The How and Why of Household Reactions to Income Shocks*

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Abstract

This paper studies how and why households adjust their spending, saving, and borrowing in response to transitory income shocks. We leverage new large-scale survey data to first quantitatively assess households' intertemporal marginal propensities to consume (MPCs) and deleverage (MPDs) (the "how"), and second to dive into the motivations and decision-making processes across households (the "why"). The combination of the quantitative estimation of household response dynamics with a qualitative exploration of the mental models employed during financial decisions provides a more complete view of household behavior. Our findings are as follows. First, we validate the reliability of surveys in predicting actual economic behaviors using a new approach called cross-validation, which compares the responses to hypothetical financial scenarios with observed actions from past studies. Participants' predicted reactions closely align with real-life behaviors. Second, we show that MPCs are significantly higher immediately following an income shock and diminish over time, with cumulative MPCs over a year showing significant variability. However, MPDs play a critical role in household financial adjustments and display significantly more cross-sectional heterogeneity. Neither is easily explained by socioeconomic or financial characteristics alone, and the explanatory power is improved by adding psychological factors, past experiences, and expectations. Third, using specifically-designed survey questions, we find that there is a broad range of motivations behind households' financial decisions and identify four household types using machine learning: Strongly Constrained, Precautionary, Quasi-Smoothers, and Spenders. Similar financial actions stem from diverse reasons, challenging the predictability of financial behavior solely based on socioeconomic and financial characteristics. Finally, we use our findings to address some puzzles in household finance.

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1 Introduction

An important question for governments designing fiscal policy is how households spend each dollar they receive. The ”marginal propensity to consume” (MPC), which measures how much households spend out of extra income, is a critical parameter of interest for both research and policymaking. Of specific interest is understanding how households respond to temporary rather than permanent changes in their income. More recently, attention has shifted toward understanding households' spending decisions over time, captured by the ”intertemporal marginal propensity to consume” (iMPC). Aggregating these individual spending responses is important for accurately evaluating the impact of fiscal and monetary policies within heterogeneous-agent models (Auclert et al., 2020; 2024).

This paper dives into the mechanisms and motivations underpinning household responses to transitory financial shocks: it studies both *how* they adjust their spending and debts, and *why* they choose these specific actions. To address these questions, we use new large-scale surveys of representative samples of the US working-age population. The first goal (the "how") is to estimate household-level intertemporal marginal propensities to consume and deleverage out of unexpected income changes, positive and negative, received at different horizons. Estimating the dynamic paths of spending, deleveraging and saving has been challenging with traditional datasets and a survey approach offers promising new opportunities. It allows us to look closely at these changes, including how big the shocks are, whether they are gains or losses, and when they happen. It also permits incorporating more household heterogeneity—not only in traditional aspects like demographics or financial positions but also personal concerns, obligations, and anticipations. Furthermore, we can analyze not only spending but also deleveraging, a critical and generally less-studied adjustment margin.

The second goal of the paper is to explain *why* households react the way they do, i.e., to understand the rationales behind their decisions. Identical observed financial behaviors may stem from completely different motivations. For example, two households might spend more money for very different reasons—one might be splurging, while the other might be buying necessities. Given that various theoretical models could predict similar outcomes, we need more information to discern the cognitive frameworks guiding household financial decisions. This is where survey questions that probe into the thought processes behind specific actions undertaken (e.g., reasons for saving) and decisions to refrain from certain financial moves (e.g., reasons against taking on or increasing debt) come in. Such analysis helps us group households into different "types" based on their decision-making principles.

The how and why parts are complementary. By combining the quantitative estimation of household response dynamics with a qualitative exploration of the mental models employed during financial decision-making, we can provide a more complete view of household financial behavior in response to income fluctuations. We then leverage our combination of quantitative estimates and underlying reasoning to explain some key puzzles in the household finance and macro literatures.

Our third contribution is methodological. Can we really trust what survey respondents say they would do in hypothetical situations to mirror what they would actually do? We perform a new analysis, which we call "cross-validation" to show that surveys are reliable for understanding how people might react in real economic situations. We give survey participants scenarios very similar to those studied in earlier work, specifically using observational data, asking them how they would respond. Their answers closely match actual behaviors observed in past research. We believe this accuracy comes from focusing on everyday financial decisions (like handling an unexpected $1000 expense) rather than rare, life-changing events (like winning a lottery jackpot). When the scenarios are grounded in common everyday experiences, people can more accurately predict their reactions. This shows that for everyday financial decisions, what people say they would do closely matches what they actually do. The cross-validation exercises further bolster the view that surveys can be invaluable tools to forecast and anticipate responses in macro and policy settings.

Our main findings can be summarized as follows. In the quantitative estimation of intertemporal Marginal Propensities to Consume (iMPCs), we observe interesting dynamic behaviors. MPCs are significantly higher on impact (i.e., in the quarter in which the transfer is received or the expense incurred) and tend to be lower over subsequent quarters. Cumulative MPCs over a year are quite distinct from the impact ones in the first quarter (e.g., 0.42 and 0.16, respectively for positive $1,000 income shocks). Impact MPCs show less variability among different people, while the cumulative ones display more heterogeneity. For example, those with greater liquidity consistently show higher MPCs—a puzzle we revisit later. If the shock is anticipated one or two quarters in advance, many households begin to adjust early, except those who are very financially constrained. Smaller and negative shocks generally lead to larger MPCs.[1]

Yet, MPCs only tell part of the adjustment story. Marginal Propensities to Deleverage (MPDs) are substantial (averaging 0.23 immediately and 0.42 over the year for positive $1,000 shocks) and debt adjustment is a crucial strategy for many.[2] MPDs show the greatest diversity among people with different social and economic backgrounds, with those under financial strain exhibiting much higher levels and relying more on debt adjustment.

Interestingly, differences in MPCs and MPDs are not well explained by socioeconomic factors alone. Information on worries, psychological aspects, past experiences, and future plans prove to be informative. To better understand this result, consider for instance households with low liquidity; this condition is a momentary snapshot that could result from various factors, including a lack of patience, self-control, or adverse past events. Indeed, households with low liquidity exhibit notably different MPCs and MPDs based on their specific circumstances.

Our second set of findings centers around the second contribution, namely how households explain their decisions and the thought processes behind them. We find a wide variety of reasons,

[1] Thus, for negative $1,000 shocks, the average cumulative MPC is 0.48 and the average impact MPC is 0.17. For positive shocks equivalent to 10% of income, which are larger than $1,000 for essentially everyone in the sample, cumulative and impact MPCs are 0.37 and 0.12 respectively; the corresponding estimates for negative proportional shocks equivalent to 10% of income are 0.32 and 0.09.

[2] For negative income shocks averaging 0.1 and 0.25, respectively. For additional information, see Figure 2.

underscoring that people can take the same actions for vastly different reasons, and thus, the same behavior might fit into various theoretical frameworks. By applying a machine learning approach to classify these explanations, we identify four primary types of households based on their reasoning for their actions or inactions: the Strongly Constrained (18% of the sample), the Precautionary (16%), the Quasi-Smoothers (18%), and the Spenders (33% of the sample). These categories align to a significant (but not full) extent with models of household behavior found in existing research, showing that these diverse types co-exist in the population. Notably, which category a person falls into cannot be predicted well by their socioeconomic characteristics alone; we see a mix of these types within any socioeconomic group, whether they are lower or higher income, demonstrating the complexity of financial behavior across the spectrum. We also find that heterogeneous-agent incomplete markets model commonly used in the literature are not able to properly reflect the co-existence of such types in steady state – thereby calling for extensions of the current models.[3]

Our third set of findings sheds light on certain puzzles concerning household financial behaviors. First, why do constrained households have lower MPCs than we might expect? These households mostly focus on deleveraging and the most distinguishing feature across households with different assets is in their MPDs rather than MPCs. Second, why do liquid households exhibit high MPCs? They tend to spend on leisure and luxury because they either enjoy splurging or are saving for significant future expenditures, thus facing term liquidity constraints. Conversely, households with limited liquidity prioritize spending on basic needs and essentials due to their immediate necessities. Third, households respond asymmetrically to positive and negative shocks for different reasons: some smooth their consumption following positive shocks but reduce spending after negative ones due to future uncertainties, while others increase spending in response to positive shocks and smooth out the effects of negative ones, motivated by a desire to indulge when possible but otherwise maintain steady consumption levels.

Related Literature. Our paper contributes to two main strands of the literature. First, it is connected to a recent and growing literature studying the role of heterogeneity in macroeconomic models, which we will refer to in the paper when we compare or discuss the relevance of our results. Among others, Kaplan and Violante (2014), Berger et al. (2018), Kaplan et al. (2018), and Auclert (2019) highlight the importance of MPCs in tracing the partial equilibrium effects of fiscal and monetary policies, as well as of changes in asset prices such as housing. Auclert et al. (2020, 2024) argue that a limited set of moments, intertemporal MPCs, are key sufficient statistics to study the general equilibrium propagation of shocks and policies. Wolf (2021) uses iMPCs to characterize the perfect substitutability between stimulus checks and conventional monetary policy. Many of these papers highlight the missing empirical evidence on the spending response to anticipated income changes - a gap which we aim to fill with our survey-based estimates.

