least \$500 per year. In both model and data, we split the sample into 5 age bins $s = [1, \cdots, 5]$ among households aged 25–65.

The first row of Table 6 reports our benchmark estimates of $\{\beta, \gamma, \kappa, \psi, \pi_i\}$. In order to match the targeted statistics, the model estimates that 12 percent of households hold mental accounts preferences and that the strength of the penalty function is $\psi = 0.78$, similar to the value in our back-of-the-envelope calculation for the simple model in Section IV.C.

C. Model Fit and Mechanisms

We now assess the fit of our mental accounts model to the data. Figure 7 illustrates 30-day MPCs out of anticipated income receipt across the distribution of liquid wealth as well as the life-cycle profile of liquid assets-to-income. These are the statistics specifically targeted in our estimation.

The mental accounts model provides a close fit to the data. Panel (a) shows that the first quintile of households by liquid wealth exhibit large MPCs of around 0.30 at the date of income receipt. MPCs then decline smoothly with liquid wealth, until the highest quintile of households where MPCs are around 0.10 on average. Low wealth households lack the ability to self-insure against income shocks and so spend a lot out of an income receipt. Higher wealth households are not constrained by lack of wealth, but many of them spend a lot around the date of income receipt due the dissavings aversion induced by mental accounts behavior. Panel (b) shows that households accumulate wealth over the life-cycle. They do

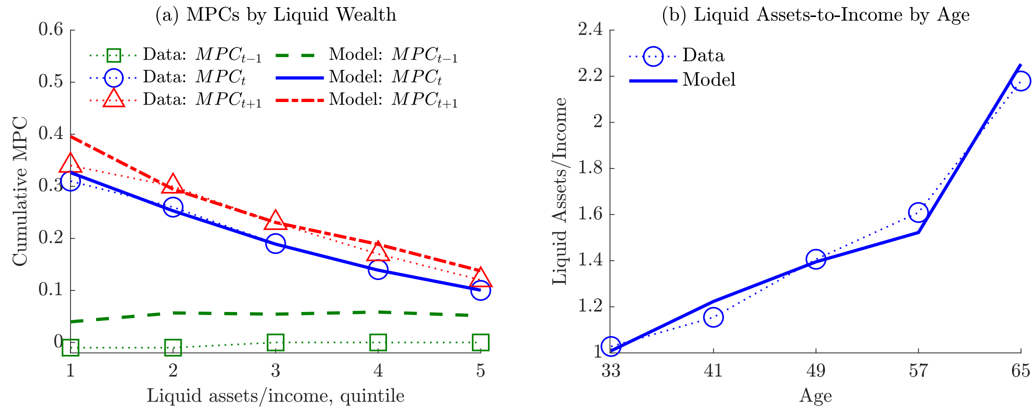

Figure 7. : Model Fit for Estimated Mental Accounts Model

Source: Authors' calculations using financial institution data and the SCF.

this because because young households first want to build precautionary savings buffers while older households then want to save for retirement (see Gourinchas and Parker, 2002). As in the data, the youngest households have small liquid asset holdings equivalent to around one month of income, while older households enter retirement with over 2 months worth of income in liquid assets on average.

In Panel (a) of Figure 7 we also report consumption responses that are not targeted in our estimation. The green dashed line and the square markers show MPCs for the 30-days prior to income receipt in the model and data, respectively. While the model generates very small anticipated spending responses to income receipt, it does not produce the near-zero responses observed in the data. Instead, model MPCs are around 0.05 across the distribution of liquid wealth. The red dash-dotted line and the triangle markers show 60-day MPCs in the model and data, respectively. In both the model and data there is significant front-loading of expenditure as indicated by the small increase in spending between 30 days and 60 days. Moreover, this front-loading is also evident across the liquid wealth distribution.

