Consumption Behavior Across the Distribution of Liquid Assets

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Abstract

I study household consumption responses to predictable income using transaction data from a U.S. financial institution. I document large consumption responses that are highly front-loaded to income receipt, decline moderately in levels of liquidity, and are significant for households with substantial liquid assets; in contrast with canonical buffer-stock theory. To interpret these facts, I develop a model of mental accounts in which households partition their consumption choice set between a current income and a current asset account. The model nests the buffer-stock and hand-to-mouth consumption models as limiting cases. I estimate the model and show that these two extremes are inconsistent with the timing and magnitude of the documented consumption responses. I show that an intermediate case, in which households are moderately averse to dissaving, predicts consumption responses across levels of liquidity that are consistent with the data. The sensitivity of households to income fluctuations has direct positive implications for the design of fiscal stimulus policies. The model predicts a redistributive stimulus to liquidity-constrained households is 53% less effective relative to a standard buffer-stock economy.

Keywords: Consumption, excess sensitivity, fiscal stimulus

JEL Classification: E21, E62, E70

1. Introduction

Household consumption responses to income fluctuations are fundamental for understanding the dynamics of individual behavior and are at the core of any model in macroeconomics. Informed by an extensive empirical literature documenting deviations from permanent income theory, structural models of household consumption have largely fo-

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cused on the role of liquidity constraints\textsuperscript{4} to rationalize the excess sensitivity of household consumption to predictable forms of income. The HANK model,\textsuperscript{5} a workhorse currently employed to study the impacts of macro-policy, considers a two asset framework with counter-factually large liquidation costs, obtaining consumption responses approaching those observed in the data by endogenously inducing a significant proportion of wealthy agents to be cash-constrained. In this paper I document empirically that liquidity constraints and transaction costs are insufficient to explain household consumption responses to predictable income. The goal of this paper is to document the relationship between liquidity and excess sensitivity, propose a structural model rationalizing salient features of household consumption responses, and assess its positive implications for the design of fiscal stimulus policies.

In this paper I utilize a novel administrative dataset of de-identified transaction data from a panel of 17.2 million households obtained from a large U.S. financial institution. At the daily frequency, I study expenditure and balance sheet responses to predictable forms of income (federal and state tax refunds, regular paychecks, and bonus paychecks) as well as likely innovations in information at tax filing, for households with varying levels of liquidity and income. In line with previous findings,\textsuperscript{6} I find that, on average, households expend 25 percent of their tax refunds towards non-durables in the quarter following receipt. However, I find that these consumption responses decline moderately in levels of liquidity and are significant even for households with high incomes and substantial liquid assets. Further, I document that 70 percent of the five month non-durable consumption response generated by tax refunds occurs within thirty days of receipt and anticipatory expenditure is insignificant.

This pattern of consumption responses - insignificant spending in anticipation, excess sensitivity at receipt, and a response that is immediate and short-lived - is pervasive. I show that these results are robust to the form and magnitude of the income studied, the category of expenditure considered, holds when one large inflow shortly follows another, and is restricted to receipt, rather than likely information innovation at tax filing. Additionally, this pattern persists across age, levels of income, and liquid assets. In accordance with the predictions of standard models, I observe a tight negative correlation between liquid balances relative to income and the estimated consumption responses. However, contrary to the predictions of standard models, I document that excess sensitivity is significant for households with substantial liquidity.

I show that a standard buffer-stock life-cycle model, estimated to match the magnitude of the cross-sectional one month consumption responses that I observe in the data, is unable to jointly obtain the degree of consumption front-loading or the liquidity available to households observed empirically. Additionally, the empirical results are inconsistent with the predictions of several notable classes of behavioral models. At odds with models of rational inattention,\textsuperscript{7} household’s consumption responses in the data are immediate

\textsuperscript{5}Kaplan, Moll, and Violante (2014)
\textsuperscript{7}Reis (2006), Gabaix (2014)
and short-lived, and there is no systematic innovation in consumption at the date of tax filing.\textsuperscript{8} In contrast with models of temptation\textsuperscript{9} and forward-looking reference-dependent utility, (Köszegi and Rabin, 2006) consumption responses are delayed until receipt, even for households with substantial liquid wealth and those with access to credit cards.\textsuperscript{10}

In order to interpret the empirical results, I develop a dynamic and tractable model of mental accounts.\textsuperscript{11} Motivated by recent empirical work documenting cases in which the fungibility of otherwise interchangeable resources fails,\textsuperscript{12} I consider a model in which agents are averse to dissaving and partition their consumption choice sets between current income and current assets. Agents in the model face a decline in marginal utility when spending out of savings and therefore take advantage of high income realizations by over-consuming relative to an agent whose income and assets are perfectly fungible. The degree of mental accounting frictions in the model is governed by a single dissavings aversion preference parameter, and the model nests canonical buffer-stock and hand-to-mouth households as limiting cases.

I structurally estimate the model’s preference parameters to jointly match the high frequency non-durable consumption responses I observe in the liquid wealth-to-income cross section as well as low frequency life-cycle wealth accumulation profiles. The nested extremes generate stark predictions for the cross-section of consumption responses to transitory fluctuations in predictable income. Whereas standard buffer-stock agents display large consumption responses only when liquidity constrained, hand-to-mouth agents consume the entirety of their income each period. The moderate decline in consumption responses across levels of liquidity that I observe in the data suggests an intermediate case. I document that the dissavings aversion preference parameter is crucial for rationalizing the magnitude and timing of consumptions responses amongst households with high levels of liquidity. These results suggest a re-evaluation of traditional aggregate business cycle models through the lens of mental-accounting frictions.

I employ the estimated model to consider a number of counter-factual experiments. I decompose the extent to which household savings decisions are due to precautionary, life-cycle, and mental accounting motives, respectively. Consistent with standard buffer-stock theory, I find that household savings decisions are driven by precautionary motives until they approach retirement. Captive to the structure of mental accounts, however, consumption in the model tracks closer to income than in the standard setup. These deviations add up - during working life the median mental accounting agent’s liquid savings buffer is roughly 40 percent less than it would be if this friction was relaxed, and

\textsuperscript{8}Filing entails a measurable allocation of resources both monetarily (the average cost to file is $82) and in terms of time taken to fill out the return. By itself, the lack of response at filing aligns with an environment in which expectations regarding the size of returns are correct, on average. But systematic inattention to the inflow in advance of filing would likely be indicated by innovations in consumption on this day.


\textsuperscript{10}Further, consumption is delayed until receipt even as the predictable future income increases in magnitude.


\textsuperscript{12}Hastings and Shapiro (2012), Hastings and Shapiro (2018)
he enters retirement with around 20 percent less liquid assets.

I next assess the model’s positive implications for the design of fiscal stimulus payments. In comparison to the standard buffer-stock model, a pre-announced redistributive stimulus to liquidity-constrained households generates an aggregate consumption response that is 53 percent smaller. This is because all households in the economy are sensitive to temporary fluctuations in income, and households with substantial liquidity decrease consumption to finance the lump-sum taxes they face. In this way, lump-sum transfers have a distortionary effect on the path of household consumption.

I compare three distinct budget-equivalent policies: 1) an un-targeted $100 stimulus to all households in an economy (comparable to the Bush tax rebates of 2001 and 2008), 2) a $500 stimulus targeted to households experiencing the bottom 20 percent of income realizations at announcement (akin to unemployment insurance or workers’ compensation payments), and 3) a $500 stimulus targeted to households in the bottom quintile of liquid asset holdings (akin to means-tested programs, such as SNAP\textsuperscript{13} or TANF\textsuperscript{14}). I show that, in comparison to a standard buffer-stock economy in which the income-targeted and asset-targeted policies are 6 and 8 times more effective than a blanket stimulus, respectively; under mental accounts the gains to targeting are significantly reduced and the relative effectiveness of these targeted policies is reversed. That is, income-targeted and asset-targeted stimulus policies are, respectively, 47 percent and 33 percent more effective than an un-targeted stimulus in economies where mental accounting frictions are present. This reversal is the direct result of households’ sensitivity to fluctuations in income, regardless of their current asset positions.

1.1. Related Literature

This paper contributes to a large empirical literature investigating the excess sensitivity of household consumption to predictable income. This includes papers documenting the tracking of consumption to income in aggregate data (Hall (1978), Campbell and Mankiw (1990)), as well as a more recent literature documenting deviations from permanent income theory in micro-data. This literature includes Zeldes (1989), who studies the interaction of liquidity constraints and consumption in the PSID, and the works of Johnson et. al (2006) and Parker et. al (2013), studying consumption responses to the government stimulus programs of 2001 and 2008, respectively. These papers document a large degree of excess sensitivity to receipt of stimulus that is consistent with models of liquidity constraints and has meaningful implications for macroeconomic aggregates.

However, a recent literature has documented contexts in which consumption responses cannot be explained by liquidity constraints alone. Keung (2018) studies the excess sensitivity of high income consumers to payments from the Alaska Permanent Fund and finds responses that are inconsistent with buffer-stock behavior and rational inattention. Olafsson and Pagel (2018) document consumption patterns in the week before and after

\textsuperscript{13}The Supplemental Nutrition Assistance Program program jointly requires household income to be below 130 percent of the poverty line ($2,252 per month for a family of three in 2019) and assets of $2,250 or less. These figures vary from state to state. Source: cbpp.org.

\textsuperscript{14}Temporary Assistance for Needy Families
paydays for a population of Icelandic households.\footnote{A large proportion of households in their population hold negative liquid assets, as Icelandic households use transaction account overdrafts to revolve unsecured debt from month to month.} They show that households with the credit space to smooth expenditure in the days immediately in advance of income display excess sensitivity to receipt. Ganong and Noel (2019) document a drop in household consumption at the exhaustion of unemployment benefits and show that this behavior is inconsistent with liquidity constraints, but can be rationalized by present-bias or myopia on the part of a population of households.

I contribute to this literature by documenting how the magnitude and timing of consumption responses vary in the cross-section of liquid assets. I also reject the explanatory power of liquidity constraints. Further, I show that the highly liquid don’t respond to information about future income (as proxied by the date of tax filing), and they display excess sensitivity even when one large inflow shortly follows another (as in the case of households receiving federal and state refunds). Additionally, I make progress towards reconciling the facts of these papers within a structural framework.

This paper also contributes to a literature concerned with the implications of excess sensitivity for aggregate fluctuations and stabilization policies. In large part, structural models since Friedman (1957) have focused on the role of liquidity constraints (Deaton (1991), Caroll (1997), Mankiw (2000)). Recently, Kaplan and Violante (2014) rationalize the large average consumption responses observed by Johnson et. al (2006) in a two asset framework with costly liquidation. This mechanism endogenously increases the proportion of households that are liquidity-constrained, as a significant population of ‘wealthy hand-to-mouth’ agents hold their wealth in illiquid form. Informed by the empirical findings that I establish, I develop a structural model in which households with substantial liquid assets display consumption responses to predictable income in line with those of the data. I show that this higher-order cross-sectional dispersion in consumption responses has important implications for policy design.

A literature studying mental accounts and the resulting positive predictions for consumption behavior dates to Thaler (1985) and Shefrin and Thaler (1988). More recently, papers have documented behavior consistent with mental accounting frictions in the context of gasoline prices (Hastings and Shapiro, 2012), food stamps (Hastings and Shapiro, 2018), household budgeting (Kőszegi and Matějka, 2018), and optimal taxation (Farhi and Gabaix, 2018). In each case, mental accounting frictions break the fungibility of otherwise interchangeable resources. In this paper I consider transfer payments in a dynamic environment where mental accounting frictions affect household consumption/savings decisions. Shefrin and Thaler (1988) posit a life-cycle model incorporating a dual preference (planner/doer) setup and mental accounts that break the fungibility of resources across current assets and present and future income. With a similar structure of mental accounts, this paper develops a setup that directly nests the traditional buffer-stock and hand-to-mouth agents. I further discipline the model by performing a structural estimation procedure to identify household’s preference parameters. I show that this class of models is able to jointly match life-cycle liquid asset accumulation, as well as the timing
and magnitude of the household consumption responses that I observe in the data.

2. Empirical Evidence

In this paper I utilize an administrative dataset of de-identified bank transaction-level data obtained from a large American financial institution. I study household expenditure and balance sheet responses to predictable forms of income including state and federal tax refunds, bonus checks, and regular paychecks. I begin by describing the data and then present the main empirical results.

2.1. Data & Empirical Strategy

The dataset includes a panel of 17.2 million U.S. households, with active checking accounts from 2012 to 2019. In addition to individual transactions, I observe checking, savings, and credit card balances, as well as non-transaction account vehicles such as money market accounts, brokerage accounts, and certificates of deposit held at the bank. Throughout the paper I aggregate all accounts to the primary account holder level, and restrict my analysis to households where the primary account holder is of working age (24 to 64).

The data allows me to track deposit, debit card, and credit card inflows and outflows at the daily frequency, providing for clean identification of household expenditure responses to income. I categorize these transactions according to IRS Merchant Category Codes (MCCs) in close accordance with the NIPA Handbook. I discuss this transaction categorization more thoroughly in the accompanying Appendix.

Crucially, I take steps to ensure that I observe the primary checking account of a household by restricting to those with at least five deposit account outflows in each month of a given calendar year. Below I provide evidence that this filtering procedure largely serves to exclude households whose primary checking accounts are held at other financial institutions. This is necessary to ensure a reliable view of household’s day-to-day financial activity and to address concerns that these households break up large portions of their expenditure across multiple banks. Table 1 reports summary statistics for the broad population of households meeting the exclusion criteria (working age, minimum account activity). Within subsequent sections analyzing particular events I further detail the subpopulations of interest (ie. refund recipients, bonus recipients).

I aggregate checking, savings, and non-transaction account balances to generate a measure of the total liquid assets available to households. The median household in the data holds around 3 weeks of monthly income in its liquid accounts, two thirds of which resides in its checking accounts. In order to assess the external validity of the results and directions of possible bias in the results that follow, I benchmark key data moments and distributions to representative national surveys of household assets, income, and expenditure. Notably, the transaction data excludes two tails of U.S. households in terms of wealth, the unbanked portion (6.5% of U.S. households in 2017) as well as those employing forms of private wealth management. As such, median levels of 2016 annual post-tax

\footnote{Source: FDIC}
Table 1: Summary Statistics

<table>
<thead>
<tr>
<th>Demographics</th>
<th>Mean</th>
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<th>Median</th>
<th>75th</th>
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<td>32</td>
<td>41</td>
<td>52</td>
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<td>Account Users</td>
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<table>
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<th>Income</th>
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<th></th>
<th></th>
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<tbody>
<tr>
<td>Total Income</td>
<td>5935</td>
<td>2273</td>
<td>3923</td>
<td>6782</td>
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<tr>
<td>Labor Income</td>
<td>4022</td>
<td>1835</td>
<td>2957</td>
<td>4754</td>
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<table>
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<tr>
<th>Balances</th>
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<th></th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td>Total Liquid</td>
<td>8673</td>
<td>473</td>
<td>1835</td>
<td>6442</td>
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<tr>
<td>Checking</td>
<td>4955</td>
<td>341</td>
<td>1255</td>
<td>3691</td>
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<tr>
<td>Savings</td>
<td>2302</td>
<td>0</td>
<td>0</td>
<td>263</td>
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<tr>
<td>Revolving Credit</td>
<td>920</td>
<td>0</td>
<td>0</td>
<td>0</td>
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</table>

Figure 1: Survey of Consumer Finances Comparison, 2016

income observed in the Survey of Consumer Finances (SCF) and transaction data are roughly equal (Table 2). Median checking account balances are comparable with the survey data, however, the transaction data likely understates the total liquid assets available to households. Additional moments of these distributions, including the procedure for post-tax adjustment of the SCF, are reported in the accompanying Appendix.

Table 2: Benchmark Comparisons, Quantiles, 2016

<table>
<thead>
<tr>
<th></th>
<th>Annual Income</th>
<th>Checking</th>
<th>Liquid Balances&lt;sup&gt;17&lt;/sup&gt;</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>25th</td>
<td>Median</td>
<td>75th</td>
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<td>SCF</td>
<td>29863</td>
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<td>85632</td>
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<td>SCPC</td>
<td>26499&lt;sup&gt;18&lt;/sup&gt;</td>
<td>54999</td>
<td>86499</td>
</tr>
<tr>
<td>BANK</td>
<td>31754</td>
<td>50568</td>
<td>82484</td>
</tr>
</tbody>
</table>

<sup>17</sup>Liquid balance measures include checking, savings, money market, brokerage accounts, and certificates of deposit (retirement account balances are excluded).