[3]It is beyond the scope of this paper to propose a fully new model that can nest these types, but we shed light on why this is both challenging and necessary in our discussion in Section 5.

Our survey is designed to elicit the planned responses to hypothetical scenarios. This "reported preference" approach has been applied to study planned spending responses to hypothetical income changes in earlier work, following the seminal contribution of Shapiro and Slemrod (2003). Jappelli and Pistaferri (2014, 2020), Bunn et al. (2018), Christelis et al. (2019), Christelis et al. (2020), and Fuster et al. (2021) elicit MPCs using survey data.[4] Koşar and O'Dea (2022) is a recent survey of the small but growing literature studying how beliefs and expectations data can be used for the estimation of structural models. Ameriks et al. (2020) use structured hypothetical scenarios to estimate the utility parameters in a structural life-cycle model.

Our paper advances this existing literature by analyzing the full quarter-by-quarter dynamics of how households react to financial shocks of varying sizes, directions, and timings. It examines various financial strategies, particularly emphasizing the significance of deleveraging, in addition to spending and saving. It delves into both conventional and unconventional factors—ranging from demographics to personal concerns and expectations. We are also validating the reliability of self-reported survey data through a novel cross-validation technique, demonstrating its consistency with actual behavior.

One obvious concern with the reported preference approach is the reliability of survey-based estimates. Limited evidence is available to test the predictive power of survey responses for actual spending decisions. Parker and Souleles (2019) study the 2008 economic stimulus payments and find that reported spending in surveys is highly informative about revealed preference propensities to spend. They also conclude that the estimated average propensities to spend are similar across the two methods. Recently, Coibion et al. (2022) use a RCT within a survey to exogenously shift the inflation expectations of a large sample of US households and study the effects on spending decisions. They find strong consistency between self-reported spending from survey data and scanner-tracked spending from the Nielsen Homescan Panel. Coibion et al. (2024) leverage self-reported spending data to study the effect of uncertainty on household behavior. The overall high quality of self-reported spending in survey data is also discussed in Bańnkowska et al. (2021), which focuses on evidence from the newly-designed ECB Consumer Expectations Survey.

Our paper more broadly adds to the body of work using surveys to understand how people think about key macroeconomic phenomena and policies such as taxation (Stantcheva, 2021), inflation expectations (Weber et al., 2022), inflation preferences (Stantcheva, 2024), trade (Stantcheva, 2022b), and the propagation of macroeconomic shocks (Andre et al., 2021, 2022). Fuster and Zafar (2023) is a review of how surveys are used to study the link between expectations and behavior. Our paper focuses mainly on household behavior following income shocks.

The rest of the paper is organized as follows. Section 2 describes the data, sample, and surveys structure. Section 3 discusses the main cross-validation exercises. Section 4 presents the quantitative estimation of intertemporal MPCs and MPDs. Section 5 dives qualitatively into the reasons

[4] These papers use data from the Bank of Italy Survey of Household Income and Wealth, the Bank of England/NMG Consulting survey, from the Dutch National Bank CentER Internet panel, the ECB Consumer Expectations Survey, and the NY Fed Survey of Consumer Expectations respectively.

behind households' financial behaviors and identifies the different types of households in the data. Section 6 combines the quantitative and qualitative findings to explain some puzzles in households' financial behaviors. Section 7 discusses the implications of our results and concludes.

2 The Survey and Data

2.1 Sample

Our primary sample comes from an online survey conducted on U.S. residents who are in the labor force at the time of the interview, and are aged between 25 and 65. The survey was conducted between November 2022 and January 2023. It was distributed through Lucid Marketplace, a platform that grants researchers access to multiple suppliers of survey takers—such as panels, communities, groups—hence pooling the respondents provided by each supplier. Respondents receive an incentive (cash or other rewards) for completing the survey. The survey is constrained through quotas to be representative along the dimensions of gender, age, total gross household income, and race. For more details about the technical implementation of these surveys, we refer to Stantcheva (2021) and Stantcheva (2022a).

We complement this main survey with a previous survey conducted in May–October 2021 (1293 respondents) focused on the quantitative elicitation of iMPCs and two cross-validation surveys (presented in Section 3). See Table A-2 for sample statistics on the previous wave.

Data quality. Our final primary sample has 2923 observations. To ensure data quality, we excluded respondents who took less than 12 minutes and more than 1 day to complete the survey. We also dropped respondents who misreported gender and age in the survey, who replied to multiple-choice questions by selecting answers in a row, or who responded inconsistently to open-ended questions. Respondents took, on average, 44 minutes to complete the survey (median time 34 minutes).[5] Appendix A-1.1 provides more details. We also check that our core results are robust if we adopt a more conservative approach and trim more respondents from the sample (see Appendix A-3.8).

Sample representativeness. Tables 1 and A-1 show the characteristics of our sample, as compared to the U.S. population in the labor force aged between 25 and 65 years old.[6] Our samples are broadly representative of the targeted US population. By construction, we match well with the targeted age, gender, and income distributions. The share of Black/African-American respondents is close to representative, but we are under-sampling Hispanic/Latinos and Asian/Asian-American individuals.

In addition, our sample is representative over non-targeted characteristics such as employment status, assets, and liabilities, as shown in Table A-1. We closely match the ownership rates and

[5] Excluding respondents who took more than 90 minutes to complete the survey (5% slowest respondents) the average and the median are respectively 36 and 33 minutes. See distribution of completion times in Figure A-1.

[6] Details on the construction of shares from the U.S. population from the CPS-ASEC (2022) and SCF (2019) are in Appendix A-1.2.

values for primary residences, businesses, and checking accounts, as well as the shares of households with mortgages, and the values for residential mortgages and credit card balances. We also match the amount of total household assets and liabilities quite well.

2.2 The Survey

Figure 1 shows an outline of the survey flow and the different levels of randomizations. In this section, we describe the content of some of the main blocks of the survey. The full questionnaire is in Appendix A-7.

2.2.1 Household socio-economic and decision-making blocks

Household socio-economic background. We collect information on respondents' gender, age, income, location of residence at the ZIP code level, race and ethnicity, marital status, number of children, household size and composition, employment status, highest level of education achieved, main field of study in college, main occupation and sector, political leanings, government transfer receipts, and health insurance. Since many questions in the survey are related to household-level decisions, we ask the respondent whether they are actively involved in the economic and financial decisions in the household.[7]

Households' financial decision-making process. We ask detailed questions about households' decision-making processes, such as who makes the decision, how carefully they keep track of their finances, their long- and medium-term financial goals, the frequency of their planning, their actual planning horizon, and any rules they follow.

Hurdles, problems, and response to news/shocks. The block asks questions about major hurdles affecting households' finances and budgeting, obstacles and concerns preventing households from spending and saving as desired, future income uncertainty, concerns about future credit access, the maximum unexpected and large emergency expense that the household would be able to cover. We use closed-ended questions.

Usual spending and saving behavior. This block elicits information about spending volatility, spending commitments, frequency of unexpected expenses larger than $1000. It also elicits a self-reported measure of self-control (following a similar question to Parker, 2017), risk and time preferences (following a similar set of questions to those introduced by Falk et al., 2018).

[7]To ensure respondents' understanding of the correct concept of *household*, we provide in the survey the Census definition for household (i.e., *"a household consists of all the people who occupy a housing unit"*) before questions about the household's size and composition are asked.

2.2.2 Response to income shocks

In the main part of the survey, we elicit how individuals respond to income shocks. First, we estimate iMPCs and iMPDs quantitatively, then we turn to understand in more detail how and why households use specific margins of adjustment (i.e., spending, debt, savings, working hours).

Elicitation of iMPCs and iMPDs using hypothetical scenarios. Respondents are asked to allocate hypothetical income shocks to additional spending, debt repayments, and savings over four quarters. We randomize (i) the shock size (fixed and worth \$1000, or 10% of the household's total annual net income); (ii) the shock sign, either positive (unexpected one-time payment) or negative (unexpected one-time expense).[8] Section 4.1 describes these elicitations in more detail. Furthermore, we also vary the timing of the shock. Each respondent is presented with two scenarios. In the first scenario, common to all respondents, the income shock occurs right away. In the second scenario, a randomly selected half of the sample is asked to consider an income shock occurring in one quarter, and the other half a shock occurring in two quarters in the future.

Qualitative response to income shocks. We then elicit adjustment margins used by the household in response to both positive and negative income shocks of the same size as in the previous block.[9] Then, conditional on selecting or not selecting a given adjustment margin (i.e., spending, debt, savings, working hours), respondents are asked a set of questions about *why* they are using or not using that given margin. Section 5.1 describes these elicitations in more detail.