In Figure 8 we explore the importance of various model mechanisms by comparing the data, benchmark model, and three perturbations of the model. First, the red dashed lines illustrate the effect of shutting down the mental accounts mechanism, $\pi_i = 0$. Panel (a) shows that anticipated MPCs are slightly larger, Panel (b) and (c) shows that MPCs after income receipt are significantly lower, and Panel (d) shows a small increase in life-cycle wealth accumulation. Second, the green dotted lines illustrate a model in which all households exhibit mental accounts behavior, $\pi_i = 1$, while holding ψ fixed. Panel (a) shows that anticipated MPCs fall to zero, Panel (b) and (c) show that post-receipt MPCs rise significantly and no longer decline with household wealth, and Panel (d) shows a sharp decrease in savings at all ages.

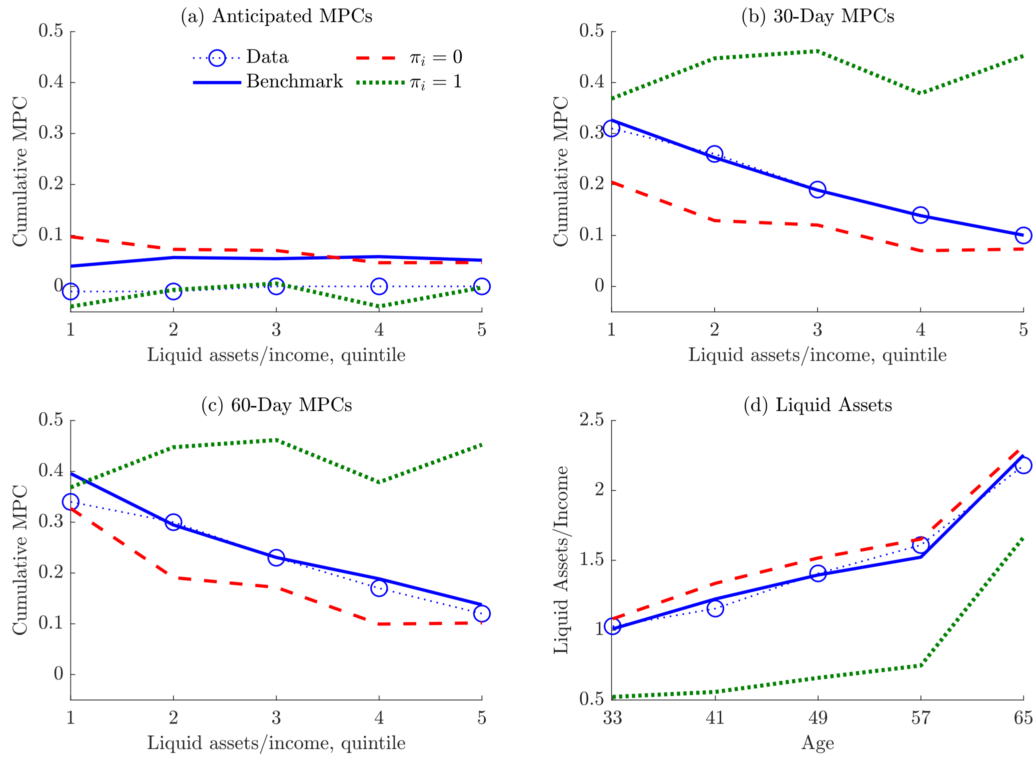

Figure 8. : Exploring Mechanisms in the Estimated Mental Accounts Model

Source: Authors' calculations using financial institution data and the SCF.

This exercise has several important implications. First, the mental accounts mechanism helps to generate large MPCs after income receipt. Second, increasing the number of mental accounts households helps to reduce anticipated MPCs. However, with too many mental accounts households consumption is far too sensitive to income receipt across the distribution of liquid wealth. Hence, the model requires both a large dissavings aversion parameter ψ but only requires a moderate number of mental accounts households π_i among the population.

D. Comparison to Standard Life-Cycle Models

In order to highlight the relative successes of the mental accounts model, we conduct two model comparison exercises.