<sup>18</sup>SCPC respondents report in which of eighteen intervals their combined household income falls. Here I report the median of the interval housing each percentile.
I categorize expenditures in close accordance with the 2019 NIPA Handbook, notably separating non-durable goods and services for the purposes of benchmarking. The transaction data tracks closely to the Consumer Expenditure Survey (CEX) micro-data for non-durable goods and food services (Table 3). In the accompanying Appendix I describe the taxonomy I develop in detail, and I compare these expenditure figures to those reported in other datasets, including the Personal Consumption Expenditures (PCE) index and U.S. Department of Agriculture (USDA) Food Expenditure series.

The transaction data’s coverage of durable goods purchases is markedly lower than the external benchmark. This is due to a combination of factors making these purchases difficult to identify: a large extensive margin and installment payment structures. An additional complication, affecting all categories of expenditure, is transactions made via paper check, cash, or unobserved credit cards.

<table>
<thead>
<tr>
<th>Source</th>
<th>Expenditure</th>
<th>Non-Durables</th>
<th>Durables</th>
<th>Services</th>
<th>Food Services</th>
<th>Groceries</th>
</tr>
</thead>
<tbody>
<tr>
<td>CEX</td>
<td>4775.92</td>
<td>980.92(^{20})</td>
<td>633.67(^{21})</td>
<td>2386.83(^{22})</td>
<td>337.42(^{23})</td>
<td>303.17</td>
</tr>
<tr>
<td>BANK</td>
<td>5347.84</td>
<td>1059.18</td>
<td>168.40</td>
<td>1252.30</td>
<td>306.41</td>
<td>220.49</td>
</tr>
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</table>

These unclassified expenditures represent roughly a third of average monthly expenditure (Figure 2). In order to assess models of consumption and derive direct comparisons to the literature, I develop an imputation procedure to assign these unclassified to transactions to non-durables and durables. I describe this procedure below. In the accompanying Appendix I explore a subgroup for which the sum of payments to unobserved credit cards and transfers to unobserved deposit accounts is less than $100 each calendar year. This subsample represents roughly 40% over the overall population.

![Expenditure Basket by Month](https://www.bea.gov/sites/default/files/methodologies/nipa-handbook-all-chapters.pdf)

Figure 2: Monthly Household Expenditures

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20 CEX measure includes: Food at home, laundry and cleaning, postage/stationery, apparel, motor oil/gasoline, entertainment, smoking supplies, and drugs.

21 Housekeeping and other household supplies, furnishings, and equipment; reading; medical supplies; auto repairs; and vehicle purchases.

22 Food away from home, alcoholic beverages, transportation, insurance, education, housing services, personal services, telecommunications, and other bills.

23 Food away from home and alcoholic beverages.
I measure expenditure and consumption responses to predictable events at the daily frequency via the following distributed lags specification

\[
c_{i,t} = \alpha_i + \lambda_t + \sum_{n=0}^{N} \sum_{j=-l}^{L} \delta^n_j I^n_{i,j} + \epsilon_{i,t}
\]

Where \(c_{i,t}\) denotes the outcome variable of interest (i.e. total expenditure, food services consumption). Intercepts \(\alpha_i\) and \(\lambda_t\) are household and time specific respectively (I include day of week, day of month, and year fixed effects), and \(I^n_{i,j}\) represents the amount of the \(n\)th inflow at lead/lag \(j\) days for household \(i\) (i.e. the receipt of a second tax refund in the same calendar year).

Estimated parameters \(\delta^n_j\) measures the proportional change in \(y_{i,t}\) associated with an increase in inflow \(I^n\) at lag \(j\). Identification relies on variation in calendar time \(t\) and time between each event \(n\). This variation is explicitly plotted in Figure 2. I provide more formal arguments for identification in the Appendix. I adopt the convention of the literature in referring to the estimated parameters, \(\{\delta^n_j\}_{j=1}^{t+L}\), as marginal propensities to consume or expend. To control for extreme outliers I trim the top 5 - 10% expenditure days. The results are robust to more stringent winsorization.

2.2. Consumption Responses to Income

I consider consumption responses to various forms of predictable income including tax refunds, regular paychecks, and bonus paychecks. Notably, I find that excess sensitivity pervades the liquid wealth and income distributions. This excess sensitivity is restricted to receipt of income (rather than potential news at tax filing), is evident when a large inflow is received shortly after another (as in the case with households receiving state and federal refunds), and is evident across all sources of income. Further, consumption responses are highly front-loaded to receipt, meaning that, absent the large consumption response in the month or so following receipt, expenditure is largely smoothed.

I begin by documenting household consumption responses to tax refund receipt. According to the IRS, roughly 80% of tax filers each year receive federal refunds, and 20% make federal tax payments. The magnitude of a household’s tax refund is largely determined jointly by the IRS income tax withholding tables and worker’s withholding allowances. Workers can reduce withholdings at any time by claiming allowances. These adjustments can be claimed for any number of reasons, including changes in marital status, status of dependents, etc. Given claimed allowances employers calculate withholdings using worker’s pay frequency and wages. This, in combination with household’s other income (capital gains/losses, tax credits, etc.) determines the magnitude of their tax refund. In aggregate, the IRS processes roughly $200 billion in tax refunds by the end of March each year, with an additional $75 billion processed by the end of tax season in May\(^{24}\).

The size of an individual’s tax refunds is a source of uncertainty that is largely resolved

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\(^{24}\)Appendix C. quantifies the effects of tax season on quarterly aggregate consumption - likely as much as 3.3% of Q1 aggregate consumption.
given their prior year’s income and previous returns, and is all but certain at the date of filing (but for complications or mistakes in the individual’s return). Additionally, the exact date of refund arrival is unknown, though 94% of refunds arrive within 30 days of filing, with 97% arriving within 60 days. Due to the size of the data I restrict the analysis to households receiving tax refunds in 2014 or 2015. The resulting sample is 1.7 million distinct households observed across the two years.

Table 4: Summary Statistics, Monthly, Tax Refund Recipients

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>25th</th>
<th>Median</th>
<th>75th</th>
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<tbody>
<tr>
<td>Liquid Balances</td>
<td>7279</td>
<td>581</td>
<td>1828</td>
<td>5699</td>
</tr>
<tr>
<td>Income</td>
<td>5259</td>
<td>2425</td>
<td>3868</td>
<td>6245</td>
</tr>
<tr>
<td>Expenditure</td>
<td>4949</td>
<td>2323</td>
<td>3677</td>
<td>5882</td>
</tr>
<tr>
<td>Tax Refund</td>
<td>2072</td>
<td>360</td>
<td>1120</td>
<td>2993</td>
</tr>
</tbody>
</table>

Table 7 reports summary statistics for the subpopulation observed receiving tax refunds. I report liquid balances and income as measured from the average across the 9 months to 1 month prior to the initial refund receipt in order mitigate both contamination from response to the future refund and tax activity in the previous year. This population earns median monthly income that is 1.4% lower and liquid balances that are just $7 less than the broader population (see Table 1). Roughly 30% of those households observed receiving one refund also receive a second\(^{25}\). In what follows I estimate consumption responses to the first tax refund a household receives in a calendar year.\(^{26}\) Together, the combination of state and federal refunds represent over 3 weeks of income on average. The refunds observed in the data are of similar magnitude to those reported by the IRS. For federal refunds, the IRS reports that the average refund is $2860, versus $2844 in transaction data. For state and local refunds these figures are $1622 and $1218, respectively.

Using specification (1) I estimate household balance sheet responses to tax refund receipt and plot the resulting vectors \(\{\delta_j^{t+v}L\}_{t-v}^{v+L}\) for each regression along with their 95 percent confidence intervals. I separate the flow of tax refund dollars towards expenditures (roughly 60% over 150 days post-receipt),\(^{27}\) non-transaction accounts transfers (20%),\(^{28}\) and those that remain in household’s transaction (checking and savings) accounts (12.5%). A small proportion goes towards paying down credit card balances both at the bank and elsewhere (6%),\(^{29}\) with the rest going towards illiquid debt payments (student and auto

\(^{25}\)The actual proportion is likely much higher. Households might receive a second refund that is not identified as such. In any case the identifications arguments still apply.

\(^{26}\)In the Appendix I consider those experiencing multiple refund events

\(^{27}\)Defined as all account (credit and deposit) outflows, excluding credit card balance payments for which card purchases are observable and account transfers.

\(^{28}\)Defined as transfers to brokerage, money market, retirement and certificates of deposit

\(^{29}\)This includes some double counting, as observable credit card expenditures assigned to the time of purchase are included in the total expenditure measure, while this panel measures excess payments towards credit card balances. I report the path of revolving balances around refund receipt in the
loans) or being transferred to demand deposit accounts at other financial institutions.

In what follows I restrict my focus to the non-durable component of total expenditure (denote this measure $e_{iND}$, where $i$ indexes a particular household). To construct this measure I aggregate all household expenditures at the daily frequency that represent purchases of non-durable goods such as groceries, entertainment, fuel, discount and drug stores, direct market catalogs, as well as non-durable services such as utilities, telecommunications, insurance, health expenses, other bills, food services, travel services and other personal and professional services. Additionally, I perform an imputation procedure to assign cash, unclassified checks, and payments to unobserved credit card accounts for individual $i$ (denoted $e_{iC}$) to contemporaneous non-durable expenditure. Define the mean observable proportion assigned to non-durables for individuals in population $q$, $\xi_q \equiv \frac{1}{N} \sum_{i=1}^{N} \frac{e_{iND,q}}{e_{i,q}}$, where $e_{i,q}$ denotes total expenditure. The imputed non-durable consumption responses for population $q$ at lag $j$ are then obtained via $\delta_{i,q}^{ND,t,j} = \delta_{j}^{ND,q} + \xi_q \cdot \delta_{j}^{C,q}$. Expenditures used to compute the expenditure share $\xi$ are taken from the month prior to tax refund receipt.

This procedure relies on two assumptions. First, that the proportion of cash, unclassified checks, and payments to unobserved credit card accounts that the household expends on non-durables is commensurate with that of the identifiable portion of total expenditure, and, second, that the excess response of these categories at refund receipt scales proportionally. For the first assumption, the SCPC provides some suggestive evidence. In 2018 roughly 40% of cash and paper check transactions represented purchases of retail goods. Likewise, roughly 36% of payment card (credit, debit, pre-paid) transactions were toward retail goods. For the second assumption, in the accompanying Appendix I show that shifts in the composition of expenditure around refund receipt are small. For speci-
fications employing the imputation procedure, I also report pre-imputation values in the accompanying Appendix.

Using specification (1) I estimate household non-durable expenditure responses to tax refund receipt. Figure 3 plots the resulting parameters for the thirty days before and 150 days after income is received. This figure is illustrative of the consumption responses I observe across all categories of expenditure and forms of income.\(^{30}\) Notably, on average, anticipatory expenditure is insignificant, responses are immediate (in the present case, 4.1 cents of every dollar received are expended within a day of receipt, 19.3 cents are expended within 30 days, and 28 cents within 150 days), and highly front-loaded to income receipt (70\% of the 150-day non-durable response to tax refunds occurs within 30 days of receipt). The response of non-durables represents 47\% of the average total expenditure response over the five months post-refund receipt. These estimates are in line with average non-durable consumption responses to forms of predictable income previously reported in the literature.\(^{31}\)

![Figure 4: Non-Durable Expenditure Response, Tax Refunds](image)

This characterization of consumption responses is not special to tax refunds, where the magnitude and timing of receipt are, to a degree, driven by self-selection. I consider a population of 163,300 households receiving large bonus checks. In the accompanying Appendix I describe the procedure for identifying these payments in transaction data. The average bonus recipient holds over six weeks of income in their liquid accounts. Compared to the average household receiving a tax refund, the average bonus recipient pay holds roughly 74\% more liquid assets and earns 56\% more in monthly income.

The features of the non-durable consumption response to bonus checks is similar to that of tax refunds (Figure 5). Namely, insignificant anticipatory spending and a large degree of front-loading to receipt, with 64\% of the 150 day response coming in the first thirty days.

In the accompanying Appendix I show that households also display excess sensitivity to

\(^{30}\)These results are reported in the accompanying Appendix.

\(^{31}\)See Appendix for comparisons to the literature.
Table 5: Summary Statistics, Monthly, Bonus Check Recipients

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>25th</th>
<th>Median</th>
<th>75th</th>
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<tr>
<td>Liquid Balances</td>
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<td>13609</td>
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<tr>
<td>Income</td>
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<td>9396</td>
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<tr>
<td>Expenditure</td>
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<td>4042</td>
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<td>9626</td>
</tr>
<tr>
<td>Bonus Check</td>
<td>11445</td>
<td>3290</td>
<td>5733</td>
<td>10802</td>
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</tbody>
</table>

Figure 5: Non-Durable Expenditure Response, Bonus Checks

their regular paychecks, as show by Olfasson and Pagel (2018) and Gelman et. al (2018). Additionally, I show that the results above are robust to the category of expenditure considered. In combination, the observed responses to predictable forms of income (tax refunds, bonuses, regular paychecks) indicate that households excess sensitivity is neither a direct bi-product of the population receiving each inflow; nor driven by self-selection in the timing or magnitude of cash flow events, nor unpredictability in the timing of receipt. However, these responses are consistent with the predictions of models in which a large subset of each population is liquidity-constrained. I further explore this dimension in the section that follows.

2.3. Consumption Responses & Liquidity

In order to assess the impact of liquidity constraints on consumption responses I classify households according to available liquid balances relative to monthly income. Standard models predict a tight correlation between this measure of liquidity and consumption responses to income. This ratio is calculated according to average of the ratio of month end total liquid balances (checking, savings, money market, brokerage, and certificates of deposit) to total monthly income in the calendar year prior to tax refund receipt. This averaging serves to avoid short-run endogenous responses in anticipation of refund receipt significantly contaminating the ratio.\textsuperscript{32} In order to prevent households with low incomes

\textsuperscript{32}In the accompanying appendix I perform a variance decomposition of expenditure responses and show that once the long-run average is controlled for, the marginal explanatory power provided by the
distorting the measure, I restrict to those with average monthly income of $500 or more in the baseline period (roughly 98% of households in the raw sample of refund recipients).

As documented above, this measure likely underestimates the liquidity available to households, especially amongst higher income individuals. Additionally, the measure is in terms of gross liquid assets and not liquid net worth. Un-securitized debts are excluded for two reasons: 1.) the data covers credit card accounts held at the financial institution, and households might carry revolving debts on unobserved credit cards;\textsuperscript{33} and 2.) as documented above, observable credit card debts are held by a minority of households at any given time and, while substantial, are relatively short lived.\textsuperscript{34} In the accompanying Appendix I consider additional measures of liquidity, deciling liquid assets in levels, deciling liquid assets relative to monthly expenditure, and by terciling households according to levels of annual income in levels before partitioning according by liquid assets to income. The results are robust to these alternative measures.