2.2.3 Detailed assets and liabilities

We also ask detailed questions about the household's assets and liabilities, building on standard household finance questionnaires, such as the Fed's Survey of Consumer Finance and the ECB's Household Finance and Consumption Survey.

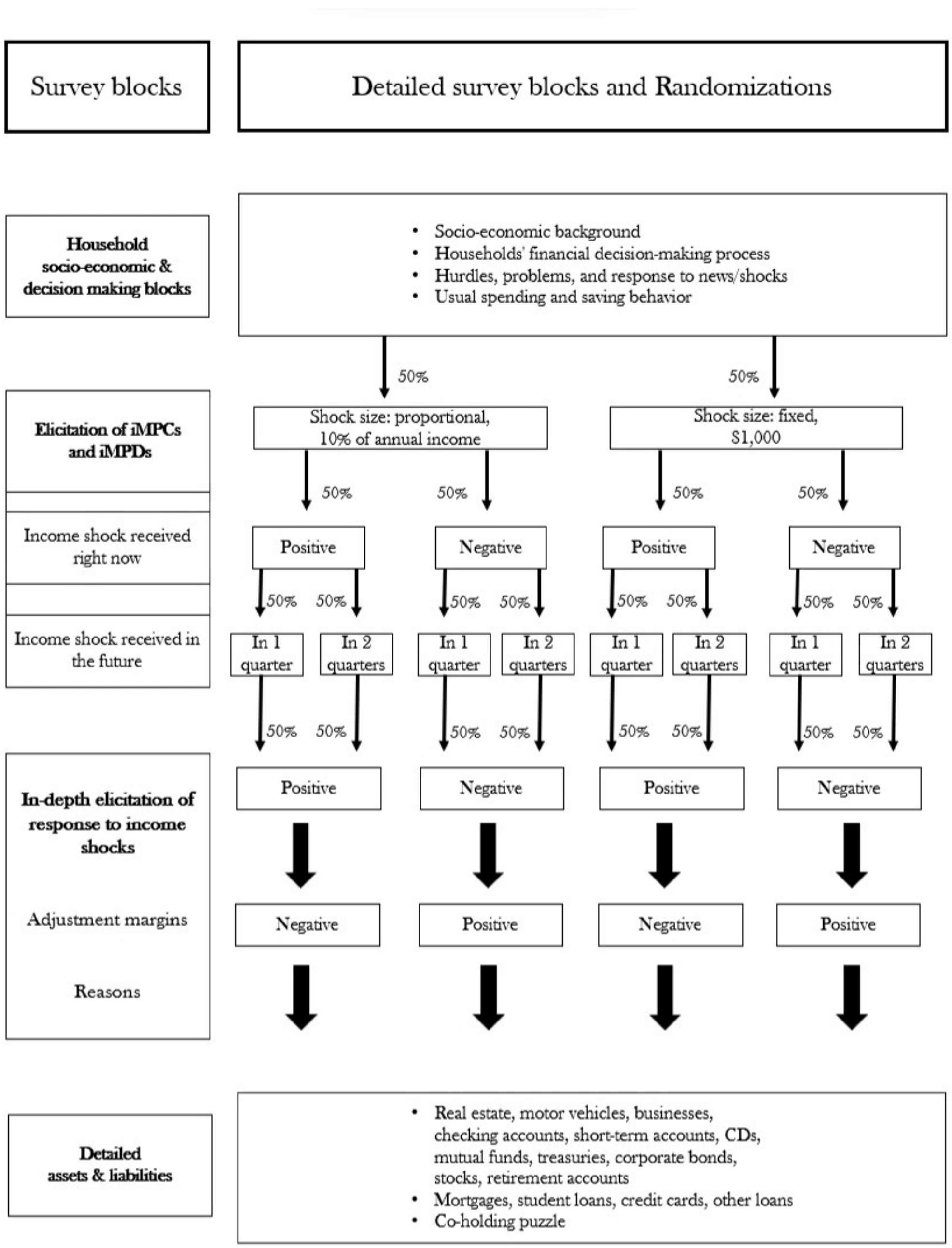
We collect information on debts and loans: mortgages, student loans, credit card debts, and other loans. We also collect detailed information on real assets (housing and real estate, motor vehicles, values of private businesses). We ask about financial assets, separating them by liquidity and risk profiles: checking accounts, other short-term savings (savings/money market accounts, brokerage accounts or shares in money market mutual funds), certificates of deposit, shares of mutual funds, ETFs, or hedge funds, direct US Treasuries and other government bonds holdings, direct municipal bond holdings, direct stock holdings, direct corporate bond holdings, retirement and pension accounts balances (401(K) and IRAs).

We then ask a series of questions on the household's credit card usage and debt as well as the highest FICO score within the household. Finally, we ask households a series of questions aimed

[8]The source of the income shock is not specified and it can be either government or non-government. In the first wave, we specified the source of the shock and it made no difference to the estimation.

[9]The order of these blocks depends on what respondents were asked in the elicitation of iMPCs/iMPDs block, see Figure 1.

Figure 1: Outline of Surveys



Notes. The figure shows the main blocks of the survey and the main randomizations. The numbers next to the arrows represent the shares of the sample in each branch. See Section 2.2 for details.

at directly studying the co-holding puzzle, namely that households tend to hold at the same time high-interest rate debts and liquid assets that could, in principle, be used to repay this debt.

Cross-validation surveys. We run two additional surveys ("cross-validation surveys") to show that survey questions can accurately predict households' behavior, even when asking them about hypothetical scenarios. To do so, we ask a set of questions designed to mimic the setting in existing work that leverages quasi-experimental or experimental (non-survey) variation. The full survey questionnaires are in Appendix A-7 and Section 3 details our cross-validation surveys and exercises.

3 Cross-Validating Responses

In two cross-validation surveys, we ask respondents a series of questions to replicate estimates from the literature, primarily those using observational (non-survey) data. Table 2 reports, for each cross-validation exercise, the reference paper, the target estimate, the sample for the original study, the value estimated in the study, and our survey estimate. The main takeaway is that survey responses can be reliable predictors of households' behaviors. This is likely because the situations we are asking about and which are studied in the papers mentioned are not out of the ordinary. On the contrary, they reflect decisions and trade-offs that households often have to think about. Therefore, when asked about a hypothetical scenario that closely relates what they are probably already thinking about, their predictions on average reflect what other similar households are doing in the data when actually confronted with those situations. This section discusses our cross-validation exercises and can be skipped without compromising the understanding of the rest of the paper.

Responses to unemployment shocks. Patterson (2023) estimates the MPC out of income losses due to unemployment, i.e., due to a large and persistent decline in personal labor income, using Panel Survey of Income Dynamics (PSID) data and imputing total household consumption from the Consumer Expenditure Survey (CEX). In our survey, we present (employed) respondents with a hypothetical situation where they are asked to think about a scenario in which they lose their job and, as a consequence, they face an income loss corresponding to about 30% of their personal labor income.[10] Finally, we ask respondents how they would reduce their food consumption, non-

[10]Firstly, we ask respondents to report their personal labor income net of taxes and transfers. Then, the relevant income loss is computed by taking into account initial labor earnings, the average unemployment duration in the U.S. (around 6 months, data from January 2021, BLS), the unemployment insurance (UI) replacement rate (around 0.45) and the maximum possible length of UI (6 months). We use the following formula (at the annual frequency), where Y is initial labor earnings and U is income conditional on becoming unemployed:

$$U = Y(1 - duration) + duration \cdot Y \cdot repl\ rate = 0.725 \cdot Y \tag{1}$$

$$income\ drop = Y - U = 0.275 \cdot Y \tag{2}$$

durable consumption other than food, and durable consumption out of this hypothetical income loss - after describing in detail each category. Summing over these items, we can recover the reduction in total consumption. The first line of Table 2 shows that our survey-based estimate is closely aligned with the estimate derived by Patterson (2023) using the CEX and PSID data. Clearly, Patterson (2023)'s data is also survey-based. But respondents are asked to report income and consumption in a careful manner and not reactions to hypotheticals, which makes this a valuable cross-validation.

Comparing to other well-established surveys. A lot of existing research relies on well-established surveys such as the Survey of Consumer Finances (SCF) and the Consumer Expenditure Surveys (CEX). These surveys are carefully conducted by various agencies and employ every technique to ensure representative, high-quality samples. The advantages of custom surveys through commercial samples, like ours, is that they allow for full flexibility in the types of questions asked. But do they yield high quality answers like well-established surveys? Tables 1 and A-1 already showed that the answer is yes when it comes to reported socioeconomic and financial characteristics. But we can also study variables that are direct results of behaviors.

First, Kaplan et al. (2014) estimate the shares of households exhibiting behaviors called "wealthy and poor hand-to-mouth (HtM)" in the U.S. using data on income and assets from the SCF. We closely replicate their results with our survey data following their baseline estimation strategy. Appendix A-2.4 provides a detailed explanation of how we defined wealthy and poor HtM households following Kaplan et al. (2014). We also study these households in more depth in Section 6.