First, we take a standard life-cycle model ($\psi = 0$) and estimate the parameters $\{\beta, \gamma, \kappa\}$ with three different SMM weighting schemes, $\Omega \in \{0.5, 1, 0\}$. The estimated parameters are reported in Table 6. Figure 9 illustrates the model fit to the same MPC and wealth statistics targeted in our mental accounts estimation. The blue solid lines in Panels (a) and (b) show that a standard model cannot si-

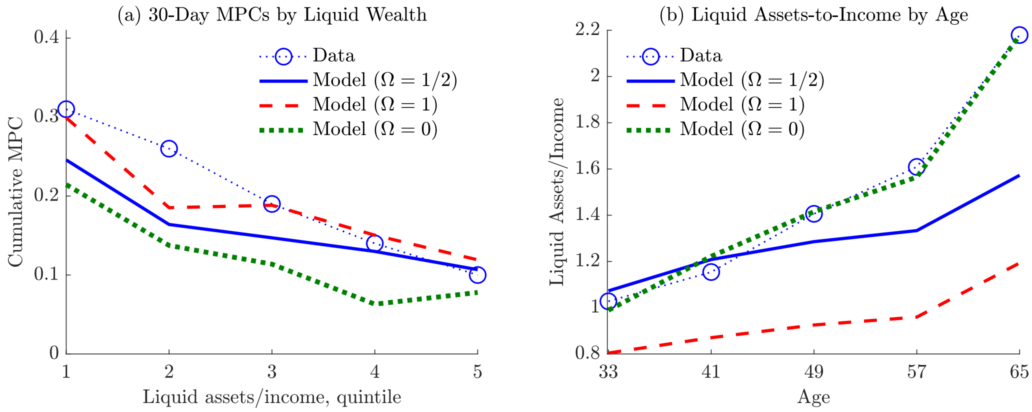

Figure 9. : Model Fit for Estimated Life-Cycle Models

Source: Authors' calculations using financial institution data and the SCF.

multaneously match consumption responses across the liquid wealth distribution and the life-cycle profile of wealth accumulation (i.e $\Omega = 0.5$). The red dashed lines show that the model is moderately better job at generating the profile of MPCs if it targets those statistics in isolation (i.e $\Omega = 1$), however it does so at the cost of significantly understating life-cycle wealth accumulation. In contrast, the green dotted lines show that the model does a good job of matching the life-cycle profile of liquid wealth if it targets those statistics in isolation (i.e. $\Omega = 0$), but this comes at the cost of significantly understating the wealth profile of MPCs.

Second, we modify the standard life-cycle model ($\psi = 0$) to give it the best chance of matching the MPC and wealth statistics targeted in our mental accounts estimation. The model is similar to that described in Section V.A, except that we allow for heterogeneous discount factors $\beta_i \in \{\beta, \beta_L\}$ where π_i is now the fraction of households with the low discount factor $\beta_i = \beta_L$. In Figure 10, the blue solid lines and circle markers show that the model closely matches the data with regard to both contemporaneous consumption responses across the wealth distribution and to the life-cycle profile of liquid assets-to-income. In this respect, the model with heterogeneous discount factors is competitive with our mental accounts model.

However, this model produces consumption responses to income receipts that are inconsistent with the lack of anticipation and substantial front-loading of spending observed in the data. The green dashed line shows that the model generates large anticipated MPCs, particularly for low-wealth households. And the even spacing between the green dashed, blue solid, and red dotted lines shows a similar marginal MPC in each of the periods before, during, and after an income receipt. Thus, unlike our mental accounts model, a standard life-cycle model with heterogeneous discount factors is unable to capture the lumpy response of consumption to anticipated income receipts.