Households’ balance sheets display significant variation in \( \frac{\text{Liquid Assets}}{\text{Income}} \), ranging from around a week of income available in liquid accounts at the first decile, to over 20 weeks of income amongst households in the tenth decile (Table 6). The level of average monthly income increases across the lowest deciles and flattens out above the median, while average liquid balances are roughly increasing across deciles (Figure 6). The results are robust to deciling by transaction account balances relative to income.\textsuperscript{35}

<table>
<thead>
<tr>
<th>Decile</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
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</thead>
<tbody>
<tr>
<td>Trans. Assets/Income</td>
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<td>0.20</td>
<td>0.28</td>
<td>0.38</td>
<td>0.50</td>
<td>0.65</td>
<td>0.96</td>
<td>1.45</td>
<td>2.55</td>
<td>4.91</td>
</tr>
<tr>
<td>Liquid Assets/Income</td>
<td>0.21</td>
<td>0.36</td>
<td>0.49</td>
<td>0.64</td>
<td>0.80</td>
<td>1.0</td>
<td>1.35</td>
<td>1.91</td>
<td>3.09</td>
<td>5.11</td>
</tr>
<tr>
<td>Total Income</td>
<td>4348</td>
<td>4860</td>
<td>5163</td>
<td>5420</td>
<td>5680</td>
<td>5909</td>
<td>6026</td>
<td>6088</td>
<td>6017</td>
<td>5840</td>
</tr>
<tr>
<td>Tax Refund</td>
<td>2049</td>
<td>1999</td>
<td>2020</td>
<td>2029</td>
<td>2096</td>
<td>2132</td>
<td>2161</td>
<td>2154</td>
<td>2110</td>
<td>2097</td>
</tr>
</tbody>
</table>

I estimate specification (1) by deciles of \( \frac{\text{Liquid Assets}}{\text{Income}} \). Figure 7 plots the results. Notably, the non-durable expenditure response are significant across the liquid wealth-to-income distribution and decline moderately in levels of liquid wealth. One month MPCs ranging from 0.32 at the first decile to 0.09 at the tenth decile. Further, responses display significant front-loading to receipt, from 89% of the 120 day response coming in the first thirty days at the first decile to 66% at the tenth decile (Figures 5 and 6). In dollar terms, excess total expenditures across deciles range from an additional $1,347 to $580 in the orthogonal component of income and cash balances immediately in advance of receipt is negligible.

\textsuperscript{33}The results are quantitatively similar after restricting to the subset of households with no payments to unobserved credit card accounts describe above.

\textsuperscript{34}The half life of revolved balances, on average, is less than 4 months. Additionally, a variance decomposition across observables suggests credit card revolving balances account for less than 4% of explainable variation in consumption responses.

\textsuperscript{35}The correlation of deciles across the two measures is 0.92 and the results are virtually identical. Likewise, the results are robust to including alternate measures of income in the numerator (ie. only labor income or categorized income)
The cross-sectional responses (Figures 7 and 8) nest several salient facts that are helpful in distinguishing across models of consumption. Firstly, the large degree of excess sensitivity at receipt combined with no significant anticipatory spending that is observed amongst households with large amounts of liquidity is inconsistent with a model of externally imposed borrowing constraints. In contrast with the predictions of models of rational inattention (Reis (2006), Gabaix (2011)), household’s consumption responses are immediate and short-lived. That the bulk of the consumption response comes in the month of receipt for the unconstrained, as opposed to in advance, is in stark contrast with the predictions of models of temptation (Laibson (1997), Gul and Pesendorfer (2001)), and forward-looking reference-dependent utility (Köszegi and Rabin, 2006).
The results characterizing household consumption responses:

- Are robust to the form (tax refunds, bonus checks, and regular paychecks) and magnitude of the predictable income (as measured relative to baseline monthly income and monthly expenditure).

- Are not driven by the non-durable measure. The results hold for purchases of non-durable and durable goods as well as categories more aligned with contemporaneous consumption, such as grocery purchases and food services.

- Are robust to the measure of liquidity employed (I consider levels of liquid assets, \( \frac{\text{Liquid Assets}}{\text{Expenditure}} \), income brackets and deciles of \( \frac{\text{Liquid Assets}}{\text{Income}} \)).

I highlight the robustness of the results to the form of income because of two notable features of tax refunds. One is possible endogeneity in refund size (as households can self-select these magnitudes to a degree), and another is that the exact date of refund arrival is the source of some uncertainty (however, as documented above, over 97% of refunds arrive within thirty days). In contrast, the dates of arrival for bonuses and paychecks are known or ascertainable in advance of receipt. The results are also robust across populations and consumption responses are restricted to income receipt, that is they:

- Hold across age groups, levels of income, and the cross-section of income volatility, and are robust to different measures of liquidity.

- Persist even when one large inflow comes shortly after another (in the case of households receiving state and federal tax refunds in the same year).

- Is restricted to receipt as opposed to the date of tax filing, even for households with substantial liquidity. The date of tax filing jointly represents a resolution of uncertainty and an allocation of household attention.

In the accompanying Appendix I instead measure household consumption responses non-parametrically, and exploit variation in households’ year-to-year liquidity positions. I show that the tight correlation between \( \frac{\text{Liquid Assets}}{\text{Income}} \) and consumption responses, as well as the large responses of the highly liquid, are not driven purely by individual self-selection into levels of liquidity.
These results are consistent with a model in which households follow rules-of-thumb for consumption/savings and make budgeting decisions on a short-term basis. Households likely employ such rules in order to internally impose constraints on present consumption and prevent over-spending from month-to-month. Household responses to paycheck receipt illustrate this point particularly saliently. Households among the fourth and fifth quintiles of $\frac{\text{Liquid Assets}}{\text{Income}}$ lump an extra day’s worth of non-durable goods expenditure into the week following paycheck receipt relative to the week before, even though they have the requisite liquidity to smooth these discretionary expenses across paychecks. Similarly, household responses to surplus cash coming in the form of tax refunds or bonus checks are immediate and short-lived, indicating that fungibility between these inflows and a household’s liquid balances only fails for a short period of time.

3. A Model of Mental Accounts

I develop a dynamic and tractable model of mental accounts that rationalizes both the timing and magnitude of consumption responses in the cross-section of liquidity documented above. Fundamentally, I break the fungibility between an agent’s current income and current assets that is assumed in standard consumption models. In the mental accounts model, agents follow simplified rules of thumb for savings guided by one salient reference point: current assets. Overriding these internal processes entails utilitarian costs in the form of declines in marginal utility. This friction serves to partition the consumption choice set across ‘mental accounts’ pertaining to current assets and current income, in the spirit of Shefrin and Thaler (1988). I begin by presenting the mental accounts utility function, followed by a motivating exercise. I proceed by performing a structural estimation of the model’s preference parameters in a life-cycle context, and conclude by exploring the resulting positive implications for stimulus policy design.

3.1. Mental Accounts Utility

The mental accounts utility function is of the form

$$\nu(c) \equiv u(c) + \psi \cdot d(a', a^d)$$

(2)

Where $u(\cdot)$ denotes the usual consumption utility ($u'(c) > 0$, $u''(c) < 0$) and $d(\cdot)$ a savings deviation function, accepting as arguments an agent’s current savings decision ($a'$) and some default rule-of-thumb for savings ($a^d$). Agents face a utility cost when deviating below their default, the intensity of which is parameterized by $\psi$. The following form for the savings deviation function is assumed:

$$d(a', a^d) = \begin{cases} 0 & \text{if } a' \geq a^d \\ < 0 & \text{if } a' < a^d \end{cases}$$

and $\frac{\partial d(a', a^d)}{\partial a'}|_{a' < a^d} > 0$, so that in the loss domain (where $a' < a^d$) deviation losses decrease as the agent approaches the default. Agents face the usual constraint $c + a' \leq y + a(1+r)$. It is useful to define the consumption allocation at the default, $\bar{c} = y + a(1+r) - a^d$. 

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I impose the following structure. First, I assume agents’ rule-of-thumb for savings is guided by their current asset positions, \( a^d = a(1 + r) \). Second, I assume the following functional form for the deviation function

\[
d(a', a^d) = \begin{cases} 
0 & \text{if } a' \geq a^d \\
-(u(c) - u(c^d)) & \text{if } a' < a^d 
\end{cases}
\]

This functional form (Figure 7) is continuous and induces a natural bound for \( \psi \in [0, 1] \). When \( \psi = 0 \) then \( v(c) = u(c) \) and the standard permanent income agent is recovered. At the other extreme, when \( \psi = 1 \), agents face marginal utility \( u'(c)(1 - \psi) = 0 \) when \( c > y \), and are hand-to-mouth in each period \( (c = y) \).\(^{36}\) For intermediate values of \( \psi \in (0, 1) \) agents exhibit dissavings aversion.

\[\text{Mental Accounts, Utility Function}\]

![Utility Representation](image)

The savings deviation function induces a kink in the standard utility function, partitioning an agent’s consumption choice set between mental accounts pertaining to current income and current assets. Agents consider the income they receive each period separately from the assets they have accumulated over time. Unconsumed resources obtained as income in period \( t \) are re-labeled as current assets in future periods. Agents face the standard utility function when consuming out of current income, and a decline in marginal utility when consuming out of their current asset balances.

3.2. Consumption Responses in a Perfect Foresight Model

In this section I build intuition for the consumption responses generated by the mental accounts utility presented above. Consider an environment with no uncertainty and

\(^{36}\)In environments where income is allowed to be 0, reference points may be determined by \( c^d = \max\{y, \epsilon\} \) for \( \epsilon \) arbitrarily small. This prevents indeterminacy without altering the economics.
perfect foresight. An agent lives for $T$ months, receives no initial endowment ($a_0 = 0$), and income only in the initial period ($y_0 > 0$, $y_t = 0 \ \forall \ t > 0$). The agent has time preference $\beta$, aversion to dissaving $\psi$, and consumption utility that is CRRA with risk aversion parameter $\gamma$. The agent earns a given monthly rate of return on savings, $(1 + r)$, and faces no credit constraints, but for a constraint on terminal wealth. The agent solves

$$\max \sum_{t=0}^{T} \beta^t \left[ \frac{c_t^{1-\gamma}}{1-\gamma} + \psi \cdot d(a_{t+1}, a_t(1 + r)) \right]$$

$$c_t + a_{t+1} \leq y_t + a_t(1 + r)$$

$$a_{T+1} \geq 0$$

where the deviation function is of the form described in (3). Solving for consumption $c_t = c_0 \cdot [\beta(1 + r)]^{\frac{t}{T}} \cdot (1 - \psi)^{\frac{1}{\gamma}}$, substituting this expression into the present value constraint, and differentiating with respect to $y_0$ yields an expression for the marginal propensity to consume out of income in the initial period:

$$\frac{\partial c_0}{\partial y_0} = \left(1 + \left(1 - \psi\right)^{\frac{1}{\gamma}} \cdot \left[\beta^{\frac{1}{\gamma}}(1 + r)^{\frac{1}{\gamma}} - (1 + r)^{-T}(\beta(1 + r))^{\frac{T}{\gamma}}\right]\right)^{-1}$$

In all future periods the agent consumes out of the current asset account, thus mental accounts align across periods, and $c_t = c_1[\beta(1 + r)]^{\frac{t-1}{T}}$. Plugging $a_1 = y_0 - c_0$ into the period 1 present value constraint and solving

$$\frac{\partial c_1}{\partial y_0} = \theta \left[1 - \left(1 + \left(1 - \psi\right)^{\frac{1}{\gamma}} \cdot \left[\beta^{\frac{1}{\gamma}}(1 + r)^{\frac{1}{\gamma}} - (1 + r)^{-T}(\beta(1 + r))^{\frac{T}{\gamma}}\right]\right]\right]^{-1}$$

Where $\theta = \frac{(1+r)-[\beta(1+r)]^{\frac{1}{\gamma}}}{1-(1+r)^{-T}[\beta(1+r)]^{\frac{1}{\gamma}}}$. From the expression for relative consumption, it follows that $\frac{\partial c_{t+1}}{\partial y_0} = \frac{\partial c_0}{\partial y_0} [\beta(1 + r)]^{\frac{t}{T}}$ for all $t > 0$. Abstracting from violations of Inada conditions, expression 3 immediately highlights the dissaving aversion parameter’s role in dictating the degree of consumption front-loading, as well as the nested extremes:

- $\psi = 0$: the condition collapses to that of the standard model permanent income model ($\frac{\partial c_0}{\partial y_0} \rightarrow 0$).
- $\psi = 1$: the agent consumes the entirety of the endowment in the initial period and is hand-to-mouth ($\frac{\partial c_0}{\partial y_0} = 1$)

Note the independent roles of $\beta$ and $\psi$ in this environment. At their respective extremes ($\psi = 1$, $\beta = 0$) these parameters induce the same path of life-time consumption ($\frac{\partial c_0}{\partial y_0} = 1$). On the intermediate interval, however, the paths they induce are distinct. Mental accounts have an asymmetric effect on the path of consumption (as unconsumed resources move from the current income account in the initial period to the current asset account in all future periods). In contrast, the time preference parameter induces a path of consumption that decays geometrically (ie. $\frac{\partial c_{t+1}}{\partial y_0} = \frac{\partial c_0}{\partial y_0} [\beta(1 + r)]^{\frac{t}{T}}$).
To build further intuition I parameterize the perfect foresight model. Given a time horizon $T$, a value for the risk aversion parameter, $\gamma$, and the empirically observed relative consumption responses ($\frac{\partial c_t}{\partial y_0}$, $\frac{\partial c_{t+1}}{\partial y_0}$, $\frac{\partial c_t}{\partial y_0}$ for all $t > 0$) it is straightforward to back out the remaining preference parameters, $\beta$ and $\psi$. For this back-of-the-envelope calculation I use the average consumption responses of the highest cash-on-hand quintile receiving tax refunds, since this population’s consumption decisions are the least likely to be distorted by their proximity to an externally imposed liquidity constraint. Amongst this group $\frac{\partial c_4}{\partial y_0} / \frac{\partial c_3}{\partial y_0} \approx 0.986$. Choosing $(1+r) \approx 1$ (a reasonable assumption at the monthly frequency) and $\gamma = 1$ (log utility), it follows that $\beta = 0.986$. For the same group of households $\frac{\partial c_0}{\partial y_0} \approx 0.095$. Plugging the recovered value of $\beta$ into this expression and solving for $\psi$ yields a dissaving aversion factor of 0.867.

![Perfect Foresight Consumption Responses](image)

This stylized economy is illustrative of how household’s time preference and dissaving aversion parameters can be disentangled. Figure 8 depicts the consumption responses generated by the mental accounts model alongside those generated by the data. In the next section I turn to a life-cycle environment, structurally estimate the mental accounts preference parameters, and perform a series of counter-factual policy experiments.

### 3.3. Mental Accounts Life-Cycle Model

In this section I explore the implications of mental accounting frictions in a life-cycle context and assess the quantitative performance of the model. I structurally estimate the model’s preference parameters, calibrating these parameters to match two sets of moments: low frequency life-cycle liquid asset accumulation and high frequency consumption responses to a pre-announced payment. In order to assess the counter-factual implications of the model in comparison to a standard buffer-stock case, I also estimate the model with mental accounting frictions turned off. I allow the standard buffer-stock model to attempt to match both sets of moments jointly, and to match only the observed consumption responses.
I consider the canonical buffer-stock life-cycle model studied by Carroll (1996), Parker and Gourchinas (1999), and Cagetti (2003), amongst others, calibrated to the monthly frequency, and augmented by the mental accounting utility function described above. Households in the model retire at \( t = 480 \) (40 years of working life) and perish with certainty at \( T = 660 \) months (80 years of age). They solve

\[
\max \mathbb{E} \left[ \sum_{t=0}^{T} \beta^t \nu(c_t) + \beta^{T+1} v_{T+1}(a_{T+1}) \right] \\
\text{st.} \\
c_t + a_{t+1} \leq y_t + a_t (1 + r) \\
a_{t+1} \geq a
\]

Utility, \( \nu(c) \), is as defined above and \( u(c) = \frac{c^{1-\gamma}}{1-\gamma} \). The function \( v_{T+1}(\cdot) \) represents a bequest function of the form \( k \frac{(a_{T+1})^{1-\gamma}}{1-\gamma} \). The income process during working life is determined by \( y_t = p_t y_t \). Where \( p_{t+1} = \Gamma_{t+1} p_t \) and the process \( \{\Gamma_t\}_{t=0}^{T} \) is a deterministic life-cycle income growth profile. During working life household face income uncertainty. When a household is employed their income, \( y_t \), follows an AR(1) process with persistence \( \rho \) and volatility \( \epsilon_t \sim (0, \sigma^2) \). With exogenous probability \( p_u \) households become unemployed and receive unemployment insurance \( u_i \). Households regain employment with probability \( p_e \).