Second, Chetty and Szeidl (2007) use CEX data to compute the share of a household's consumption that is "committed" (i.e., corresponding to spending categories that are subject to infrequent adjustments). In our survey, we ask respondents to report (out of 100) the share of monthly expenditures that are committed[11] or adjustable (the total should give 100). Using CEX data, we have first updated the Chetty and Szeidl (2007) estimates, finding that committed expenditures currently constitute around 60% of US households' total expenditures - a value that is slightly larger than the original Chetty and Szeidl (2007) estimate and closely matches our survey estimate.

Responses to expected shocks. Another interesting cross-validation relates to the responses to expected shocks. Baugh et al. (2021) study the consumption response of U.S. households to expected tax refunds and payments, using data from an account aggregator for the period 2011-2015. Their sample contains households that have had both refunds and payments in different years and are somewhat more liquid than the typical US household. They find that households have asymmetric responses to refunds and payments: consumption does not increase in anticipation of the refund and increases afterwards, but remains smooth before and after tax payments.

In our cross-validation survey, we ask respondents whether they have ever received payments or refunds. Then, conditionally on having received one or both of them, we present them with a

[11]We carefully describe committed spending as those expenses that cannot be easily adjusted or postponed, following Chetty and Szeidl (2007) definition.

hypothetical scenario in which they are asked how they would behave in response to a refund or a payment. To mimic the setting in the paper, we first ask respondents to imagine that, after filing their taxes, they learn about a refund worth $2,500 that will be received in the following weeks (but there is uncertainty about the precise date).[12] We then ask them whether and by how much they would increase their spending in the subsequent 30 days (before receiving the refund) and then, in the 60 days after receiving it. Separately, we ask respondents to imagine that they have to make a tax payment of $1,500 due in 30 days and whether and how they would change their spending before and after the payment. Table 2 shows that respondents' answers align closely with those estimated in the observational data, especially when accounting for the difference in time period and liquidity for the observational sample.

Responses to mortgage payments. Mortgages are a major part of households' liabilities, and it is interesting to see whether self-reported survey responses to changes in mortgage rates or payments can mimic real-world responses. Di Maggio et al. (2017) consider how automatic reductions in monthly mortgage payments for ARMs (originated between 2005 and 2007) affect durable consumption (as proxied by car purchases net of loan financing) and mortgage or house loan repayments. In the paper, monthly mortgage payments fall by around 50% upon reset, and the decline is persistent (2 years).

In our survey, we first ask respondents who have a mortgage on their primary house to report their monthly mortgage payment. Then, we present them with the hypothetical scenario in which their monthly mortgage payments fall by 50% (for at least one year), to mimic the decline in mortgage payments in Di Maggio et al. (2017). We then ask them whether and by how much they would increase their car spending, other durable spending, and debt repayments (specifically, mortgages, auto loans, student loans, and credit card debt) and normalize their response by their initial mortgage payments. Our estimates are only very slightly larger than the ones estimated in the paper. One reason is that some car purchases may be financed using car loans.[13]

Retrospective cross-validation. Another related concern is whether survey responses are accurate when people are asked about how they responded to past situations. To check this, we study the responses to the first Economic Impact Payment (EIP) made during Covid. The most suitable study for us to replicate is Karger and Rajan (2021), who use bank-account data from Facteus. Two other studies estimate these responses too, but at the aggregated zip code level: Misra et al. (2022), also using (aggregated) data from Facteus, and Chetty et al. (2023) with aggregated data on credit and debit card spending from Affinity Solutions Inc. The estimates from these three

[12] All amounts reported are chosen to be equal to the average refunds and payments in the paper.

[13] Another small difference between our cross-validation survey and the observational setting is that we sample individuals who hold a mortgage for their primary home, regardless of whether it is an ARM, due to the small share of ARMs. Point estimates are, however, very similar using the subsample with ARMs only.

studies are similar to ours and centered around 0.50.[14]

In our survey, we ask respondents to report the amount of the first EIP that they received and how much of it they spent on non-durable and durable consumption, on debt repayments, and savings over the three months following the receipt.[15]

Benchmarking to other survey estimates and papers. Furthermore, Section 4 will benchmark our estimates against a range of other survey-based estimates or estimates from other countries. The difference to the "cross-validation" performed here is that we did not explicitly try to mimic the setting in these papers.

4 Intertemporal MPCs and MPDs

In this section, we present the results from our survey method for estimating the intertemporal marginal propensities to consume (iMPC) and deleverage (iMPD) in response to both anticipated and unanticipated shocks. Our survey data helps highlight patterns and heterogeneities that are usually hard to capture with observational data. Specifically, we can study i) the intertemporal responses, quarter-by-quarter; ii) positive and negative shocks of different magnitudes; iii) MPDs, which are usually less documented and yet exhibit interesting patterns when compared to MPCs; iv) a rich set of covariates, including concerns, preferences, recent experiences, and constraints, above and beyond socioeconomic characteristics.

4.1 Elicitation of iMPCs and iMPDs

The iMPCs and iMPDs of individual or household I are defined as

$$iMPC^I_{t,s} = \frac{\partial c^I_t}{\partial y^I_s} \qquad iMPD^I_{t,s} = \frac{\partial d^I_t}{\partial y^I_s} \tag{3}$$

$iMPC^I_{t,s}$ is the change in I's consumption at time t, c^I_t, in response to a dollar increase in after-tax income at time s, y^I_s. $iMPD^I_{t,s}$ is the decrease in I's debt in response to a dollar increase in after-tax income at time s. Note that, when considering a negative shock, the MPC represents an decrease in spending and the MPD an increase in leverage (borrowing). Holding s fixed and varying t, the iMPCs and iMPDs allow us to capture the dynamic response of spending and deleveraging to changes in net income at time s. In some settings, these individual-level responses combined with

[14] Chetty et al. (2023) find that the MPC from the first EIP varies between 0.37 and 0.61 for households in the first and last quartile of income distribution, respectively. Baker et al. (2023) estimate the MPC out of the First EIP to be 20 cents over the first 10 days following the check receipt. They use high-frequency transaction data from SaverLife, a non-profit financial technology firm, and the concern is that this sample is significantly selected, since it includes people who are using the app in order to save more.

[15] We focused on a three-month period to ensure we capture all spending that was the result of the check. The studies listed above show that most of the response is concentrated in the very early weeks.

income data permit to aggregate and trace the effects of policy changes as discussed in Auclert et al. (2024).

Eliciting iMPCs and iMPDs in a survey setting is subject to three main challenges. First, we need to ensure that respondents understand precisely what is meant by savings, borrowing, deleveraging, and consumption. To do so, we provide clear and simple definitions in the survey.[16] Second, we have to clarify that we are eliciting the incremental, additional saving or spending responses to a shock, and not the spending and saving that a respondent would have done absent the shock. Asking about the additional response relative to a counterfactual is not obvious, but we make sure to specify the instructions clearly (see Figure A-52, Panel B). Third, we need to ensure consistency and simplify computational difficulties. We do this thanks to an interactive matrix design, explained below, which forces the amounts specified to add up and be consistent, and which assists respondents with their computations.

We randomly present survey respondents with hypothetical income shocks that differ in two dimensions, size and sign. Shocks can be proportional – worth 10% of the total annual net household income –, or fixed - worth $1000. They can either be positive (i.e., an unexpected one-time payment) or negative (i.e., an unexpected one-time expense).

We first ask the respondent to report their household's total net annual income in the year before the interview, as shown in Figure A-52, Panel A. This information is then used to compute the size of the income shock for the proportional-shock randomization. We then present the hypothetical scenario in which the respondent's household receives a one-time payment or expense worth either $1000 or 10% of their income. We carefully define the three categories over which they can allocate the positive (negative) shock: additional spending on non-durables and durables, additional debt repayments, and savings. For the negative shock, these categories are reducing spending, reducing debt repayments/increasing borrowing, and drawing from savings.[17]

We then ask the respondent to allocate the one-time payment over four quarters to additional spending and debt repayments. Whatever is not spent over the four quarters constitutes savings carried over to the next year. We use a matrix format (see Figure A-52, Panel C), where each row corresponds to a quarter and each column to a margin (either spending or debt-adjustment). The corresponding changes in savings are computed in real-time and shown to the respondent. The matrix is interactive: each time a respondent writes a number in one of the boxes, savings are immediately updated. We also constrain the amounts allocated to each box to be non-negative. However, we allow the total allocated across quarters to exceed the value of the income shock.[18]

[16]We define: "spending" as purchases of durable goods or non-durable goods that do not last for a long time; "debt repayments" as principal and interest payments to reimburse outstanding debt; "savings" as amount of income that is neither spent nor used to repay debt and that is instead left by depositing in checking, savings, or pension accounts, or by purchasing financial assets; "draw from savings" as tap into checking or savings accounts, sell financial or physical assets, etc. See Panel B of Figure A-52 for these definitions.