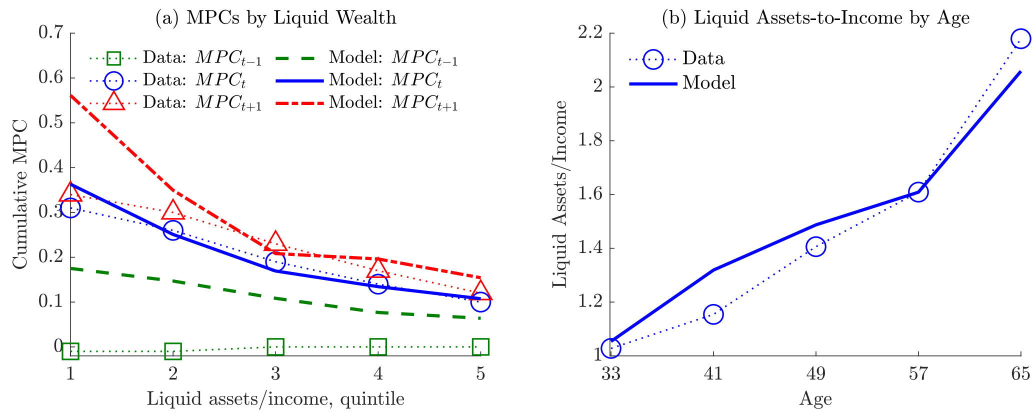

Figure 10. : Model Fit for Life-Cycle Model with Heterogeneous Discount Factors

Source: Authors' calculations using financial institution data and the SCF.

E. Implications for Fiscal Stimulus Policies

Finally, we assess implications of our mental accounts model for the design of fiscal stimulus payments. We conduct a simple exercise by assuming that a fiscal authority plans to spend a fixed amount of resources and considers three budget-equivalent policies: a universal or untargeted stimulus payment, an income-targeted stimulus payment, and an asset-targeted stimulus payment. We study the response of aggregate household consumption to assess the relative effectiveness of these policies.

Untargeted stimulus payments are similar to the tax rebate policies of 2001 and 2008 (Johnson, Parker and Souleles, 2006; Parker et al., 2013) and the COVID-era stimulus checks of 2020 and 2021 (Parker et al., 2022; Carroll et al., 2020).[14] Income-targeted stimulus payments are similar to the Federal Pandemic Unemployment Compensation supplement in the CARES Act of 2020 (Ganong, Noel and Vavra, 2020). Unemployed workers, among the lowest income individuals in the U.S., received an additional $600 per week while they remained jobless. Asset-targeted stimulus payments do not resemble any recent stimulus policy, but other government social insurance schemes such as Supplemental Nutrition Assistance Program (SNAP) or Temporary Assistance for Needy Families (TANF) include asset tests for eligibility (Hastings and Shapiro, 2018).

In our experiments, we abstract from general equilibrium and the particular policies that might be required to balance the government budget constraint. This resembles the implementation of many government stimulus programs where funds are quickly allocated during a recession but government deficits and rising debt balances are left to be addressed at a later date.

[14]Note that these stimulus policies were not entirely untargeted, as payments phased out for households with very high incomes.