I begin by assuming no borrowing \((a = 0)\). Writing the model recursively and normalizing by \( \{\Gamma_t\}_{t=0}^{T} \), as in Carroll (2012), yields

\[
v_t(y_t, a_t) = \max_{c_t} \left\{ \nu(c_t) + \beta \cdot \hat{\beta}_t \cdot \mathbb{E}_t [\Gamma_{t+1}^{1-\gamma} v_{t+1}(y_{t+1}, a_{t+1})] \right\} \\
\text{st.} \\
c_t + a_{t+1} \leq y_t + a_t \frac{(1 + r)}{\Gamma_{t+1}} \\
a_{t+1} \geq a
\]

The model in levels is recovered via \( x_t = p_t \cdot x_t \). Here I introduce the discount factor correction term, \( \{\hat{\beta}_t\}_{t=0}^{T} \), studied by Attanasio et al. (1999), which deterministically adjusts the period discount factor for the number of adults and children in the household. The income process \( \{(\rho, \sigma^2, \Gamma_t)_{t=0}^{T}\} \) is determined via a first-stage estimation. Initial assets, \( a_0 \), are chosen to match quintiles of the liquid asset holdings amongst 24 year old SCF respondents. I proceed by estimating the four preference parameters \( \{\beta, \gamma, \psi, \kappa\} \) via the method of simulated moments to match life-cycle wealth accumulation observed in the SCF (8 moments, one for each five year interval of working life) and high frequency consumption responses observed in the transaction data (10 moments - one for each decile of liquidity). Table 6 summarizes the model's parameters.

Standard arguments for parameter identification apply for determination of the time preference and risk aversion parameters. Agent’s motives for saving are both precautionary and to smooth the income drop at retirement. As agents approach retirement and
Table 7: Model Parameters, Monthly Calibration, Liquid Assets

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
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<tr>
<td>Primitives</td>
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<tr>
<td>Rate of Return</td>
<td>( r )</td>
<td>0.78%</td>
<td>60-Month CD(^{34} )</td>
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<tr>
<td>Initial Endowment</td>
<td>( a_0 )</td>
<td>0</td>
<td>SCF</td>
</tr>
<tr>
<td>Demographic Correction</td>
<td>( { \hat{z}<em>t }</em>{t=0}^T )</td>
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<td>Cagetti (2003)</td>
</tr>
<tr>
<td>Income</td>
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<td></td>
</tr>
<tr>
<td>UI Replacement</td>
<td>( u_t )</td>
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<td>OUI</td>
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<td>Job-Finding Probability</td>
<td>( p_e )</td>
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<td>CPS</td>
</tr>
<tr>
<td>Separation Probability</td>
<td>( p_u )</td>
<td>0.011</td>
<td>CPS</td>
</tr>
<tr>
<td>Stimulus Payment</td>
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<td>Deterministic Income</td>
<td>( { \Gamma_t }_{t=0}^T )</td>
<td>( \cdot )</td>
<td>First Stage</td>
</tr>
<tr>
<td>Income Persistence</td>
<td>( \rho )</td>
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<tr>
<td>Income Volatility</td>
<td>( \sigma_\epsilon )</td>
<td>0.073</td>
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<tr>
<td>Preferences</td>
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<tr>
<td>Dissaving Aversion</td>
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<tr>
<td>Bequest Motive</td>
<td>( \kappa )</td>
<td>239</td>
<td>SMM</td>
</tr>
</tbody>
</table>

Income uncertainty is resolved, the importance of the former motive (driven by the degree of risk aversion, \( \gamma \)) gives way to the latter (driven by the degree of impatience, \( \beta \)). Identification of the dissaving aversion parameter, \( \psi \), relies on the model-generated cross-section of consumption responses to predictable income. As shown above, this parameter largely governs the consumption response of households with high levels of liquidity and the degree of consumption front-loading to the period of income receipt.

3.3.1. First Stage Estimation

I estimate the components of the income process, \( \{ \rho, \sigma^2_\epsilon, \{ \Gamma_t \}_{t=0}^T \} \), from a combination of BLS Consumer Expenditure Survey (CEX) data at the annual frequency, and bank income data at the monthly frequency. The deterministic growth path (\( \{ \Gamma_t \}_{t=0}^T \)) is obtained from the 2000, 2005, 2010, and 2015 waves of the CEX public-use micro-data adjusted to 2016 dollars. The restrictions to the sampling criteria are standard (see, for example, Cagetti, 2003). I define total income as total income less taxes, pension contributions, education and health expenses, and asset income.

The estimation is performed separately for working and retired adults. The former is restricted to individuals ages 24 to 64 who are married, have completed high school, report working at least 35 hours each week, and whose total earnings for the year exceed $500. Retired individuals are allowed to be single and are restricted to being over 60 years of age. These restrictions yield samples of 6322 and 3328 working age and retired consumers, respectively. The deterministic profile, \( \{ \Gamma_t \}_{t=0}^T \), is obtained from the fitted values of a regression of log total income on a fourth degree polynomial in age, controlling for cohort effects, calculated separately for retired and working individuals. In order to obtain a monthly series I divide each annual series across twelve months and use a simple moving average to smooth the income path from year to year.

In order to focus the analysis to liquid asset accumulation, while retaining the life-cycle
profile of earnings, I abstract from the drop in income at retirement. This modeling choice has a natural interpretation - a proportion of household income is placed into an illiquid savings account during each period of working life. This account subsequently pays out with certainty in each month of retirement. In the accompanying appendix I consider an estimation procedure in which I match total household net worth instead. Figure 9 plots the resulting profiles of $\{\Gamma_t\}_{t=0}^T$ and from the first-stage estimation procedure as well as the beta correction, $\{\beta_t\}_{t=0}^T$, obtained from Carroll (2012).

Figure 11: Deterministic Profiles

In order to estimate high-frequency movements in income I utilize the bank transaction data. I restrict to those households that are observed for at least 60 consecutive months, do not experience an observable unemployment spell (as measured by UI income), and whose primary account holder is male. To control for extreme outliers I trim households experiencing outcomes in the 1% tails of total income months and the 5% tails of monthly income growth. To control for the deterministic age component I obtain residuals from a first stage regression of log income on age, and then estimate the following AR(1) process

$$y_{i,a} = \rho y_{i,a-1} + \epsilon_{i,a}$$

I obtain values for $\rho$ and $\sigma^2$ of 0.8962 and 0.073, respectively. Additionally, I obtain monthly job finding and separation rates from the CPS Labor Force Statistics data for the year 2016. I obtain unemployment insurance replacement rate data from the Office of Unemployment Insurance UI Replacement Rates Report for 2016.

3.3.2. Preference Parameter Estimation

In order to structurally estimate the model’s four preference parameters $\{\beta, \gamma, \psi, \kappa\}$ I utilize a simulated method of moments approach. I estimate the model’s preference parameters to fit both life-cycle liquid asset accumulation (the median liquid assets of 8 age groups) and the cross-section of consumption responses observed in the transaction data (the average thirty day consumption response for each decile of $\frac{\text{LiquidAssets}}{\text{Income}}$). In order
to obtain estimates of liquid assets I utilize data from the Survey of Consumer Finances between 2001 to 2016. As in the other samples, I restrict to households of working age (24 to 64) who are married. Employing the SCF sample weights, Figure 12 plots median wealth for individuals within eight age groups constructed from five year increments, along with the 25th and 75th percentiles.

Figure 12: Data moments

Due to the large skewness in wealth profiles, I follow the literature and perform the estimation to match the median wealth within each age group. For high frequency consumption responses, I utilize the estimates obtained from the transaction data for tax refund recipients. I plot the set of eighteen moments to be matched in Figure 12. In the model, agents are alerted $l$ periods in advance to an inflow, $T$, to be deposited at time $t$. The size of the inflow is calibrated to match the average tax return relative to income observed in the transaction data. Parameters are calibrated to satisfy\(^{38}\):

$$
\min_{\beta, \gamma, \psi, \kappa} \sum_{a} d_{a}^{\text{liq}} - m_{a}^{\text{liq}}(\beta, \gamma, \psi, \kappa) + (1 - \Theta) \sum_{j} d_{j}^{\text{mpc}} - m_{j}^{\text{mpc}}(\beta, \gamma, \psi, \kappa) . \tag{6}
$$

This objective function includes a life-cycle liquid assets component ($\text{liq}$) and a cross-sectional consumption responses component ($\text{mpc}$). The relative importance of these two components is governed by the parameter $\Theta \in [0, 1]$, which is adjusted to account for the relative magnitudes of each term. The first component measures the median absolute distance between $d_{a}^{\text{liq}}$, the median value of liquid assets for SCF respondents amongst each

\(^{38}\)As suggested by Carroll (2012), I also consider the following objective, which allows for SCF measurement error:

$$
\min_{\beta, \gamma, \psi, \kappa} \sum_{i} \omega_{i}^{a} d_{i,a}^{\text{liq}} - m_{a}^{\text{liq}}(\beta, \gamma, \psi, \kappa) + (1 - \Theta) \sum_{j} d_{j}^{\text{mpc}} - m_{j}^{\text{mpc}}(\beta, \gamma, \psi, \kappa) . \tag{5}
$$

Where $d_{i}^{a}$ denote the empirical value of liquid assets for SCF respondent $i$ and $\omega_{i}^{a}$ denotes the weight assigned to each observation, obtained from SCF sample weights. The results are robust to this alternate objective.
each group, and $m^{liq}_a$ denotes the model-constructed liquid wealth holdings for each age group at the parameter values $\{\beta, \gamma, \psi, \kappa\}$.

In the case of the second component, $j$ indexes deciles of the liquid wealth distribution in advance of income receipt. This component measures the median absolute deviation of model implied average consumption responses by decile ($\{m^{mpc}_j\}^{10}_{j=1}$) from their empirical counterparts ($d^{mpc}_j$). In order to obtain the former, I simulate the model and decile households by liquid wealth in advance of stimulus announcement. Consumption responses are then obtained non-parametrically from the simulated data (i.e. for a stimulus announced $l$ periods in advance of time $t$, $mpc_{j;i} = \frac{c_{t;i} - c_{t-l-1;j;i}}{R_{t;i;j;i}}$). This amounts to running the same reduced form regressions on the model generated data as the transaction data. I search across the parameter space via a four-dimensional Sobol sequence. I solve the model for each set of generated parameters, simulate the lifetimes of forty thousand agents and obtain the model-generated moments. I choose the set of parameters that minimize the objective (4).

3.4. Estimation Results & Life-Cycle Savings Decomposition

In this section I report the results for the structural estimation procedure and perform a decomposition of life-cycle savings. Additionally, I compare these results to those obtained from a structural estimation of the standard buffer-stock model. This establishes the unique role for mental accounts frictions in rationalizing the data.

The results suggest moderate levels of impatience and risk aversion (Table 7). Dis-saving aversion is found to be significant (0.346). On the interval between buffer-stock ($\psi = 0$) and hand-to-mouth ($\psi = 1$), the results suggest households tend towards the former. Figure 11 plots the model generated moments against the data. Average one month consumption responses observed in the data and those generated by the model are 0.2 and 0.17, respectively. The average responses amongst the tenth decile of liquid asset holders is 0.09 in the data, compared to 0.12 in the model. Along the dimension of liquid assets, the model matches both the level and profile of median life-cycle liquid asset accumulation. In addition to generating a correlation between assets-to-income and consumption responses in line with the data, the mental accounts model is able to capture the degree of consumption front-loading to receipt.

Table 8: Estimation Results

<table>
<thead>
<tr>
<th>Model</th>
<th>$\beta$ (Annual)</th>
<th>$\gamma$</th>
<th>$\kappa$</th>
<th>$\psi$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mental Accounts</td>
<td>0.9344</td>
<td>2.481</td>
<td>238.7</td>
<td>0.346</td>
</tr>
<tr>
<td>Buffer-Stock</td>
<td>0.8994</td>
<td>2.330</td>
<td>278.0</td>
<td>\cdot</td>
</tr>
<tr>
<td>Buffer-Stock, $\Theta = 0$</td>
<td>0.7480</td>
<td>1.043</td>
<td>287.8</td>
<td>\cdot</td>
</tr>
</tbody>
</table>

To assess parameter identification, I report contours for each set of moments, plotting the median absolute distance against key model preference parameters (Figure 14). For each plot I fix the absent parameters to a small window around their estimated values. Darker blue shades indicate smaller distances between the model generate moments and
their empirical counterparts. Consistent with the previous literature, I find weak identification for $\beta$ and $\gamma$ in determination of life-cycle liquid asset accumulation. Intuitively, increasing impatience can be traded off with an increased level of risk aversion to obtain similar liquid asset profiles. The consumption response contours indicate a similar trade-off between increasing patience ($\beta$) and increasing dissaving aversion ($\psi$). Jointly, the plots indicate that for a fixed level of $\gamma$, obtaining consumption responses closer to the data requires ascending the steep gradient away from the liquid asset minima.

I re-estimate the model with the restriction $\psi = 0$. This is the standard buffer-stock case. I estimate the restricted model, first to match the same objective as the mental accounts model, and, second, to match the profile of consumption responses only ($\Theta = 0$). The latter serves to give the standard model the best odds of obtaining the dispersion in consumption responses observed in the data. The estimation results are reported in
Table 7. Figure 12 plots the cross-sectional consumption and median liquid asset life-cycle profiles against those of the data for each of the three estimations. Additionally, the distribution of liquid assets in advance of stimulus announcement is reported, along with the median (solid line) and the 20th and 80th percentiles (dashed lines) of liquid asset holdings.

The standard buffer-stock model is unable to obtain a significant degree of excess sensitivity amongst highly liquid households. The standard model is able to generate a dispersion in thirty day consumption responses in line with the data, but at the cost of counter-factually collapsing the liquid wealth distribution. Under this parameterization households at the 80th percentile of liquidity hold less than 7% of monthly income in liquid assets. Additionally, the standard model is unable to capture the degree of consumption front-loading evident in the data. In the accompanying Appendix I further illustrate the role of each preference parameter by varying each in turn. Additionally, I report contours,
plotting each parameter pair against the objective distance they generate.

All else equal, the introduction of mental accounts push estimates for both the patience and risk aversion parameters upwards. The latter implies a decreased sensitivity of household consumption growth to changes in the rate of return on savings. It is instructive to disentangle the role of mental accounting frictions from other factors that affect life-cycle consumption/savings decisions. By shutting down income uncertainty, relaxing the ad-hoc constraint on borrowing, and turning off the mental accounting friction in turn, I decompose the extent to which household savings decisions are due to precautionary, life-cycle, and mental accounting motives, respectively.

I first shut down the mental accounting friction and obtain the counter-factual life-cycle savings profile (Figure 14). Captive to the structure of mental accounts, households in the model construct their budgets on a monthly basis and their consumption tracks closer to income than a traditional buffer-stock agent. These deviations add up - during working life the median mental accounting agent’s savings buffer is roughly forty percent less than a traditional agent, and he enters retirement with about twenty percent less in liquid assets. I next uncover the proportion of household savings held for precautionary reasons by shutting down income uncertainty and solving the model at the estimated parameters. Consistent with previous studies, I find that household savings decisions are driven by precautionary motives until households approach retirement age. This result is robust to whether or not mental accounts are present.
4. Implications for Fiscal Stimulus Policies

In this section I assess the model’s positive implications for the design of fiscal stimulus payments by performing two experiments. In the first experiment I consider a redistributive policy in which the fiscal authority taxes households with substantial liquid wealth, and uses the revenue to provide a targeted stimulus to the most constrained households in the economy. In the second experiment I endow fiscal authority with a fixed amount of resources and consider three budget-equivalent policies: an un-targeted stimulus, an asset-targeted stimulus, and an income-targeted stimulus. In both cases I compare the aggregate consumption responses from the estimated mental accounts model to the counter-factual economy in which mental accounts are turned off, and a baseline buffer-stock economy estimated to match life-cycle liquid asset accumulation.

I assume a small open economy. Agents take the rate of return, $r$, as given and the liquid savings technology, $a$, is external to the economy. I parameterize economies using the preference parameter estimates from above (Table 8). Each agent solves the problem described in Section 3.3, subject to the parameterization described in Table 7.

Index each generation of agents by the period of birth $j$. Each generation begins working life with initial assets distributed to match the 10th, 30th, median, 70th, and 90th percentiles of liquid assets amongst 24 year olds as reported in the SCF. Agents live from $t = j$ to $j + 660$ periods and retire at $t = j + 480$. I simulate the economy for 480 months with 250 agents born each month. The government is endowed with $M$ resources and seeks to redistribute them to households. It faces the budget constraint

$$M = \sum_t \int_i T^i_t \cdot \Gamma^i_t di$$

In all cases, the requisite stimulus policy is announced to agents in the economy $t - 1$ periods in advance of implementation. Households fully internalize the announcement before making their time $t - 1$ consumption and savings decisions.