[17]See Figure A-52, Panel B, for the description of the categories as shown to each respondent.

[18]For instance, respondents may be willing to increase their spending by more than their income shock if they decide to take a lumpy expense thanks to the income shock. In the latter case, respondents are shown a pop-up message notifying them that they are allocating an amount greater than the size of the income shock.

In the case of an unexpected expense, we ask respondents how they would cover it using spending reductions and additional borrowing. Any amount not covered comes from savings.

We also ask each respondent how they would allocate an income shock received either one or two quarters after the news (randomized with a 50% probability), as shown in the survey flow in Figure 1.[19]

4.2 Main estimates

iMPCs and iMPDs. Figure 2 reports the estimates of average MPCs (Panel A) and MPDs (Panel B) out of positive and negative unanticipated income shocks received. Circles (diamonds) refer to MPCs/MPDs out of a proportional (fixed \$1000) shock. We summarize the dynamics of spending and deleveraging/borrowing by reporting the impact iMPC/iMPD (i.e., over the first quarter) in blue and the cumulative iMPC/iMPD (i.e., summing over the four quarters) in red, but will show the full quarter-by-quarter dynamics below.[20]

In our data, following a positive income shock of \$1000, the average impact MPC after one quarter is 0.16 and lower (between 0.08 and 0.1) in subsequent quarters. The MPD in the first quarter is 0.25. Overall, over the first year, households allocate around 0.42 and 0.45 of the income shock to spending and debt repayments, respectively. The MPCs for the 10% proportional positive shock, which is larger than the fixed shock for almost all households, are lower: 0.12 in the first quarter and 0.37 over the year. The corresponding MPDs are 0.21 and 0.39.

Turning to the fixed \$1000 negative income shock, the MPC in the first quarter is 0.17, and between 0.9 and 0.12 over the next three quarters. The cumulative one-year MPC equals 0.48. The impact MPD is 0.10 in the first quarter and the cumulative one-year MPD is 0.26. For the proportional 10% negative income shock, households have an MPC of 0.09 in the first quarter and 0.32 cumulatively; the corresponding MPDs are 0.09 and 0.23.

These benchmark results refer to an unweighted mean of MPCs and MPDs across respondents. However, Auclert et al. (2024) claim that income-weighted (i.e., weighted by household net income) average intertemporal MPCs are sufficient statistics for the response of output to fiscal and monetary policy. Existing estimates find that the annual average MPC out of a contemporaneous income shock, when weighted by net income, ranges between 0.44 (with data from the 2016 Italian Survey of Household Income and Wealth) and 0.51 (Fagereng et al., 2021, with Norwegian administrative data). In our data, we find an income-weighted average annual MPC of 0.46 for the proportional (positive) income shock and of 0.39 for the fixed (positive) income shock (see Appendix Figure A-10 for a comparison of our results with arithmetic and income-weighted averages).

[19] For anticipated shocks, we also ask respondents whether they would be able to increase spending and debt repayments (or whether they will cut spending or increase borrowing) in anticipation of the income shock, as shown in Figure A-53.

[20] We exclude from the analysis on iMPCs and iMPD outliers, i.e., respondents with MPCs and MPDs larger than 2 (cumulative and in each period), representing 2% of the total sample. Only for the analysis of iMPDs out of a positive income shock, we also exclude respondents who have positive MPDs out of a positive income shock but report no debts in the liabilities section of the survey, representing 14% of the total sample.

To benchmark our findings to the literature, Table 3 reports estimates of MPCs and MPDs from various papers. There is wide variation in existing estimates, but where the comparison is possible, our numbers for the impact and cumulative MPCs appear consistent with existing estimates. The table also underscores the importance of using survey elicitation to improve our estimates of MPCs and MPDs. Indeed, the evidence is quite scarce for different horizons, sizes of shocks, and for negative shocks or MPDs particularly.

Size effect and asymmetry. The proportional shock of 10% of income is larger than the fixed shock of \$1000 for almost all households. We find that – both for positive and negative shocks – iMPCs and iMPDs out of the (smaller) fixed shock are greater than those out of the (larger) proportional one. The difference is particularly significant for MPCs out of a negative shock, a finding consistent with the literature (see Fagereng et al., 2021 and Kaplan and Violante, 2022 for a review of the size effects).

In addition, we observe an asymmetry related to the sign of the shock, with MPCs out of negative fixed shocks being larger than those out of positive fixed shocks (Bunn et al., 2018; Christelis et al., 2019; Fuster et al., 2021). We study the explanations for this asymmetry in responses in Section 6.

Stability of MPCs. We use previous survey waves (May - October 2021) to explore the stability of our estimates of MPCs over time. Figure A-11 shows that the cumulative MPCs are somewhat smaller in the earlier wave. This could be because of the liquidity provided to households thanks to the cash transfers during Covid (Cox et al., 2020).

Dynamics and anticipation effects. Figures 3 to 4 show the full dynamic quarter-by-quarter responses for a fixed income shock (worth \$1000), for anticipated and unanticipated shocks.[21] The figures show that for both positive and negative unanticipated shocks, the impact is largest in the first quarter, and declines in subsequent quarters. The decline is much sharper for MPDs than for MPCs.

For anticipated positive shocks (two or three quarters in advance), there are significantly higher MPCs at the time the shock is received, but there are also clear anticipation effects and less abrupt declines in the MPCs in the quarters following the receipt. These MPCs represent averages across households who are able to anticipate the shock and those who are not; we depict the dynamic paths separately for these two types of households in Appendix A-3.2. For the positive fixed income shock, 35% of respondents report not being able to anticipate the shock; the share is 29% for the proportional shock. For the negative income shock, 24% of respondents do not take actions before the payment is due for the fixed shock, and 19% for the proportional shock. The paths for households who can anticipate the shocks are not sensitive to the timing of the shock, since households start to smooth it ahead of time. On the contrary, the time paths for households who are unable to anticipate the shocks show significant spikes at the exact time when the income flow

[21] For the proportional shock, see Appendix Figures A-2 and A-3.

or expense occurs. In a similar pattern, but much more muted, the figures in Appendix A-3.3 show dynamic responses comparing constrained and unconstrained respondents (defined according to an index based on liquid assets, credit card debts, and credit scores).[22]

MPDs also show clear anticipation effects due to households starting to deleverage ahead of an anticipated positive shock. For both MPCs and MPDs, there are larger anticipation effects for negative shocks: the dynamic paths look more similar for different timings of the shock. For MPDs, it is likely that households delay repaying debts ahead of time.

Robustness to the source of shocks and framing effects. In the first wave of our survey (May - October 2021) we additionally randomized across the source and the horizon of the income shock. In particular, the source of the shock can either be a direct Federal transfer such as a stimulus check, or a generic non-government transfer such as a bonus, gift, or lottery win. Appendix A-3.7 shows that the source of the shock did not play a significant role for the estimated iMPCs or iMPDs.

We tested whether asking respondents to allocate the shock over four or eight quarters made any difference. We find that respondents allocate funds very consistently over the first four quarters, regardless of whether the horizon is four or eight quarters. However, the framing of the question matters, as we illustrate in Appendix A-3.7, and it is important to phrase the questions in a clear and neutral way.

4.3 Heterogeneity in iMPCs and iMPDs

Different households exhibit different responses to the positive and negative shocks, and we can study a rich set of covariates, including concerns, preferences, recent experiences, and constraints.

MPCs following a positive shock. Figure A-12 depicts the correlations between various key household characteristics and MPCs and MPDs.[23] Some of the correlations are standard in light of the existing literature, especially as relates to MPCs in response to positive shocks (Panel A). For instance, younger households, those with children, with higher illiquid assets, and lower liquid and illiquid debt have higher MPCs, especially cumulatively over the year. However, the distinction between impact and cumulative MPCs provides an additional layer to earlier evidence. For instance, while debt and assets matter substantially for MPCs after one year (cumulatively), they are not significantly correlated with immediate, first-quarter responses.

[22]We classify as unconstrained and constrained those respondents who fall respectively in the bottom and top terciles of the constrained index distribution. The index is defined as the sum of indicators for not owning checking accounts, having low checking accounts balances (i.e., less than $1300), not having credit cards, having high credit card balances relative to the credit card limit (i.e., usually use more than 75% of credit card limit), have a high credit card usage (i.e., current credit card outstanding balances more than 75% of the credit card limit), have bad FICO (i.e., below 625).

[23]Full regressions are in Appendix Tables A-3 and A-4.

Why do households have low liquidity to begin with? Our detailed survey data also allows us to focus on why households have low liquidity in the first place: they may have either experienced negative recent shocks, have generally low income, or be impatient and lack self-control. Figure 5 focuses on illiquid respondents distinguishing between those who are "impatient" or with "low self-control" and those who had "negative past experiences" (defined as self-reported worsening in the household economic and financial situation over the past two years). Moreover, we distinguish between those with low income with and without recent negative past experience (i.e., households who are generally low income) and those with low income because of a negative past experience (i.e., who happen to be surveyed at a time of unusually low income). Impatient households tend to have higher MPCs and lower MPDs than those who had recent negative experiences. Furthermore, among those who are low income, those who are doing temporarily worse have lower MPCs and higher MPDs relative to those who are usually low income. We will take up these patterns again when considering the "liquidity puzzle" in Section 6.2.