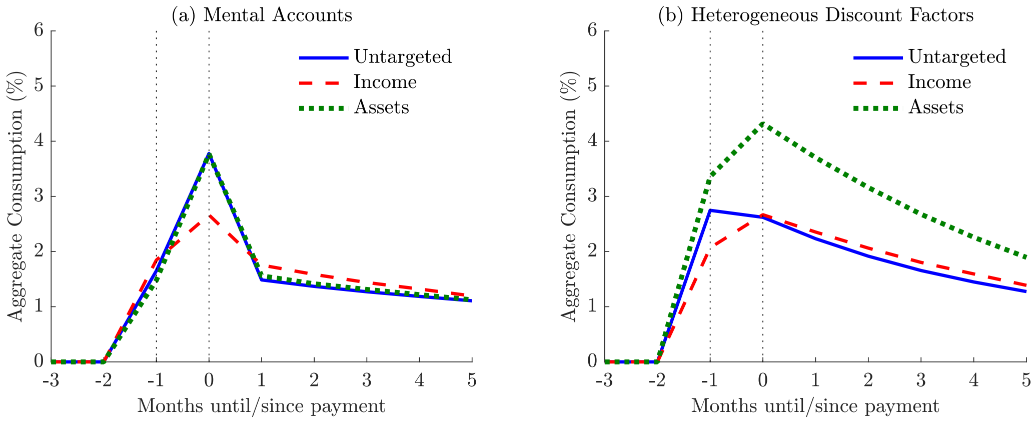

Figure 11. : Response to Stimulus Payments Under Competing Models

Source: Authors' calculations.

The economy begins in steady state, each policy is announced one month in advance, and all payments are distributed in a single month. The untargeted stimulus consists of a \$1000 payment to every household. This is within the range of payments per household under the 2008 tax rebates and COVID-era stimulus payments (see Parker et al., 2013, 2022), and close to the median tax refund in our data (see Table 1).[15] The income- and asset-targeted policies consist of $5 \times \$1000 = \$5000$ payments to each of the poorest 20 percent of households by income and liquid assets-to-income, respectively. Finally, we compare the response of aggregate consumption to these stimulus policies under two competing models: the mental accounts model, and the model with heterogeneous discount factors.

Panel (a) of Figure 11 shows the aggregate consumption responses to the three policies under the mental accounts model. For each policy, the model generates a small increase in spending at announcement, a sharp increase in spending in the month of payment, and smaller but persistent spending in the months that follow. There is very little difference between aggregate spending responses to the untargeted policy and the asset-targeted policy, while the income targeted policy produces much smaller aggregate spending responses.

Panel (b) shows the aggregate consumption responses to the three policies under the life-cycle model with heterogeneous discount factors. For each policy, there is a substantial increase in spending at announcement that persists into the month of payment, with a smoothly declining profile of spending thereafter. In this case, there are large differences in the aggregate spending responses to targeted versus untargeted stimulus payments. Targeting payments to the poorest households by

[15] In Online Appendix D.3 we compare aggregate spending responses to baseline transfers of \$500, \$1000, and \$1500. There is some size-dependence in the response of consumption under the mental accounts model, but essentially no size-dependence under the model with heterogeneous discount factors.

asset balances generates an aggregate spending response nearly 100 percent larger than an untargeted stimulus.

Our simple experiments have two important implications for models with mental accounts households. First, stimulus policies should be implemented quickly as there is little short-term consumption response to the announcement of future payments. Second, there is little gain from targeting stimulus towards the poorest households by income or assets, and thus fiscal stimulus policy need not be especially concerned about the targeting of payments.

VI. Conclusion

In this paper we employ high-quality bank transaction data for U.S. households to study the response of household consumption expenditures to anticipated income receipts. We find that households do not spend in anticipation of income receipt, there is significant front-loading of expenditure with respect to the date of receipt, and even households with large liquid asset balances exhibit significant consumption responses to receipts.

We rationalize these findings in a simple model of mental accounts in which households are averse to dissaving out of current asset balances. These households exhibit lumpy consumption behavior with respect to anticipated income: they spend freely at the time of receipt, but consume very little in advance of or in the periods that follow an inflow of funds.

We show that the mental accounts framework enables a quantitative heterogeneous household model to account for both the responses of consumption to anticipated income across the distribution of liquid wealth, and the life-cycle profile of household wealth accumulation. The model also largely captures the lack of anticipated spending and front-loading of consumption responses. Standard life-cycle models fail to match these facts.

Finally, we re-assess the effectiveness of targeted and untargeted fiscal stimulus policies in the mental accounts model. These model exercises provide some straightforward policy lessons: stimulus payments should be dispersed promptly and there is little additional aggregate spending to be gained by targeting payments to lower income or wealth households.

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