4.1. A Redistributive Stimulus

In this section I consider a redistributive stimulus policy, in which the government issues a targeted stimulus to households holding low levels of liquid assets by taxing those with high levels of liquidity. As before, the government announces the time $t$ policy at time $t - 1$. The government has no resources ($M = 0$) and must implement a balanced budget policy ($\sum_t \int_i T^i_t \cdot \Gamma^i_t di = 0$).

Here I consider an example in which the government implements a lump sum transfer system, redistributing $2500$ households amongst the fifth quintile ($q = 5$) of liquid balances at the time of announcement to households in the bottom quintile ($q = 1$). That is, $\sum_{q=1}^5 \int_i T^{i,q}_t \cdot \Gamma^i_t di = 0$, with $\int_i T^{i,1}_t di > 0$, $\int_i T^{i,5}_t di < 0$ and $\sum_{q=2}^4 \int_i T^{i,q}_t di = 0$. Ex-post, the $2500$ transfer amounts to roughly a third of monthly income for agents in quintile 1.

Compared to the standard buffer-stock case, the redistributive stimulus policy is 53% less effective over two quarters under mental accounts (Figure 17, left panel). In the standard model agents with high levels of liquidity remain at their target consumption...
levels even in the face of a substantial lump-sum tax on their liquid wealth. This is in symmetry with their muted responses to predictable increases in income (see Figure 14). However, in the presence of mental accounts even lump-sum taxes are distortionary. Due to their reluctance to consume out of their current asset accounts, the agents facing a wealth tax adjust their consumption downwards during the month of payment (Figure 17). This downward adjustment offsets the high degree of excess sensitivity among constrained households receiving a transfer.

The results stand in stark contrast with the predictions of models in which heterogeneity in marginal propensities to consume are driven by households’ proximity to an externally-imposed liquidity constraint. Whereas in the standard buffer-stock model a redistribution from households with high levels of liquidity to those with low levels of liquidity is essentially ‘for free’, under mental accounts the decline in consumption amongst highly liquid households facing the lump-sum tax has a first order effect, depressing the government spending multiplier.

### 4.2. A Targeted Stimulus

Stimulus policy design is largely a matter of evaluating which population segments will have the largest propensity to expend the funds they receive. Another component is evaluating the feasibility of such targeting and the gains from doing so. In this section I explore these dimensions through the lens of the mental accounts model. I compare three distinct budget-equivalent policies:

1. **Un-targeted Stimulus**: A $100 blanket stimulus to all households in the economy
2. **Income-targeted Stimulus**: A $500 stimulus targeted to households experiencing the bottom 20 percent of income realizations at announcement
3. **Asset-targeted Stimulus**: A $500 stimulus targeted to households in the bottom quintile of liquid asset holdings

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39Assuming 100 million U.S. households, each policy requires $M = $10 billion
The un-targeted stimulus policy is comparable to the Bush tax rebates of 2001 and 2008. In the case of the former, passage of the Bush tax cuts triggered a rebate of $300 – $600 for all taxpayers that filed a return in the previous year. An income-targeted stimulus policy is comparable to unemployment insurance or workers’ compensation policies. Unemployment programs replace roughly half of a workers pre-unemployment income, regardless of their current asset position. An asset-targeted stimulus is akin to means-tested programs, such as SNAP or TANF. The former jointly requires household income to be below 130 percent of the poverty line and assets of $2,250 or less.

In comparison to a standard buffer-stock economy in which the income-targeted and asset-targeted policies are 6 and 8 times more effective than a blanket stimulus, respectively; under mental accounts the gains to targeting are significantly reduced and the relative effectiveness of these targeted policies is reversed. Consistent with the data, the decline in consumption responses across levels of liquidity is moderate, meaning the increased “bang for the buck” coming from targeting is stifled.

Income-targeted and asset-targeted stimulus policies are, respectively, 47 percent and 33 percent more effective than an un-targeted stimulus in economies where mental accounting frictions are present. This reversal is the direct result of households’ sensitivity to fluctuations in income, regardless of their current asset positions.

These results have direct implications for policy. Namely, the relative gains to targeting under mental accounts are roughly an eighteenth of those in the standard buffer-stock case. This indicates the feasibility, both financially and politically, of implementing such policies likely carries greater weight than previously thought. Additionally, the mental accounts model generates a key positive prediction: policies targeted towards households with temporarily low income, regardless of their current liquid asset positions, are particularly potent. This indicates a role for unemployment insurance programs with increased income replacement rates during economic downturns.

Figure 18: Aggregate Consumption Responses Across Policies by Model
5. Conclusion

In this paper I document the relationship in micro-data between household liquidity and consumption responses to predictable forms of income. I document significant responses amongst households with high levels of liquidity that are highly front-loaded to receipt. In order rationalize these dimensions of consumption responses I propose a model of mental accounts in which households are averse to dissaving. I show that the model nests standard buffer-stock and hand-to-mouth agents as limiting cases and that the data is consistent with an intermediate case, in which households are moderately averse to dissaving.

The model represents a gentle, parsimonious, and tractable departure from full rationality, and is able to generate consumption responses in line with the data. Through the lens of this model I re-evaluate fiscal stimulus policy design. Notably, I show that a redistributive stimulus to liquidity constrained households is approximately $50\%$ less effective than in a standard buffer-stock economy. Additionally, I show that the gains to moving from a blanket stimulus policy to a targeted one are significantly less than indicated by the canonical one asset setup.

References


Data Appendix

Below all appendices regarding the data sections of the paper.

Appendix A. Transaction Categorization

I categorize expenditures in accordance with the 2019 NIPA Handbook. Expenditures include credit, debit, and deposit outflows categorized according to Merchant Category Codes (MCCs), attributed to the time of purchase. Within the total expenditure category I attribute payments to unobservable credit accounts as contemporaneous expenditure. Where appropriate I test the robustness of this assumption and attribute these outflows to debt repayment instead, or restrict to a subset of the population that does not make any payments to unobservable credit card accounts. Throughout the paper expenditures are classified as follows:

- **Total Expenditure** ($e$): All account (credit and deposit) outflows, excluding account transfers and credit card balance payments for which card purchases are observable.
- **Non-Durables** ($e_{ND}$): Groceries, entertainment, fuel, discount and drug stores, direct market catalogs, or services such as utilities, telecommunications, insurance, health expenses, other bills, food services, travel services and other personal and professional services.

Additionally, I construct a taxonomy decomposing Total Expenditure $e$ as follows:

- **Non-Durables Goods** ($e_{NDG}$): Groceries, entertainment, fuel, discount and drug stores, direct market catalogs.
  - **Groceries** ($e_{NDG_F}$): Grocery, drug, and liquor stores (ie. food at home).
- **Services** ($e_S$): Education, healthcare, travel, telecommunications, utilities, housing, rent, other bills, financial services, personal or professional services, and food services.
  - **Food Services** ($e_{SF}$): Restaurants and bars (ie. food away from home).
- **Durables** ($e_D$): Auto purchases, repairs, and parts; healthcare equipment; home improvement goods and appliances.
- **Illicit Debt Payments** ($e_B$): student loans, auto loans.

The remainder of total expenditure not attributed to one of the subcategories above includes unclassified paper checks, cash outflows, and payments to unobserved credit card accounts. This unclassified proportion makes up roughly one third of average monthly total expenditure.

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I develop an imputation procedure to assign outflows in the forms of cash, paper checks, and payments to unobserved credit card accounts to expenditure categories. I detail this procedure in the main text. Throughout the paper income is classified in the following manner:

- **Categorized Income**: Labor income (direct deposit and payroll), tax refunds, social security payments, unemployment insurance, investment income.

- **Total Income**: Categorized income plus paper checks and cash deposits.

Roughly 73% of income in the transaction data is categorized by source (ie. payroll, social security, unemployment insurance, etc.) while the rest comes in the form of paper checks (11%), cash (2.5%), and ACH deposits and miscellaneous inflows. Balance sheet variables are defined in the following manner:

- **Transaction Account Balances**: The sum of checking and savings account balances.

- **Total Liquid Balances**: Transaction account balances plus observable brokerage, money market, and certificates of deposit.

Furthermore, the taxonomy of inflows and outflows from transaction accounts is completed by defining transfers to illiquid savings accounts and unobserved demand deposit accounts. At the daily frequency, while checking and savings accounts are perfectly fungible (money can be transferred immediately between these accounts within the bank), money market and brokerage account transfers operate on some delay (usually one to two business days), while liquidations of retirement accounts and certificates of deposit often entail some cost.

### Appendix B. External Validation

Here I report supplemental external validation measures. I compare transaction and account data to survey micro data (SCF, CEX, SCPC) and per-capita macro data (PCE, USDA, IRS) for the year 2016. Each of the data sources overlap in this year. In a manner similar to Baker(2015), I also compare the distributions of observables within the transaction data to those of the SCF. The purpose of these benchmarking exercises is twofold: (1) to evaluate the directions of possible bias in the results that follow, and (2) in the spirit of (1) to alleviate concerns that the data’s lens on household’s overall financial activity is limited.

#### Table B.9: Expenditure Comparison, Monthly Averages, 2016

<table>
<thead>
<tr>
<th>Source</th>
<th>Expenditure</th>
<th>Non-Durables</th>
<th>Durables</th>
<th>Services</th>
<th>Food Services</th>
<th>Groceries</th>
</tr>
</thead>
<tbody>
<tr>
<td>CEX</td>
<td>4775.92</td>
<td>980.92</td>
<td>633.67</td>
<td>2386.83</td>
<td>337.42</td>
<td>303.17</td>
</tr>
<tr>
<td>PCE</td>
<td>8455.85</td>
<td>1754.98</td>
<td>891.89</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>USDA</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>548.84</td>
<td>627.98</td>
</tr>
<tr>
<td>BANK</td>
<td>5347.84</td>
<td>1059.18</td>
<td>168.40</td>
<td>1252.30</td>
<td>306.41</td>
<td>220.49</td>
</tr>
</tbody>
</table>
I benchmark household income measures to the CEX and Survey of Consumer Finances (SCF), and tax return outcomes to those reported by the Internal Revenue Service (IRS). Total monthly take-home income tracks above the CEX measure, driven in part by the exclusion of unbanked households in the transaction data. While the CEX and transaction data measure take-home (post-tax) income, the SCF survey requests that households report gross (pre-tax) annual income. I adjust SCF income to post-tax levels using Congressional Budget Office (CBO) data on average tax rates within pre-tax income brackets. This procedure is described below.

<table>
<thead>
<tr>
<th>Source</th>
<th>Monthly Income</th>
<th>Federal Tax Refund</th>
<th>State/Local Tax Refund</th>
<th>Federal Tax Payment</th>
</tr>
</thead>
<tbody>
<tr>
<td>CEX</td>
<td>5347.92</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>IRS</td>
<td>-</td>
<td>2860</td>
<td>1622</td>
<td>5422</td>
</tr>
<tr>
<td>BANK</td>
<td>5949.35</td>
<td>2844.61</td>
<td>1218.37</td>
<td>1591.59</td>
</tr>
</tbody>
</table>

I compare the transaction data to the SCF and the Survey of Consumer Payment Choice (SCPC). Both surveys are designed to be broadly representative. While the SCF measures the total value of accounts held by households, the SCPC asks respondents to exclude accounts exclusively held by their spouse or partner and represents the sum of primary and secondary checking accounts. The transaction data substantially understates total liquid balances available to households, but tracks transaction accounts (checking and savings) quite well. This understatement appears to be more pronounced at higher levels of liquid assets.

<table>
<thead>
<tr>
<th>Source</th>
<th>Checking</th>
<th>Savings</th>
<th>Liquid Balances(^{46})</th>
<th>Credit Card Debt</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25th</td>
<td>Median</td>
<td>75th</td>
<td>25th</td>
</tr>
<tr>
<td>SCF</td>
<td>300</td>
<td>1700</td>
<td>5600</td>
<td>0</td>
</tr>
<tr>
<td>SCPC</td>
<td>200</td>
<td>1000</td>
<td>3500</td>
<td>-</td>
</tr>
<tr>
<td>BANK</td>
<td>338</td>
<td>1251</td>
<td>3687</td>
<td>0</td>
</tr>
</tbody>
</table>

\(^{41}\)CEX measure includes: Food at home, laundry and cleaning, postage/stationery, apparel, motor oil/gasoline, entertainment, smoking supplies, and drugs.

\(^{42}\)Housekeeping and other household supplies, furnishings, and equipment; reading; medical supplies; auto repairs; and vehicle purchases.

\(^{43}\)Food away from home, alcoholic beverages, transportation, insurance, education, housing services, personal services, telecommunications, and other bills.

\(^{44}\)Food away from home and alcoholic beverages.

\(^{45}\)Calculated from U.S. BEA annual Personal Consumption Expenditures and U.S. Census Bureau Total Household data.

\(^{46}\)Liquid balance measures include checking, savings, money market, brokerage accounts, and certificates of deposit (retirement account balances are excluded).
Additionally, the SCPC surveys how many checking and savings accounts consumers manage. Conditioning on at least one checking account, I compare the frequencies of holding additional accounts across the datasets (Table 6). The transaction data understates the number of checking accounts available to consumers. However, according to the SCPC survey the median balance in secondary checking accounts is $0, and the 75th percentile of secondary checking account balances is just $100. This provides suggestive evidence that primary accounts are largely representative of day-to-day financial activity.

<table>
<thead>
<tr>
<th>Source</th>
<th>Checking 1</th>
<th>Checking 2</th>
<th>Checking 3+</th>
<th>Savings 0</th>
<th>Savings 1</th>
<th>Savings 2</th>
<th>Savings 3+</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCPC</td>
<td>0.665</td>
<td>0.247</td>
<td>0.087</td>
<td>0.208</td>
<td>0.471</td>
<td>0.205</td>
<td>0.116</td>
</tr>
<tr>
<td>BANK</td>
<td>0.879</td>
<td>0.107</td>
<td>0.014</td>
<td>0.61</td>
<td>0.345</td>
<td>0.039</td>
<td>0.012</td>
</tr>
</tbody>
</table>

Appendix B.1. SCF Post-Tax Adjustment

In order to obtain a measure of take-home income from the pre-tax figures reported by SCF respondents I utilize the CBO’s 2016 Distribution of Household Income report. Specifically, I utilize the income thresholds reports by the CBO for two-person households across quintiles and for the top one percent of earners. The adjustment includes federal taxes only - namely personal income, payroll, excise, and corporate income taxes. Table A.24 reports the adjustment made within each income bracket.

<table>
<thead>
<tr>
<th>Bracket</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q5</th>
<th>99th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bounds</td>
<td>&lt;32.5</td>
<td>32.5-54.8</td>
<td>54.8-81.8</td>
<td>81.8-126.1</td>
<td>126.1-546.8</td>
<td>&gt;546.8</td>
</tr>
<tr>
<td>Average Tax Rate</td>
<td>0.017</td>
<td>0.094</td>
<td>0.139</td>
<td>0.179</td>
<td>0.265</td>
<td>0.333</td>
</tr>
</tbody>
</table>

In addition to the distribution of annual income reported in the main text, here I report moments of the SCF income distribution (before and after adjustment), as well as moments of annual take-home income observed in the transaction data.

<table>
<thead>
<tr>
<th>Source</th>
<th>25th</th>
<th>Median</th>
<th>75th</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCF</td>
<td>30,379</td>
<td>58,733</td>
<td>104,302</td>
</tr>
<tr>
<td>SCF, Adjusted</td>
<td>29,863</td>
<td>50,569</td>
<td>85,632</td>
</tr>
<tr>
<td>BANK</td>
<td>31,754</td>
<td>50,568</td>
<td>82,484</td>
</tr>
</tbody>
</table>

It is important to note that the SCF adjusted measure is not adjusted for state income taxes. Accounting for this component adds substantial complication. In addition to substantial variation in personal income tax rates across states, there is substantial variation across households within states. A number of states have no personal income
tax (including Florida and Texas) while others levy substantial personal income taxes (California at 13.3% and New York at 8.82% among the highest\textsuperscript{47}). According to the Tax Policy Center, 30 percent of taxpayers itemized their deductions in 2016. Those who itemize can deduct state income taxes from their federal return. According to the Tax Foundation the choice to itemize is overwhelmingly weighted towards those facing high federal tax rates. Amongst those earning gross income of one hundred to two hundred thousand 76% choose to itemize, and of those earning over two hundred thousand 93.4% itemize.