Response to negative shocks and MPDs. The ability to compare and contrast positive and negative shocks is also valuable. For the negative shock (Panel B of Figure A-12), we see that younger respondents have higher cumulative MPCs. Credit card debt predicts lower first-quarter MPCs.

There is generally less evidence regarding MPDs, especially in response to negative shocks. The figure shows that households with higher levels of debt, lower assets, and older households have significantly larger MPDs in response to a positive shock (Panel A), both on impact and cumulatively. Turning to the negative shock (Panel B), older respondents have lower cumulative MPCs and MPDs, meaning that they mainly respond to a negative income shock by dipping into savings. Moreover, illiquidity and high credit card debts predict higher MPDs, while high total debts predict lower MPDs.

The role of additional survey variables: concerns, preferences, and constraints. Finally, we can showcase the role of concerns, preferences, and constraints, above and beyond socioeconomic characteristics. These variables seem to matter especially for MPDs following a positive shock. Households with high self-reported self-control, high concerns on a range of dimensions, and who feel they lack enough for basic needs have significantly higher propensities to deleverage after a positive shock. The full regressions in Appendix Tables A-3 and A-4 show that these variables matter and contribute to explanatory power above and beyond socioeconomic and financial characteristics. They are not fully accounted for by baseline characteristics. Overall, it is not easy to explain MPCs or MPDs with socioeconomic and financial variables; the share of explained variance is very small. Adding concerns, constraints, and preferences improves the explanatory power but does not make it sufficient, which justifies us digging deeper as we do in the next section.

5 Heterogeneity in Models across Households

In this section, we directly dive into how households reason about and react to unexpected and temporary changes in income or expenses.

5.1 Eliciting reasons for household behaviors

We proceed in three steps. First, we present each respondent with a hypothetical scenario in which they or their household receives the news of an unexpected one-time positive payment (a positive shock) and a scenario in which they face an unexpected expense (a negative shock). As illustrated in Figure 1, we randomize the size of the shocks at the respondent level (between a fixed size worth \$1000 and 10% of total household net income). The respondent is therefore asked about a shock of the same size as in the quantitative elicitation block presented in Section 4.1, and the shock is of equal magnitude but with different signs for the positive and negative scenarios. We also randomize the order in which the positive and negative shock scenarios appear.[24]

In a second step, we ask the respondent what they would do with the extra money or how they would cope with the expense, providing them with a detailed series of options, i.e., "margins of adjustment," the order of which is randomized. Figure A-54 shows an example of this set of questions to elicit adjustment margins in the case of a positive shock. The options in the list can be grouped into four main adjustment margins: i) spending, ii) debt, iii) savings, iv) labor supply (i.e., hours worked).[25]

In the third step, we ask respondents about their reasons for using each of the adjustment margins, not using it, or not using it more. Figure A-55 shows an example of the questions used to elicit reasons following the choice of margins. We selected reasons based on existing models in the literature and complemented them with additional options.

Figure A-20 provides a complete tabulation of the reasons for taking or not taking specific actions in response to positive and negative shocks. Respondents were asked to evaluate the answer options as "Not at all relevant," "Somewhat relevant," "Very relevant," or "Extremely relevant." The figure reports the share of respondents who select each of these relevance options, where reasons are presented in descending order of importance.

5.2 Adjustment margins

We start by focusing on the frequency of adjustment margins used in response to positive and negative shocks. Panel A of Figure A-21 shows how margins are used in combinations for the positive and negative shocks.[26] Panel B shows more detailed adjustment margins selected by

[24] We always show first the shock sign corresponding to the one presented in the iMPCs/iMPDs blocks, where we show only one of the positive or negative scenarios.

[25] We leave the following as residual categories: (for a positive shock) making gifts or donations, lending money to someone else; (for a negative shock) selling small-ticket and large-ticket items, leaving part or all of the expense unpaid since there are no ways of covering it now.

[26] Figure A-19 shows the tabulation of margins, unconditionally on the use of the others.

respondents.

Most households use a combination of margins, rather than a single margin in response to either positive or negative shocks. Close to 90% of households partially adjust through savings; 80% through debt. There are no major differences in the frequency of margin use based on the sign of the income shock. However, starker asymmetries emerge for the spending and work margins. A larger fraction of respondents adjusts spending in response to a negative shock. The response along the working margin is the most asymmetric: While only 18% of the respondents cut working hours out of a positive shock, 66% plan to work more when they face a negative shock.

In Panel B, we see that, following a large unexpected expense, households will borrow predominantly through credit card use, but around one third of them will leave bills unpaid, use overdraft provisions, or costly short-term loans. Most households will cut spending on non-essentials and postpone big planned expenses. Cash, checking or savings accounts and emergency funds are used to pay unexpected expenses; a quarter of households will dip into retirement funds. Following a positive shock, more than half of households will make use of the extra funds to purchase necessities, repay bills, loans, and credit card debt. Three-quarters of them will stash some money into an emergency fund and 60% will save for long-term goals and future spending.

5.3 Reasons for specific behaviors

Recall that Figure A-20 lists the options to respondents in the survey to elicit their reasons for taking a given action. For the analysis in the next sections, we will group and streamline these reasons. This is to ensure that we group together statements that are very similar or equivalent and to account for the fact that some reasons to engage in one behavior (e.g., to save) can be viewed as a reason not to engage in another one (e.g., not to spend). Our grouping is explained in Appendix A-2.2. The results are shown in Figure 6, which depicts the share of respondents who consider a reason to be at least "very relevant" for doing something, not doing something more, or not doing it at all in the case of the fixed shock. Appendix Figure A-22 reports this distribution for the case of the proportional shock.

5.3.1 Spending

After a positive shock. Figure 6 shows that, following a positive shock, the most selected reason is that households usually save for long-term goals. This is in line with the "term savings" model of Campbell and Hercowitz (2019), in which the expectation that liquid wealth will be low in the future can induce households with substantial assets to display high MPCs today, as they foresee an approaching large expenditure, such as a home purchase, college tuition payments, or planned health expenses and therefore anticipate to be liquidity constrained in the future. The more detailed Figure A-20 suggests that some households specifically mention that they have most of their wealth invested and they do not like to disinvest it, hence they use income shocks to increase their spending ("We don't like selling assets for spending. It's nice to have extra cash to spend more freely").

Also highly mentioned are the wish to splurge (as in Baugh et al. (2021), Olafsson and Pagel (2018), and Carroll et al. (2023) and related adjustments in the consumption basket on "higher quality items," as in the model with non-homothetic preferences in Andreolli and Surico, 2021), and the wish to minimize the cognitive burden ("This amount of money is not enough to spend time thinking about it," consistent with rational inattention model as reviewed by Maćkowiak et al. (2023)).[27]

The fourth most-cited reason is that the household members "really need some items" they cannot otherwise afford, in line with borrowing constraints in many models, e.g., Zeldes (1989). Similarly common is a planned lumpy purchase: households were planning to make a significant purchase, and the extra money allows them to do so. This aligns with papers using data on both durable and non-durable consumption (Berger and Vavra, 2014; McKay and Wieland, 2021; Laibson et al., 2022).

Slightly less than one-third of respondents report spending the extra income because they are worried about rising prices. The link between inflation expectations and spending has been shown in Burke and Ozdagli (2023), Weber et al. (2015), and Coibion et al. (2023) among others. Finally, households also report less common reasons: Lack of self control (Gul and Pesendorfer, 2001) and impatience (related to the literature on present-bias in Laibson (1997) and Angeletos et al. (2001)).

When asked why they do not increase spending (in the rare situations where that is the case) or, more commonly, why they do not increase their spending by more, more than half of households say that they are worried about the future. This reasoning can be interpreted as the classic precautionary motives from the literature.[28] Around half of all households also say that they like to keep their consumption stable, in line with the core consumption smoothing behavior. This groups households who report that they do not like to splurge, that they like to keep their spending stable, or that they are self-disciplined and stick to plans and habits. A similar share of households say that they do not need anything at that moment.

After a negative shock. After an unexpected expense, households who cut spending report doing so because they are able to substitute consumption (away from non-essential items and shift spending towards less expensive, lower-quality items (Straub, 2019)), because they are worried about the future, and because they can postpone planned lumpy purchases (as in Berger and Vavra (2015) and Attanasio et al. (2022)).

Reasons for not reducing spending at all or by more following an unexpected expense include the

[27]See also Kueng, 2018), where there are costs associated with deviating from consumption smoothing rules. When the shock size is small relative to the household's earnings, the costs of this deviation are small. Hence, it is less costly for rich households to spend the income shock than to smooth it over time. Boutros, 2022 consider planning horizons to be endogenous to the size of the income shock relative to the household's income. Households have diminishing returns to consumption from smoothing it over a longer horizon. Hence, when the income shock is small relative to their income, it is less costly to (sub-optimally) spend it immediately since benefits from smoothing are smaller than planning costs.