Appendix C. Identification

Identification relies on variation in the timing of inflows with respect to calendar time, each other, and to the date of filing in the case of tax refunds and payments. This section outlines these arguments.

Appendix C.1. One Event

In the case of one event identification relies on calendar variation in the timing of individuals’ shocks. Consider specification

\[ y_{i,t} = \alpha_i + \lambda_t + \delta^1_{t+s} I^1_{i,t+s} + \delta^1_{t+s-1} I^1_{i,t+s-1} + \epsilon_{i,t} \]

Taking expectations, assuming \( \mathbb{E}[\epsilon_{i,t} - \epsilon_{i,t-1}|I_{i,t+s}, I_{i,t+s-1}] = 0 \), and differencing across time \( t \) and individuals \( i \) and \( j \)

\[ \mathbb{E}[\Delta y_{it} - \Delta y_{jt}] = \mathbb{E}[\delta^1_{t+s}(I^1_{i,t+s} - I^1_{j,t+s}) + \delta^1_{t+s-2}(I^1_{j,t+s-2} - I^1_{i,t+s-2})] \]

Variation in the calendar timing of treatment (simplest case in which individual \( i \) receives \( I^1 > 0 \) at time \( t + s \) and individual \( j \) receives \( I^1 > 0 \) at time \( t + s + k, k \geq 1 \)) yields

\[ \mathbb{E}[\Delta y_{it} - \Delta y_{jt}] = \mathbb{E}[\delta^1_{t} I^1_{i,t}] \]

Which is the parameter of interest. Identification of the anticipatory response follows in a similar manner. Below I plot the observed calendar variation in dates of filing and tax refund receipt.

![Figure C.19: Timing of Tax Refunds](image)

\textsuperscript{47}Source: Turbotax
Appendix C.2. Multiple Events

For the case of multiple events, consider specification

\[ y_{i,t} = \alpha_t + \lambda_t + \delta_1^t I_{i,t}^1 + \delta_1^t I_{i,t-1}^1 + \delta_2^t I_{i,t+s}^2 + \delta_2^t I_{i,t+s-1}^2 + \epsilon_{i,t} \]

Assuming \( \mathbb{E}[\epsilon_{i,t} - \epsilon_{i,t-1}|I_{i,t-1}^1, I_{i,t-1}^1, I_{i,t+s}^2, I_{i,t+s-1}^2] = 0 \), and differencing as above

\[ \mathbb{E}[\Delta y_{i,t} - \Delta y_{j,t}] = \mathbb{E}[\delta_1^t (I_{i,t}^1 - I_{j,t}^1) + \delta_1^t (I_{i,t-2}^1 - I_{j,t-2}^1) + \delta_2^t (I_{i,t+s}^2 - I_{j,t+s}^2) + \delta_2^t (I_{i,t+s-2}^2 - I_{j,t+s-2}^2)] \]

Variation in the timing of treatment (simplest case in which individual \( i \) receives \( I_1^1 > 0 \) at time \( t \) and individual \( j \) receives \( I_1^1 > 0 \) at time \( t + k \) (1 \( \leq k < s \)), individual \( i \) receives \( I_2^2 > 0 \) at time \( t + s \) and individual \( j \) receives \( I_2^2 > 0 \) at time \( t + s + k \))

\[ \mathbb{E}[\Delta y_{i,t} - \Delta y_{j,t}] = \mathbb{E}[\delta_1^t (I_{i,t}^1) + \delta_2^t (I_{i,t+s}^2)] \]

In addition to variation in calendar time, as in the one shock case, identification here further relies on variation in timing between the two shocks, \( I_1^1 \) and \( I_2^2 \) (simplest case, individual \( h \) that receives \( I_1^1 > 0 \) at time \( t \) and \( I_2^2 > 0 \) at time \( t + s + l \), \( l \neq k \)). Differencing again yields

\[ \mathbb{E}[(\Delta y_{i,t} - \Delta y_{j,t}) - (\Delta y_{i,t} - \Delta y_{h,t})] = \mathbb{E}[\delta_1^t I_{h,t}^1] \]

Which is the parameter of interest. Below I plot the observed variation in the time between filing and refund receipt as well as the days between receipt for those receiving federal and state refunds.

![Figure C.20: Time Between Events](image-url)
Appendix D. Obtaining Cumulative Coefficients

In order to interpret the coefficients as the cumulative change in \( y_{i,t} \) as a proportion of the inflow, \( I^1 \), I normalize the regression. Consider the simplest case

\[
y_{i,t} = \alpha_i + \lambda_t + \delta_0 I_{i,0} + \delta_1 I_{i,1} + \epsilon_{i,t}
\]

\[
= \alpha_i + \lambda_t + \delta_0 I_{i,0} + \delta_1 I_{i,1} - \delta_0 I_{i,1} + \epsilon_{i,t}
\]

\[
= \alpha_i + \lambda_t + \delta_0 (I_{i,0} - I_{i,1}) + (\delta_1 + \delta_0) I_{i,1} + \epsilon_{i,t}
\]

\[
= \alpha_i + \lambda_t + \beta_0 \Delta I_{i,0} + \beta_1 I_{i,1} + \epsilon_{i,t}
\]

In a more general case such as

\[
y_{i,t} = \alpha_i + \lambda_t + \sum_{j=t-1}^{t+L} \delta^1_{t,j} I^1_{i,j} + \epsilon_{i,t}
\]

this procedure proceeds recursively

\[
y_{i,t} = \alpha_i + \lambda_t + \beta^1_{t-1} \Delta I^1_{i,t-1} + \ldots + \beta^1_{t+L-1} \Delta I^1_{i,t+L-1} + \beta^1_{t+L} I^1_{i,t+L} + \epsilon_{i,t}
\]

Where \( \beta^1_{t-l} = \delta^1_{t-l}, \beta^1_{t-l+1} = \delta^1_{t-l} + \delta^1_{t-l+1} \ldots \beta^1_{t+L} = \sum_{j=t-1}^{t+L} \delta^1_{t,j} \).

Appendix E. Tax Refund Season, Aggregates

This section documents estimates of the aggregate impact of tax refunds on quarterly consumption. Figure B.6 plots the total amount of refunds processed by week from 2014 to 2016. Weekly variation in 2016 relative to prior years caused by tax day falling on Monday, April 18th of that year (week 16). On average, roughly $225 billion in refunds are processed within the first quarter of each year.

A back of the envelope calculation, utilizing a combination of BEA non-seasonally adjusted aggregate Personal Consumption Expenditures data, the IRS reports of refunds processed by week, each adjusted for inflation; and the dynamic paths of expenditure estimated in the transaction data, imply consumption out of tax refunds on average accounts for as much as 3.3% of aggregate expenditure in the first quarter of each year. This, compared to an upper bound of 7.4% of aggregate expenditure if the 1 week MPC were equal to one.

Appendix F. Tax Refund Responses

Appendix F.1. Event Identification

Tax refunds and are identified from transactions to which either a state treasury or the U.S. Department of the Treasury is the counter-party. Since counter-party identification is necessary for transaction identification, those reconciling their taxes via paper check are not included in the main analysis. For the population receiving refunds, this does not appear to be overly restrictive. The IRS reports that roughly 80% of refunds are paid via
direct deposit. Direct deposit refunds are about 26% larger, however ($2,995 on average, versus $2,370 for refunds issued via paper check in 2016\footnote{Source: IRS}). Differences in the form of refund receipt are likely driven by age, income, and whether a household is banked. I address these biases further in the external validation section above.

Tax filing dates are identified from the first payment of the calendar year that a household makes to either a brick and mortar or online tax service provider. These filing dates are identified for roughly 18% of households with observed tax refund activity. Below I show that the distribution of tax reconciliation dates for this subset largely aligns with the broader population and that the empirical results are similar across these populations; alleviating concerns of selection bias in filing date identification\footnote{It is likely that identification of filing dates restricted to brick and mortar and online tax service providers trims two tails of the income distribution: those who self-prepare, and those who employ private accountants to prepare their taxes.}.

Roughly 55% of refunds are received by the end of week 10 (early March), while an additional 13% are clustered in the two weeks around the filing deadline\footnote{Those filing early likely seek liquidity, while those filing later likely have more complicated returns or prefer to delay the task.}. Tax refunds receipt represents a significant cash flow event, equating to 39% of average monthly income. The timing of refund arrival is driven by variation in processing times within and across counter-parties, whereas variation in payments is driven by individual selection and the externally imposed filing deadlines.

\textit{Appendix F.2. Imputation Procedure}

As described in the main body of the text, I perform an imputation to assign an appropriate portion of cash outflows, unclassified checks, and payments to unobserved...
credit card accounts to non-durable expenditures. The purpose of these procedures is to overcome a significant difficulty faced by users of administrative transaction data - the categorization of unclassified transactions.

The procedure makes two broad assumptions: 1) that the proportion of cash, unclassified checks, and payments to unobserved credit card accounts that the household expends on non-durables is commensurate with that of the identifiable portion of total expenditure, and 2) that the excess response of these categories at income receipt scales proportionally. In the following section (Appendix F.3) I show that shifts in the composition of expenditure around the refund receipt are small, and so (2) is likely a reasonable approximation. For assumption (1), the SCPC provides some suggestive evidence. In 2018 roughly 40% of cash and paper check transactions represented purchases of retail goods. Likewise, roughly 36% of payment card (credit, debit, pre-paid) transactions were toward retail goods.

The pre-imputation non-durable response for the total population is reported here:

I report the cross-sectional non-durable consumption responses obtained before the imputation procedure (Figure F.20).

Define the mean observable proportion assigned to non-durables for individuals in population $q$, $\xi^q \equiv \frac{1}{N} \sum_{i=1}^{N} \frac{e^{i,q}_{ND}}{e^{i,q}_{ND} + e^{i,q}_C}$, where $e^{i,q}$ denotes total expenditure, $e^{i,q}_{ND}$ non-durables under the measure including services, and $e^{i,q}_C$ the unidentified cash, check, and credit expenditures. The imputed non-durable consumption responses for cross-sectional quantile $q$ at lag $j$ are then obtained via $\delta^{ND}_{j} = \delta^{ND}_{j} + \xi^q \cdot \delta^{C}_{j}$. Expenditures used to compute the expenditure share $\xi$ are taken from the month prior to tax refund receipt.

As reported above, the average MPCs pre-imputation are 0.121 after one month and 0.16 after one quarter. At the median, MPCs are roughly one-third lower, in line with the one third of expenditure that is unclassified. Qualitatively, the results are robust to this upward shift. As reported in the main text, post-imputation non-durable expenditures accounts for 47% of the total expenditure response. Figure F.21 plots the total expenditure results.
Appendix F.3. Expenditure Composition around Refund Receipt

Here I report the average proportion of expenditure by consumption category around tax refund receipt. On the intensive margin average expenditures on durables increases by 93% in the week of refund receipt with respect to the week prior (from $48 to $93). Additionally, durable expenditures increase from 3.6% to 4.3% of the expenditure basket (a 19.4% increase). On the extensive margin, the proportion of households observed making durable purchases of more than $100 increases from 6.9% to 8.6% to 14.8% in the month before, week before, and week of refund receipt, respectively (the increase is from
0.4% to 0.5% to 1.5% of households for purchases in excess of $1000).

![Expenditure Categories, Proportion of Total Expenditure by Time Period](image)

**Figure F.24: Weekly Consumption Basket Around Tax Refund**

However it is notable that the expenditure response is not simply story of timing large durable purchases to refund receipt. Average expenditure towards non-durable goods and services increase by 47% and 28% respectively, and their contributions to total expenditure as measured by proportions of the weekly consumption basket are largely stable - crowded out mainly by durables and cash outflows in the week of refund receipt.

The proportion of expenditure in the form of cash outflows increases from 14.6% to 19.4% in the week of refund receipt (an increase of 32.8%). For context, according to the 2016 SCPC, U.S. households reported that 27.4% of their monthly expenditure was in the form of cash. Figures 8 and 9 plot proportions of consumption basket around refund receipt and average weekly expenditure by consumption category respectively. This large jump are likely some combination of households supplementing cash balances and financing consumption that is roughly contemporaneous with withdrawal.

Below I report the expenditure composition around refund receipt for the first and fifth quintiles of liquidity:

![Expenditure Categories, Proportion of Total Expenditure by Time Period, Lowest Liq/Income Quintile](image)

**Appendix F.4. Tax Refund Expenditure Responses**

In this section I provide a view of the household balance sheet response to tax refund receipt. On average, the cumulative proportion of a tax refund expended in the month prior to receipt is 0.009 - less than one cent of every dollar received. Tax refund responses to receipt are immediate. On the day of receipt 7.4 cents of every dollar received are
expended, 41.7 cents are expended within 30 days, and 59.4 within 150 days. On average, 73% of the 150-day total expenditure response to tax refunds occurs within 30 days of receipt. This includes 66% of non-durable expenditure and 47% of food services consumption responses occurring within the first 30 days.

The residual total expenditure not spent towards non-durables or debt payments are classified as durables. I report this category below:

The findings are qualitatively robust to the category of expenditure considered. Crucially, they hold for food services expenditures (restaurants and bars), which can be largely attributed to contemporaneous consumption.

Below I show that credit card balance accumulation in advance of receipt is negligible with a less than one to two cents of every refund dollar spent towards debt repayment.
Appendix F.5. Receipt of Multiple Tax Refunds

In this section I analyze consumption and expenditure responses at the date of tax filing and subsequent refund receipt for those households receiving state and federal re-
funds in the same year. Notably, excess sensitivity is restricted to receipt (as opposed to filing), and anticipatory spending out of a second refund is muted and excess sensitivity is significant. This, even though receipt of the first occurs shortly beforehand, and both are sizable.

I begin by estimating specification (1), where $I_{1i}$ is the first tax refund received in the calendar year received by household $i$, and $I_{2i}$ is the second. Identification relies on both variation in calendar of refund arrival, and variation in the timing between receipt of the first and second refunds. The former (latter) is driven by variation within (between) state and federal refund processing times. More formal arguments for identification are outlined above. Both refunds are of a significant magnitude - the average state refund is $1218, whereas the average federal refund is $2845. On average, these two refunds arrive within ten days of one another (See Figure 2). Figure 9 plots the estimated cumulative total expenditure responses proportional to each refund.

Figure F.26: Tax Refund Responses, Multiple Refunds

With respect to 10 days prior to receipt, the cumulative expenditure out of the second refund is just 0.29 cents of every refund dollar, while the response on the day of receipt is 5.2 cents. There is thus no significant evidence that the first refund receipt is used to smooth through the second - i.e. both generate a large degree of excess sensitivity. It is, however, the case that receipt of the first refund mutes the overall expenditure response to the second. Both of these findings are consistent across categories of expenditure. While the first result could not be generated by liquidity constraints alone, the latter is consistent with any model in which the consumption policy function is concave in current assets.

I report the non-durable responses to each refund receipt below:

Appendix F.6. Tax Filing

In this section I analyze the consumption response at tax filing. Embedded within the tax filing event is a combination of a resolution of uncertainty and the allocation of household attention to future income receipt. While the date of tax refund receipt is the source of some uncertainty given variation in processing times and the risk of errors in a household’s return, the date of tax filing is directly chosen by household. As described
above, tax filing dates are identified from the first payment of the calendar year that a household makes to a brick-and-mortar or online tax services provider.

Filing dates are identified for 17.3% of the population receiving refunds. Below I show that this subpopulation is broadly similar to the general refund population in terms of observables, and that the distribution of refund arrival dates (largely driven by filing date self-selection) largely coincides across populations. The latter provides suggestive evidence that the results below are not driven by unobservables.

Table D.18 reports moments summarizing each population of refund recipients. The two groups are broadly similar in terms of liquid wealth and income, with the filing date population appearing to be slight more homogenous. Refunds for the filing date identified subgroup are slightly smaller than the broader population.