[28]Classic papers include Caballero (1990), Deaton (1991), Carroll and Kimball (1996), and Gourinchas and Parker (2001), as well as more recent work by Guerrieri and Lorenzoni (2009), Challe and Ragot (2016), McKay et al. (2016), Guerrieri and Lorenzoni (2017), and Bayer et al. (2019).

wish to smooth consumption (among 42% of respondents), the existence of spending commitments (one-third of respondents), the wish to minimize one's cognitive burden (29% of respondents), or the inability to cut consumption further given that the household already mainly spends on essentials (29% of respondents). The least common reason is lack of self-control, among one-fifth of respondents.

5.3.2 Debt

Turning to debt, the most common reasons for repaying debts out of a positive shock are worries about future credit access and one's credit score (54% of respondents), already having too many debts in need of repayment (38%), and a dislike of debts (among 39% of respondents, as in the model of debt aversion of Prelec and Loewenstein (1998) and its application in Caetano et al. (2019)). Among the respondents who do not deleverage when they receive cash, the main reason is that they do not have debts that require repayment above and beyond what is scheduled.

When confronted with a large unexpected expense, respondents who borrow do so mostly for two quite distinct reasons. 66% borrow because they believe they will be able to repay this debt easily, while 63% do so because it is the "easiest" thing to do. Reasons for not borrowing or not borrowing more are concerns about future credit access among 54% of respondents, the inability to borrow (among close to 40% of respondents), and that borrowing is too complicated (among one-quarter of respondents).

5.3.3 Savings

On the savings margin, many of the reasons for not spending mentioned above are also reasons for saving. For instance, concerns about the future lead to precautionary savings. Following a positive shock, respondents also tend to save because they feel that they need to save more and have long-term goals. While one-third of households mentioned inflation as a reason to spend more, 40% instead consider it to be a reason to save more. 32% of households want to take advantage of market returns. Reasons for not saving more include not needing more savings (for around one-half of respondents) or not having good investment opportunities (27% of respondents).

In response to a negative shock, households who dip into their savings do so because they are easily available and liquid and have been planned for that purpose. Factors limiting how much people draw on their savings include wanting to stay on track with other financial goals and not having enough or illiquid and hard-to-access savings.

5.3.4 Working hours

The final adjustment margin we study is working hours. In response to a positive shock, few respondents cut back on working hours. The reasons for this lack of adjustment are, in order of importance, that respondents do not want to reduce their labor income, that they cannot adjust their working hours, or that it is too difficult to adjust their working hours. Those who do cut hours report already working overtime and having flexible hours. Many more respondents increase their work hours in response to a large unexpected expense. They report having flexible work hours or being able to find a second job.

In sum, many different motivations – some standard in light of the existing models and some non-standard – are well-represented among respondents, suggesting that households adjust spending following a range of different models. We formalize this intuition in the next section.

5.4 Classifying households into types

We use a machine learning algorithm to classify households into "types" based on their margins of responses and reasons provided. The Latent Class Analysis (LCA) algorithm[29] is applied separately to the subsample of individuals who received the fixed \$1000 income shock and those who received the proportional income shock (worth 10% of household annual income). The main paper focuses on results from the fixed shock. Results for the proportional shock equal to 10% of households' income are shown in Appendix A-4.4 and look largely similar, even though the magnitudes of MPCs and MPDs differ.

For both types of shocks, we obtain four distinct clusters of respondents, accounting for around 87% of the sample. Thirteen percent of respondents do not fit neatly into any of these clusters.[30] Table 4 describes the key features of these types of households. This description is based on the following more detailed set of figures for the interested reader: Figure A-24 tabulates the coarser adjustment margins (Panel A) and the detailed ones (Panel B) that households use; Figure 7 shows the reasons for why households in different clusters take the actions they do, unconditional on selected margins;[31] Figure 8 plots the one-quarter (impact) and one-year (cumulative) MPCs and MPDs of each cluster, relative to the sample mean; Table 5 shows the predictors of being in each cluster; Figure 9 shows the distribution of the four clusters within different socioeconomic and other groups.[32] Furthermore, in the Appendix, Figures A-27, A-28, and A-29 provide information about how these households make decisions (how often they plan, whether they stick to the plan), their goals, and difficulties. We can summarize this information as follows.

Strongly constrained households (17.8%).

One of the clusters is households identified as "strongly constrained." Upon experiencing a positive financial shock, these households are notably more inclined to escalate their spending (on the extensive margin), particularly on necessities. However, their marginal propensity to consume

[29] Weller et al. (2020) offer a review of LCA methods. See Appendix A-4.2 for details on our application of the LCA.

[30] Figure A-23 shows the four clusters for the fixed shock (Panel A) and for the proportional shock (Panel B) subsamples.

[31] Figure A-25 shows the reasons, conditional on selected margins.

[32] Figure A-26 shows the distribution of characteristics for each cluster in response to a fixed income shock, Figure A-34 in response to a proportional income shock. Figures A-30, A-31, A-32, A-33, A-35, and Table A-7 show the equivalent figures for the proportional shock.

(MPC) remains below the average. One of the key motivations fueling their increased expenditure is the combination of genuine needs and a desire to reduce the cognitive load associated with financial decision-making.

A salient trait of these households is their tendency to allocate unexpected funds towards debt repayment, as evidenced by their significantly elevated marginal propensities to deleverage (MPD) relative to other groups. This is not confined to just credit card obligations; they also address outstanding bills and other loans. Their propensity to repay arises from pressing debts and concerns over future credit accessibility and maintaining a favorable credit score. When they do opt to save, it is often to try establishing an emergency fund and contemplating medium to long-term expenses. These households clearly state wanting and needing to save more, yet feeling hindered in doing so. Their financial position typically restricts them from capitalizing on investment opportunities (very few mention investments). They report that they cannot stick to their spending plans even if they try.

Confronted with a negative financial surprise, these households tend to curtail their expenditure. Strategies include deferring significant planned purchases and reducing both essential and non-essential spending. They do so because of apprehensions about the future and because they feel that they can opt for lower-priced/lower-quality items as a cost-saving measure. While they occasionally access funds from their emergency reserves or cash/checking accounts, they do not have ample savings cushion. Furthermore, the max unexpected expense they report being able to handle if they used all credit, savings, and other adjustments available to them is much lower than that of other households (i.e., below \$4000, as compared to \$13,000 on average for the full sample).

They also borrow significantly more than other groups after a negative shock (their MPDs for negative shocks are much higher than those of other groups). Borrowing channels encompass friends, family, and credit card usage, often without the intent of settling the full balance promptly. This borrowing behavior is typically perceived as "the easiest" available solution in the short term.

Demographically, the strongly constrained category is overrepresented among women, older individuals, and those with lower incomes. Specifically, older respondents with lower incomes feature prominently. Their financial portrait is characterized by substantial credit card debt, low assets, and all the other markers suggestive of pronounced financial constraints. Their risk aversion tends to be above average, they have heightened concerns surrounding retirement and employment, and they face a substantial share of committed expenses. They report feeling significantly more uncertain about their income over the next year than other groups. These households frequently express feeling resource-strapped, even for basic necessities, and are much less likely than others to state having long-term planned investments.

Spender households (32.6%).

Spender individuals and households are the most likely to increase spending in response to a positive shock and among the least likely to cut it when faced with a negative one. Accordingly, they have higher-than-average MPCs for positive shocks and lower-than-average MPCs for negative ones. Conversely, they have slightly higher than average MPDs for negative shocks and lower MPDs for positive ones.

They spend because they want to minimize their cognitive burden and not think about it too much, because they like to splurge, and because they feel term-liquidity constrained. They spend on all items listed – necessities, activities they like, and bigger ticket items.

Nevertheless, they do try to repay some of their debts as well because they have quite a few debts and worry about future access and ability to repay. When faced with a negative shock, they will tend to cut spending somewhat out of concerns for their future and thanks to their ability to substitute items, but they will also borrow because easy to do so and dip into their savings that they have for insurance purposes.

Their main motivations for saving are to exploit market opportunities and because they express concerns that they are not saving enough. They are somewhat represented among groups with high planned investments than among those with few planned investments.

Spenders are more likely to be male and be in households with children. They are predominantly in the younger to middle-aged bracket with higher incomes. Older individuals are less represented in this group. They do not have large shares of committed expenses. Despite their significant assets, their considerable debt levels indicate some financial constraints. A standout trait of this group is their lower self-reported discipline and a higher willingness to take risks.

Quasi-smoother households (17.7%).