I estimate specification (1), where $I_{i,1}$ is the first tax refund received in the calendar year received by household $i$, and $I_{i,0}^0$ is the return at the date of filing. Consumption responses are estimated with respect to a household’s total observed tax return (ie. $I_{i,0}^0 = (I_{i,0}^1 + I_{i,0}^2)$
Table F.15: Summary Statistics, Tax Refund Recipients, broad population versus filing dates identified subset

<table>
<thead>
<tr>
<th></th>
<th>Broad Population</th>
<th>Filing Dates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
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<tr>
<td>Liquid Balances</td>
<td>7279</td>
<td>581</td>
</tr>
<tr>
<td>Income</td>
<td>5259</td>
<td>2425</td>
</tr>
<tr>
<td>Tax Refund, First</td>
<td>2072</td>
<td>360</td>
</tr>
<tr>
<td>Tax Refund, Second</td>
<td>2057</td>
<td>317</td>
</tr>
</tbody>
</table>

Figure F.29: Filing Date Sub-Population Comparison

for a household receiving state and federal returns). For a household receiving state and federal returns).

Figures 10 and 11 report the cumulative total expenditure (less payments to tax service providers at the filing date) and non-durable consumption response around the dates of filing and refund receipt. Relative to 30 days prior to filing 0.018 cents of every tax return dollar is expended. An additional 0.57 cents are expended at the date of filing, with a 30 day response of 1.28% of the refund. In comparison, the excess sensitivity of total expenditure on the day of refund receipt is 6.20 cents relative to the day before, with 42.5% of the refund expended over 30 days.

The above result holds for total expenditure, as well as more discretionary non-durable purchases. This dichotomy between receipt and filing suggests consumption responses are unlikely to be driven by myopia on the part of households, as filing entails a measurable allocation of resources both monetarily (the average cost to file is $82) and in terms of time taken to fill out the return. By itself, the lack of response at filing aligns with an environment in which expectations regarding the size of returns are correct, on average. But systematic inattention to the inflow in advance of filing would surely produce a large degree of excess sensitivity on this day.

These consumption responses are consistent with a model in which households face externally imposed liquidity constraints. However, this result holds for households with substantial liquid wealth (Figure F.29) who receive multiple large refunds and credit card holders (according to the SCPC, roughly 75% of U.S. households held credit cards in 2016.) who could conceivably borrow interest free for the short interval in advance of

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51 Results are broadly identical when measuring with respect to only the first refund, and are qualitatively similar when the filing date is demarcated by an indicator (ie. $I_{t}^{0} = I_{t}^{0}$), in which case $\{s_{j}^{0}\}_{t_{1}-t}$ measure the response in dollar terms, as opposed to as a proportion of the return.
refund receipt. Further, this unwillingness to consume in advance of receipt is unlikely to be driven by expectations of delays in refund arrival given that the median refund arrival time is just 8 days after filing, with 94% arriving within 30 days and 97% within 60 days.

**Appendix F.7. Refund Receipt by Income & Cash-on-Hand**

I this section I subdivide the population receiving refunds into low, middle, and high income households according to annual income in the calendar year prior to the tax event. These groups include households observed earning less than $40,000, between $40,000 and $120,000, and greater than $120,000 of take home income, respectively. Within the population of households receiving tax refunds, the proportion of households within each income group is 0.345, 0.56, and 0.095. I further subdivide income groups according to low, middle, and high levels of cash on hand. These subgroups include households with below median, between the median and 75th percentile, and above the 75th percentile of Liquid Account over Total Income, respectively.

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52The $120,000 cutoff is quite extreme. According to the 2014 ACS, less than 6% of American household’s pre-tax income exceeded this figure.

53In a variance decomposition across observables, liquid balances and income account for over 75% of the explainable variation in MPCs.
Expenditure responses across these subpopulations share the qualitative characteristics of the wider population (Figure 18). Responses in levels predictably decline in cash balances within each income bracket. Amongst high income individuals in the middle cash-on-hand group (approximately 1.05 months of income in liquid accounts), the expenditure response over 120 days is 0.41. Amongst the high income, high cash on hand group (over 10 weeks of income in liquid accounts), the 120 day response is 0.34. This particular subgroup represents roughly 2.4% of the overall refund-receiving population. It is only at these high levels of income and cash-on-hand that a notable degree of anticipatory spending is observed - roughly 3.5 cents of every refund dollar in the three weeks prior to receipt. The level of excess sensitivity in the (three) week(s) following receipt, however, is an additional 9.6 (17.6) cents of every refund dollar.

Income processes estimated for each of the nine groups (Table F.16) suggest that, within income brackets, household incomes display similar levels of month-to-month persistence and volatility across levels of cash on hand. These income processes are estimated in a similar manner to that of the main text - by obtaining residuals from a first-stage regression of log income on a polynomial in age and then estimating an AR(1) process.

This suggests that households holding higher levels of cash-on-hand is not driven simply by income volatility, but rather a degree of self-selection related to household choice among savings vehicles and alternate balance sheet structures (i.e., stock market participation).

Appendix F.8. The Non-Hand-to-Mouth and Large Refunds

In this section I focus the analysis to a population of households deemed to be non-hand-to-mouth households. The criterion for this classification is chosen to be restrictive - households with ten or more weeks of income in their liquid accounts. I begin by describing this population of households and comparing observables to the population of more constrained households. In this section I present two main results. First, even amongst the population of decidedly non-hand-to-mouth households anticipatory expenditure is insignificant and excess sensitivity is great. Second, the results hold even for households receiving very large tax refunds, as measured relative to their average monthly income.
or expenditure. This result is notable - it suggests that significant promised rewards do not produce large anticipatory responses, even amongst those households with sufficiently liquidity to smooth through the cash-flow event.

In this section I restrict the analysis to the biggest tax refund of a household’s calendar year in order to test whether these large salient events can generate significant anticipatory responses. Further, I expand the sample to include all of those households with average Liquid Account $\geq 2.5$ in the year prior to the tax event for all years in the sample 2014-17. The median non-hand-to-mouth household holds almost three months of income in liquid assets, while tax refunds represent roughly 2.5 weeks of monthly income (Table 11).

Annual incomes amongst the non-hand-to-mouth largely align with those of the rest of the population (hereafter referred to as the hand-to-mouth). As shown in the previous section, levels of liquidity are not highly correlated with levels of income volatility within income brackets. Further, as reported above, these states are relatively persistent over

Figure F.32: Expenditure Responses, Income and Asset Distributions
Table F.17: Monthly Income Estimates by Bracket

<table>
<thead>
<tr>
<th>Categorized Income</th>
<th>LiquidBalance</th>
<th>Income</th>
<th>Total Income</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Income</td>
<td>Low</td>
<td>0.823</td>
<td>0.037</td>
</tr>
<tr>
<td>(&lt; 40k)</td>
<td>Middle</td>
<td>0.835</td>
<td>0.035</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>0.857</td>
<td>0.035</td>
</tr>
<tr>
<td>Middle Income</td>
<td>Low</td>
<td>0.859</td>
<td>0.04</td>
</tr>
<tr>
<td>(40k – 120k)</td>
<td>Middle</td>
<td>0.861</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>0.859</td>
<td>0.043</td>
</tr>
<tr>
<td>High Income</td>
<td>Low</td>
<td>0.786</td>
<td>0.074</td>
</tr>
<tr>
<td>(&gt; 120k)</td>
<td>Middle</td>
<td>0.774</td>
<td>0.079</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>0.810</td>
<td>0.079</td>
</tr>
</tbody>
</table>

Table F.18: Summary Statistics, the Non-Hand-to-Mouth

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>25th</th>
<th>Median</th>
<th>75th</th>
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</thead>
<tbody>
<tr>
<td>Liquid Balances</td>
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<td>4466</td>
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</tr>
<tr>
<td>Income</td>
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<td>2311</td>
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<td>6387</td>
</tr>
<tr>
<td>Tax Refund, Larger</td>
<td>3359</td>
<td>1090</td>
<td>2325</td>
<td>4605</td>
</tr>
</tbody>
</table>

time. Average ages of primary account holders across the non-hand-to-mouth and hand-to-mouth populations of refund recipients are 47 and 41, respectively. This suggests some component of liquidity may be driven by life-cycle liquid wealth accumulation.

I begin by estimating specification (1) for the entire non-hand-to-mouth population. These results are reported in the accompanying Appendix and are consistent with those of previous sections. Notably, these non-hand-to-mouth households display average 150 day responses of 44.5 cents of every refund dollar, with 67.5% of the cumulative 150-day response occurring within the first 30 days. Roughly 2.7 cents are expended over the month in advance of receipt, with an additional 15 cents expended in just the first week. Likewise, for non-durable goods, cumulative responses average of 6.43 cents of every
refund dollar, with 56% of the cumulative response occurring within the first 30 days.

In order to assess whether large refunds are associated with a greater degree of anticipatory spending or overall consumption smoothing I quantile the non-hand-to-mouth population according to \( \frac{\text{Refund}}{\text{Total Income}} \). Table 12 reports these quantiles. Above the 80th percentile, the average refund totals over $6500 and represents in excess of six weeks of household income. It should be noted that these results come with a caveat - that of a degree of self-selection in terms of refund size. I later address this by testing household expenditure responses to another form of large expected income - annual bonuses. To address the concern that responses are driven by household expenditure on big ticket items (vacations, appliances, etc.) I test non-durable consumption responses as well.

Table F.19: The Non-Hand-to-Mouth, Refund Size, Median Ratio by Quantile

<table>
<thead>
<tr>
<th>Quantile</th>
<th>40th</th>
<th>60th</th>
<th>80th</th>
<th>90th</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \frac{\text{Refund}}{\text{Total Income}} )</td>
<td>0.75</td>
<td>1.13</td>
<td>1.73</td>
<td>2.95</td>
</tr>
</tbody>
</table>

Across quantiles of the \( \frac{\text{Refund}}{\text{Total Income}} \) distribution excess sensitivity and muted anticipatory responses persist. Of the total 120-day expenditure responses the proportion coming in the first thirty days is 71%, 69%, 68%, and 73% across the 40th, 60th, 80th, and 90th quantiles, respectively. For non-durable consumption the results are similar - 74.5%, 71%, 66%, and 62%, respectively. Crucially, total anticipatory responses are insignificant - totaling less than 3.89 cents of the refund in the 3 weeks in advance of receipt amongst the 40th percentile group, and 22 cents in the next three weeks.

To put the above in monetary terms, a back of the envelope calculation implies households amongst the 90th percentile expend an additional $2861 in the month of refund receipt\(^54\). In order to address the concern that the results are driven by a levels of expenditure on the part of the household in the baseline period, I instead quantile the non-hand-to-mouth population according to \( \frac{\text{Refund}}{\text{Total Expenditure}} \). These results are robust to this alternative measure of liquidity.

\(^{54}\)As reported in plot, the average refund above the 90th percentile is $7382, while median refund amongst this group is $6050.
Appendix G. Other Forms of Income

In this section I show that the paper’s main results are robust to the form of income considered. Here I extend these analysis to regular paychecks and bonus checks. Within subsequent sections analyzing particular events I further detail the subpopulations of interest.

Regular paychecks include employer payroll and direct deposit inflows. Labor income accounts for around 75% of median monthly income, with this proportion decreasing in household total income. The average household within the population receiving refunds receives 2.6 paychecks each month, totaling $1383 apiece. I estimate the consumption responses to regular paychecks within this subset in order to derive an internally valid comparison to tax refund responses.

Bonus checks are identified for a subset of the overall population by first establishing a household’s regular pay cadence. Bonus pay is then defined as off-cadence checks from a household’s employer that are at least one standard deviation and $100 larger than an average paycheck. I provide further exposition regarding this identification procedure below. The median bonus totals $5630, and the average check represents almost six weeks of household income.

Appendix G.1. Regular Paychecks

In this section I compare regular paycheck responses to tax refund responses for the tax refund population analyzed in the main text. Unlike tax refunds, the day of receipt for a regular paycheck is fully known in advance and occurs at a regular cadence (as opposed to once or twice each year). Whereas the magnitude of a tax refund can chosen, to the extent described earlier; many workers (especially the salaried) face a fixed structure of compensation dictated by their individual employment contracts.

In comparison to the first tax refund households receive, which averages $2072 paychecks are significantly smaller, at an average of $1414. Households receive an average of 2.6 paychecks each month, a number that varies according to each worker’s cadence of pay and the number of workers within each household depositing their paychecks to the primary account. In contrast with estimation of tax refund responses, three notable complications arise when estimating consumption responses to paychecks - calendar variation necessary for identification across households, correlation of receipt with calendar-driven expenditures within households, and overlapping response periods.

Taking each of the above in turn; the variation in pay schedules provided by weekly, bi-weekly, bi-monthly, and monthly pay frequencies as well as the alterations to these schedules provided by holidays, allows for disentangling day-of-week effects from paycheck responses. Paycheck receipt, however, is inevitably tied to calendar-driven expenditures (rent, mortgage, etc.), especially early in the month. To address this issue, it is necessary to restrict the analysis to discretionary categories (food services, non-durables) in order

---

55A measurable portion of those unclassified inflows coming in form of paper checks, cash, and unclassified ACH, are likely labor income. According to the National Automated Clearing House Association (NACHA), 82% of U.S. households received their pay via direct deposit/ACH in 2016.
uncover the underlying household consumption behavior. Due to the high cadence of regular paychecks, the response periods between one paycheck and the next will overlap over long horizons, thereby biasing the results. In order to address this issue, I focus the analysis to a the week before and after a paycheck.

As with tax refunds, households exhibit excess sensitivity to receipt of regular paychecks across categories of expenditure (Figure 22) and across quintiles of the liquid balance-to-income ratio (Figure 23). Amongst the lowest liquidity quintiles, a dip in non-durable expenditure is observed, suggesting that expenditures among these subpopulations are particularly timed to paycheck receipt.

Table G.20: Cross-Section of Liquid Balance-to-Income, Regular Paychecks (Refund Population)

<table>
<thead>
<tr>
<th>Quintile</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Paycheck</td>
<td>1057</td>
<td>1301</td>
<td>1495</td>
<td>1600</td>
<td>1582</td>
</tr>
</tbody>
</table>

Figure G.35: Consumption Responses Around Regular Paychecks

Figure G.36: Non-Durable Goods Responses Around Regular Paychecks, Cross-Section

In dollar terms, the average household amongst the first quintile spends an additional $123 on non-durable goods (including an extra $46 in groceries) in the week following paycheck receipt, as compared to the week prior. Amongst this group average checking
Figure G.37: Path of Liquid Balances Around Regular Paychecks

The consumption responses at payday are somewhat surprising, given the liquid balances on hand that households could utilize to smooth day to day, even amongst the most constrained. Average daily non-durable expenditure in the week in advance of paycheck receipt amongst the first quintile is $24.59, meaning excess sensitivity to a paycheck amounts to an extra five days of baseline expenditure, on average, in the week following receipt. Households among the fourth and fifth quintiles spend an excess of $48 and $30, respectively, in the week after paycheck receipt. The deviations from perfect consumption smoothing observed amongst these populations of non-constrained households represent distortions of 10% and 7% of bi-weekly consumption.

These shifts in consumption are small relative to those induced by tax refund arrival. However, the kink in consumption responses at paycheck arrival is indicative of a preference to consume at receipt rather than at an earlier date, even for those with sufficiently liquidity. The cycles in liquid balances induced by paycheck receipt (Figure G.29) is further evidence of short-term budgeting via internally imposed constraints on the part of households.

Appendix G.2. Bonus Checks

In this section I study a population of 163,300 households observed receiving bonus paychecks. In what follows I describe the population of interest, and then estimate household expenditure responses to this cash flow event. I conclude by drawing internally valid comparisons between bonus and tax refund consumption responses for a subset of this population. Notably, the results of the main text are robust to this form of income.

Employers may aggregate bonuses and regular pay or process bonuses separately. Identifying bonus checks in transaction data requires first determining a worker’s regular

---

\(^{56}\)Figure 24 plots the average balances around paycheck receipt for each liquid balance quintile. A kink is visible on day 2 in each subplot - aligned with Sundays for most of the population (58% of all paychecks arrive on Fridays).
pay cadence, and then separately distinguishing large, off-cadence checks from their employer.\textsuperscript{57} Workers with a regular cadence are identified as those having 90% of their paychecks come 13 to 17 days apart. Bonus pay is then defined as checks from a household’s employer arriving outside this window that are at least one standard deviation and $100 larger than an average paycheck. The analysis is restricted to those workers receiving at most two such checks during a calendar year.

Figure G.30 plots the timing of bonus checks by calendar week. The majority of bonuses arrive early in the year with a significant portion arriving shortly before March 15th (the federal deadline companies face for deducting bonuses from the previous year’s earnings, otherwise known as 409A Day).

![Figure G.38: Timing of Bonus Paychecks](image)

Bonus checks are significant, representing over a months income for the average bonus recipient (Table G.18). Also reported are the magnitudes of tax refunds for the subset of bonus recipients receiving them in the same calendar year.

| Table G.21: Summary Statistics, Bonus Check Recipients |
|----------------------------------|---|---|---|---|
| Liquid Balances                  | Mean 12690 | 25th 2024 | Median 4930 | 75th 13609 |
| Income                           | 8246 | 4207 | 6182 | 9396 |
| Bonus Check                      | 11445 | 3290 | 5733 | 10802 |
| Tax Refund                       | 2818 | 582 | 1170 | 3906 |

I estimate the expenditure responses of this population to bonus check receipt. Qualitatively, the results are similar to those of the refund population. This includes insignificant anticipatory spend and a large degree of excess sensitivity at receipt, with a majority of the response coming in the first thirty days.

In order to obtain an internally valid comparison across groups, I quintile this group according to the same Liquid Asset\textsuperscript{Liquid Asset / Income} bounds as the refund population studied in the main text. Table G.22 summarizes.

I estimate the total non-durable responses to bonus receipt by quintile and report these a similar manner to the refund population (Figure G.32). The tight correlation

\textsuperscript{57} The tax code is agnostic about bonus checks arriving with regular paycheck or separately. In order to cleanly identify the magnitude of these inflows, I restrict the analysis to off-cadence checks.
between \( \frac{\text{Liquid Asset}}{\text{Income}} \) and consumption responses, along with significant responses amongst the highly liquid, is evident here.

**Appendix H. Further Cross-Sections and Variance Decomposition**

In this section I report consumption responses to tax refunds across deciles of observables at the monthly frequency and perform a variance decomposition to identify which
correlates account for variation in marginal propensities to consume. Table H.22 reports averages across observables by decile. I estimate

$$y_{i,t} = \alpha_i + \lambda_t + \sum_{j=t-L}^{t+L} \delta_j I_{i,j} + \epsilon_{i,t}$$  \hspace{1cm} (H.1)$$

at the monthly frequency, where $y_{i,t}$ denotes non-durable goods or total expenditure responses. Intercepts $\alpha_i$ and $\lambda_t$ are household and month fixed effects, respectively, and $I_{i,j}$ represents the amount of the tax refund at lead/lag $j$ days received by household $i$.

I estimate specification H.1 for a series of observables by decile. Variables in figure H.35 denoted average measure means across the nine months prior to refund receipt. Notably, there are right negative correlations between consumption responses and age, income, and liquid balances. Consumption responses are relatively flat across the distribution of CVs of income, and dips only for those households above the 80th percentile in income volatility. Consumption responses are upward sloping in account logins (mobile and online), a proxy for account engagement and attention.

<table>
<thead>
<tr>
<th>Decile</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>25</td>
<td>29</td>
<td>33</td>
<td>37</td>
<td>41</td>
<td>45</td>
<td>49</td>
<td>53</td>
<td>57</td>
<td>62</td>
</tr>
<tr>
<td>Income</td>
<td>2534</td>
<td>2675</td>
<td>3026</td>
<td>3450</td>
<td>3949</td>
<td>4543</td>
<td>5307</td>
<td>6356</td>
<td>8020</td>
<td>13725</td>
</tr>
<tr>
<td>Liquid Assets</td>
<td>133</td>
<td>378</td>
<td>635</td>
<td>968</td>
<td>1434</td>
<td>2134</td>
<td>3261</td>
<td>5264</td>
<td>9579</td>
<td>33176</td>
</tr>
<tr>
<td>C.V. of Income</td>
<td>0.08</td>
<td>0.15</td>
<td>0.19</td>
<td>0.22</td>
<td>0.25</td>
<td>0.31</td>
<td>0.39</td>
<td>0.50</td>
<td>0.70</td>
<td>1.25</td>
</tr>
<tr>
<td>Daily Logins</td>
<td>0.07</td>
<td>0.23</td>
<td>0.42</td>
<td>0.60</td>
<td>0.77</td>
<td>0.95</td>
<td>1.17</td>
<td>1.45</td>
<td>1.90</td>
<td>3.35</td>
</tr>
</tbody>
</table>

I perform a variance decomposition across observables in order to ascertain which correlates account for explainable variation in consumption responses. I calculate monthly and quarterly MPCs non-parametrically by calculating

$$MPC_{i,t} = \frac{\Delta c_{i,t}}{\Delta y_{i,t}} = \frac{c_{i,t} - c_{i,t-1}}{Refund_{i,t}}$$

Where $Refund_{i,t}$ denotes the tax refund amount and $c_{i,t}$ denotes consumption in the quarter or month $t$ of refund receipt. For any variable $x_{it}$ denote the baseline average level by

$$\bar{x}_{it} = \frac{\sum_{j=t-T}^{t} x_{ij}}{T}$$

and deviation from baseline

$$\bar{x}_{it} = x_{it} - \bar{x}_{it}$$

For this variance decomposition exercise I use the 9 months prior to refund receipt to
calculate a baseline measure. Households are identified as homeowners if they contribute at least $1000 to mortgage payments during the baseline period. Differencing derives an orthogonal component. I estimate the following specification

\[ MPC_{it} = \alpha + \gamma_1 \text{age}_{i,t} + \gamma_2 \text{liq\_bal}_{i,t} + \gamma_3 \text{liquid\_bal}_{i,t} + \gamma_3 \text{credit\_bal}_{i,t} + \gamma_3 \text{credit\_bal}_{i,t} \\
+ \gamma_4 \text{income}_{i,t} + \gamma_5 \text{income}_{i,t} + \gamma_5 \text{loan}\_sls}_{i,t} + \gamma_6 \text{loan\_sls}_{i,t} \\
+ \gamma_6 \text{home}_{i,t} + \epsilon_{i,t} \]

and perform a variance decomposition of the resulting estimates. Due to correlation in RHS variables, a variance decomposition is sensitive to the ordering of regressors. When
regressors are uncorrelated, one can remove regressors one by one and record the difference in $R^2$ as the variance of the response explained by each subsequent regressor.

In order to address this issue I use the method of Lindeman, Merenda, and Gold (1980) which derives the variance decomposition from sequential sums of squares averaged over all permutations of the RHS variables. Table E.18 presents the results of this procedure.

Table H.24: Variance Decomposition, Tax Refund Consumption Responses

<table>
<thead>
<tr>
<th>Variable</th>
<th>Proportion of Variation</th>
<th>Correlation</th>
<th>Proportion of Variation</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0.0053</td>
<td>+</td>
<td>0.0168</td>
<td>+</td>
</tr>
<tr>
<td>Liquid Balance</td>
<td>0.5841</td>
<td>−</td>
<td>0.5006</td>
<td>−</td>
</tr>
<tr>
<td>Liquid Balance, Deviation</td>
<td>0.0008</td>
<td>+</td>
<td>0.0013</td>
<td>+</td>
</tr>
<tr>
<td>Credit Card Balance</td>
<td>0.0317</td>
<td>−</td>
<td>0.0007</td>
<td>+</td>
</tr>
<tr>
<td>Credit Card Bal., Deviation</td>
<td>0.0036</td>
<td>−</td>
<td>0.0012</td>
<td>−</td>
</tr>
<tr>
<td>Total Income</td>
<td>0.1667</td>
<td>−</td>
<td>0.1333</td>
<td>−</td>
</tr>
<tr>
<td>Total Income, Deviation</td>
<td>0.0571</td>
<td>−</td>
<td>0.0515</td>
<td>−</td>
</tr>
<tr>
<td>Account Logins</td>
<td>0.0538</td>
<td>+</td>
<td>0.1399</td>
<td>+</td>
</tr>
<tr>
<td>Account Logins, Deviation</td>
<td>0.0480</td>
<td>+</td>
<td>0.038</td>
<td>+</td>
</tr>
<tr>
<td>Home Owner</td>
<td>0.0487</td>
<td>−</td>
<td>0.1147</td>
<td>−</td>
</tr>
</tbody>
</table>

Notably, the baseline measure of liquid balances accounts for over half of the explainable variation in consumption responses. Once controlling for liquid balances and income, age has very little explanatory power for consumption responses.

Appendix H.1. Non-Parametric Approach & Self-Selection

In this section I further explore the panel dimension of tax refund responses by exploiting within household variation in liquidity across years. As above, I construct monthly non-durable MPCs non-parametrically, ie. $\frac{\Delta e_{i,t}^{ND}}{\Delta \text{Income}_{i,t}} = \frac{\Delta e_{i,t}^{RD}}{\Delta \text{Refund}_{i,t}}$. I decile households by Liquid Assets as in the event study design explore in the main text. I regress the non-parametric MPCs on this grouping as follows

$$
\frac{\Delta e_{i,t}^{ND}}{\Delta \text{Refund}_{i,t}} = \alpha_i + \gamma_t + \sum_{q=2}^{10} \beta_q \frac{\text{Liquid Assets}^q}{\text{Income}}_{i,t} + \epsilon_{i,t}
$$

(II.2)

Where $\alpha_i$ represents a household fixed effect and $\gamma_t$ a time fixed effect. The coefficients of interest, $\{\beta_q\}_{q=2}^{10}$, measure the average MPC of each liquidity decile with respect to the omitted group. Figure H.41 plots the results against those obtained in the event study design.

Notably, the negative correlation between liquidity and consumption responses remains. Additionally, the non-durable responses of the highly liquid remain significant. The results indicate that the large responses of the liquidity constrained are more likely
to be driven by self-selection, indicating a role for preference heterogeneity in explaining household proximity to liquidity constraints.

I also consider an imputed version in which I run the reduced form regression $H.2$ with $\frac{\Delta e_{NC}^{r}}{\text{Refund}_{i,t}}$ on the RHS, obtaining coefficients $\{\beta_{q}^{C}\}^{10}_{q=2}$ and then obtaining imputed coefficients via $\beta_{q} + \xi_{q} \cdot \beta_{q}^{C}$ for each decile, where $\xi_{q}$ represents the identified proportion expended towards non-durables for households in population $q$ in the month prior to refund receipt.
### Appendix I. Comparison to Literature, Non-Durable Consumption Responses

<table>
<thead>
<tr>
<th>Source</th>
<th>Income</th>
<th>Data</th>
<th>Frequency</th>
<th>Non-Durables (Quarter of Receipt)</th>
<th>Methodology</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Souleles (1999)</td>
<td>Tax Refunds</td>
<td>CEX</td>
<td>Quarterly</td>
<td>0.03 (0.02)</td>
<td>OLS</td>
<td>Total response: 0.185 (0.077)</td>
</tr>
<tr>
<td>Parker et. al (2005)</td>
<td>2001 Stimulus</td>
<td>CEX</td>
<td>Quarterly</td>
<td>0.386 (0.135)</td>
<td>OLS, 2SLS</td>
<td>-</td>
</tr>
<tr>
<td>Parker et. al (2011)</td>
<td>2008 Stimulus</td>
<td>CEX</td>
<td>Quarterly</td>
<td>0.201 (0.067)</td>
<td>OLS</td>
<td>-</td>
</tr>
<tr>
<td>Kaplan &amp; Violante (2011)</td>
<td>2001 Stimulus</td>
<td>CEX</td>
<td>Quarterly</td>
<td>0.219 (0.079)</td>
<td>2SLS</td>
<td>Trim 1.5% tails</td>
</tr>
<tr>
<td>Keung (2018)</td>
<td>Alaska</td>
<td>Personal Financial Website</td>
<td>Monthly</td>
<td>0.22</td>
<td>OLS</td>
<td>-</td>
</tr>
</tbody>
</table>
Model Appendix

Below all appendices regarding the modeling sections of the paper.

Appendix A. Structural Estimation

![Life-Cycle Income Profile, Liquid Assets](image)

Figure A.44: Deterministic Component of Income, Monthly Frequency

Appendix B. Parameter Identification

Estimate standard buffer-stock model to the objective satisfy

$$\min_{\beta, \gamma, 0, k} \sum_{i}^{N} \omega_{i}^{a} | d_{i,a}^{liq} - m_{i,a}^{liq}(\beta, \gamma, 0, k) | + (1 - \Theta) \sum_{j}^{10} | d_{j}^{mpc} - m_{j}^{mpc}(\beta, \gamma, 0, k) |$$

Where third argument, $\psi$, is set to zero.

Figure D.42 plots the resulting contours for each term of the objective and indicates a
the fundamental trade-off in the standard model between matching liquid asset balances
and consumption responses.

Appendix C. Fiscal Stimulus

Here I compare the aggregate responses generated by a lump-transfer to all households
in the mental accounts economy versus the standard buffer-stock case. All households
receive two weeks of income at time $t$ ($T_i = 0.5 \forall i$). Below I plot the aggregate responses
for the six months before and after stimulus receipt. As documented above, the models
have distinct predictions for both the timing and magnitude of household consumption
responses.

In comparison to the standard buffer-stock case, the mental accounts economy generates
a response that is 4.35 times larger on impact, 2.55 times larger over one quarter, and
1.82 times larger once the stimulative effects die out after seven months. The magnitude
of these aggregate responses has
Table C.25: Pre-Financed Stimulus Response Comparison

<table>
<thead>
<tr>
<th></th>
<th>Mental Accts.</th>
<th>Buffer-Stock</th>
</tr>
</thead>
<tbody>
<tr>
<td>Announcement</td>
<td>0.009</td>
<td>0.014</td>
</tr>
<tr>
<td>Receipt</td>
<td>0.226</td>
<td>0.052</td>
</tr>
<tr>
<td>One Quarter</td>
<td>0.24</td>
<td>0.094</td>
</tr>
</tbody>
</table>

Appendix D. Alternate Economies

Appendix D.1. Infinite Horizon

Here I solve a consumption/savings problem with mental accounts at the infinite horizon. Agents solve

$$\max_{\{c_t\}_{t=0}^{\infty}} \mathbb{E}_0\left[ \sum_{t=0}^{\infty} \beta^t \nu(c_t) \right]$$

subject to

$$c_t + a_{t+1} \leq y_t + (1 + r)a_t$$
Writing the problem recursively

\[ V(a, y) = v(c) + \beta \mathbb{E}[V(a', y')] \]

\[ \text{st.} \]

\[ c + a' \leq y + (1 + r)a \]

Let \( y \in \{y_{\text{low}}, y_{\text{high}}\} \). Here I consider a savings default such that the agent attempts to save a proportion \( 1 - \delta \) of each period's income, \( a^d = a(1 + r) + + (1 - \delta) y \), pinning down default allocation \( c^d = (1 - \delta) y \). In the computational example I use log preferences. Income process \( y_{\text{low}} = 0.9, y_{\text{high}} = 1.1 \), and transition probabilities \( p_{ii} = .8, p_{ij} = .2 \). I solve the model for a variety of parameter values \( \psi \in [0, .25] \) and \( \delta \in [0, .075] \).

Figure 3 plots a typical simulated time series of consumption and assets in this economy. In the left panels I restrict to \( \delta = 0 \), pinning down a hand-to-mouth rule of thumb \( c^d = y \). Under this parameterization the agent is dissaving averse for \( \psi > 0 \). As the psychological cost of deviation increases the agent more closely adheres to the hand-to-mouth rule, and consumption more closely tracks to income. Additionally, during periods of persistently low income the agent dissaves at faster rate for lower levels of \( \psi \). In the right panels I
Figure A.47: Varying Risk Aversion, $\gamma$

Figure B.48: Parameter Identification Contours, Standard Buffer-Stock Model

vary $\delta$, allowing the agent to following a savings accumulation rule-of-thumb. For a given $\psi$, levels of assets are increasing in $\delta$.  

70
Figure C.49: Pre-Financed Stimulus Responses

Figure D.50: Simulated Paths Under Uncertainty

Figure 4 plots the consumption and savings policy functions in this economy for $\psi = 0$ and $\psi = .05$. Mental accounting frictions dominate for low levels of assets. Agents dislike dissaving, and thus consume less than otherwise in the low state, and more than otherwise in the high state. For sufficient levels of savings, agents in the high income state consume their present income. For large levels of assets the policies of the mental accounting agents coincide with those of the non-mental accounting agents.
Figure D.51: Policy Functions (Top: Entire Grid, Bottom: Zoomed In)