As is clear from the adjustment margins and MPCs of different groups, very few respondents are true textbook smoothers. However, there is a significant group of "quasi-smoothers." These households are less likely than average to spend in response to positive shocks or to reduce spending in response to a negative shock. They do have higher-than-average cumulative MPCs, due to term-savings (by far the main reason), wanting to minimize their cognitive burden, and their desire to splurge a bit. Their spending goes towards activities and things they like. They are significantly less likely to deleverage because they have no debt in need of repayment. They save because they want to save more and have significant long-term goals.

In response to a negative shock, they are significantly less likely than any other group to borrow or cut spending. They will mostly dip into their savings in the form of cash/checking accounts and emergency funds that are readily available. If they do borrow, they state that they use their credit card and will repay right away at the next statement date. As a result, these households have significantly lower-than-average MPDs – their most distinguishing feature. They also have significantly lower MPCs following a negative shock. The reasons for their behaviors in response to negative shocks are that they want to smooth consumption and are able to do so thanks to easily accessible and sufficient savings.

Quasi-smoother households tend to be older. They are relatively evenly split between low- and high-income respondents, but they have significantly higher liquid and illiquid assets, low debt, and low constraints according to all our measures. They also express few economic and financial concerns. When making financial decisions, these households are able to stick to their plans, tend to plan for longer horizons, and report being able to withstand on average much higher unexpected expenses than other households ($17000 on average).

Precautionary households (15.5%).

Precautionary households try to buffer negative shocks and stash away funds when receiving positive ones. More specifically, they are more likely than quasi-smoothers to cut consumption following a negative shock and have a high MPC, especially on impact after a negative shock. They do this because of concerns for the future. They tend to dip into their savings rather than borrow, more so than the average respondent. The reason is that they have saved for such unexpected expenses and have easily accessible savings. They are less represented among households with high concerns about health, retirement, repaying debt, or income, perhaps because they are self-insuring and building buffers.

Following a positive shock, they are less likely than average to increase spending; instead they are much more likely to save. Their MPCs following a positive shock are significantly below average, both on impact and cumulatively and even below those of quasi-smoothers. When they do spend, it is mainly on necessities and activities. Among those who spend, the most common reason is term savings, followed by the need to make a lumpy purchase. They are also not prone to deleveraging, mainly because they do not have many debts in need of faster repayment. Their MPDs resemble those of quasi-smoother households. They save in order to build an emergency fund and to plan for long-term goals and future purchases. They have significantly higher planned investments in the future, especially for retirement.

Precautionary households tend to be somewhat older and more likely to be lower-income. Controlling for other characteristics, they have more liquid assets and lower debt of all sorts. They are more likely to be patient and exhibit high self-reported self-control. While they resemble the quasi-smoothers the most, they are on the more higher risk averse, patient, and high self-control end and less wealthy than the latter.

5.5 Discussion and next steps

The empirical findings in Section 5.4 highlight that households respond to an income shock in the same way for different reasons. Put differently, there is a heterogeneity in models according to which households act. Observational data which only shows adjustments in spending, debt, or savings is going to provide limited information about the underlying model that households follow. Having information about more detailed margins of responses (e.g., using credit card debt versus leaving bills unpaid) does provide more scope to identify household types, but is not sufficient. Knowing the magnitudes of the MPCs and MPDs provides further refinement, but is not in itself sufficient to pin down household types.

The types of households we identify are clearly represented in different models in the literature. Reassuringly, therefore, we can recover common models of behaviors from the literature. The least studied type might be the spender households, which have some behavioral characteristics. We also see that these types are not only (and not even primarily) defined by their observable characteristics such as assets or income. The figures showed that within each type, there is a large variation in socioeconomic characteristics. Conversely, within any given socioeconomic group, there is a non-degenerate distribution of the four types. In the predictive regressions in Tables 5, the R^2 are small, typically in the 0.06-0.24 range. It is thus very difficult to predict a household's type based on socioeconomic characteristics, let alone on income or assets only.

Variables such as concerns, goals, and plans are more predictive but not sufficiently so. Adding them to the predictive regressions increase the R^2 to the 0.1-0.36 range. Many households have shared concerns and aspirations. It is only once we get to the underlying detailed responses and reasons for choosing these responses that we can start to delineate the distinct modes of operation of different households.

One natural question is whether these four types of households can be nested in a relatively standard model with extensions. In Appendix A-5, we present an augmented two-assets heterogeneous-agent incomplete markets model, based on the workhorse model in Kaplan and Violante (2014). The added ingredients attempt to capture the specific features of the household types we identify – such as different coefficients of risk aversion and convex adjustment costs for illiquid assets. This exercise shows that if we try to define the types of households based on the (standard) characteristics in the model (e.g. their net asset positions, and their coefficients of relative risk aversion), the predicted behavior does not align with the data. Specifically, we find two main elements of disconnect. First, strongly constrained agents in the model, unlike in the data, exhibit persistently high MPCs out of a transitory income shock. This suggests that strongly constrained agents in the data have significantly stronger precautionary and deleveraging motives than those implied by leading models. Second, quasi-smoothers and precautionary agents – the unconstrained – exhibit much larger spending propensities in the data. Canonical models thus struggle to capture the motivations that lead unconstrained agents to impatiently consume after income shocks, and which we discussed at length above. While it is beyond the scope of this paper to do so, our findings suggest the need for extensions and modifications to existing models to more accurately reflect the co-existence of different types of households.

6 Explaining Puzzles with Households' Reasoning

We leverage our data on the reasons and motivations for adjusting along different margins to study four puzzles in households' consumption and saving behaviors. First, why do some individuals who appear to be constrained in their ability to spend not use a positive income shock to spend more, i.e., why do some constrained agents have lower MPCs than expected? Second, existing empirical evidence suggests that some liquid households display high MPCs out of transitory income shocks, which a priori violates consumption-smoothing behavior and is labelled the "liquidity puzzle." Third, individuals adjust spending asymmetrically when receiving a positive or a negative income shock, the "asymmetry puzzle." Finally, a large share of households keeps rolling over high-interest-bearing credit card debt, while also having liquid account balances that could cover them, the so-called "co-holding puzzle."

6.1 Spending behavior of constrained households

Why do constrained households not spend more out of positive transfers (see for instance Parker et al., 2022)? The results from Section 5 provide a suggestive answer, namely that these households might be prioritizing deleveraging.

To study this issue in more detail, we can define constrained households in at least three different ways. First, we can define households as being constrained depending on whether they are in the bottom or top median of the constrained index, defined above (see also Appendix A-2 for a detailed definition). Recall that this index incorporates information on liquid assets, credit card positions, and FICO scores, among others. Second, we can consider those with a low total wealth-to-income ratio. Finally, we can restrict attention to those with low liquid wealth only.

Figure A-45 shows impact and cumulative MPCs and MPDs out of a positive fixed income shock, comparing households that are classified as constrained or unconstrained and those who have high and low wealth-to-income ratio.[33] Panel A and Panel B of Figure 5 similarly plot these variables by quintile of liquid assets.

Constrained households – according to all three measures – have higher MPDs. On the contrary, their MPCs are roughly similar or smaller than those of non-constrained households, depending on the measure used. Panel A of Figure A-47 presents the distribution of the four household clusters. As expected, households in the "Strongly constrained" cluster are over-represented among households with a high constraint index and a low wealth-to-income ratio. Quasi-smoothers and Precautionary households are over-represented among households with a low constraint index and higher wealth-to-income ratios.

Accordingly, the behaviors and rationales of constrained households are similar to those described for the Strongly constrained type in Section 5, as shown in Panel B of Figure A-47. Unconstrained households are more likely to spend a positive transfer on activities they like and on bigger-ticket items; constrained households are more likely to spend it on necessities. The reasons for spending which are more common among unconstrained households are term-liquidity constraints (due to saving for longer-term goals) and a wish to splurge. For constrained households, reasons to spend are instead that they want to minimize their cognitive burden, have needs, worry about inflation, or lack self-control. Twice as many constrained households express strong concerns

[33] Figure A-46 reproduces the figure for a positive proportional income shock. Figure A-48 shows instead MPCs and MPDs against wealth-to-income in a more granular, binscatter plot.

about having many debts in need of repayment and worrying about future credit access and their credit score.

Therefore, our findings are in line with Kosar et al. (2023) who find that, in the data, constrained households tend to use extra funds to deleverage rather than to consume.

6.2 The liquidity puzzle

Classic consumption theory as in Modigliani and Brumberg (1954) predicts small MPCs out of transitory income shocks, since agents smooth consumption over time. High MPCs are usually explained by incomplete markets and borrowing constraints, whereby households who are at the constraint or close to it display higher MPCs.

Kaplan et al. (2014) show that 30-40% of U.S. households behave as hand-to-mouth (HtM), exhibiting high MPCs out of transitory income shocks. Kaplan and Violante (2014) distinguish between low liquidity households with low illiquid assets ("poor HtM") or with high illiquid assets ("wealth HtM"). Around two-thirds of HtM households are wealthy. Baugh et al., 2021 document that highly liquid households increase consumption when receiving expected tax refunds. Olafsson and Pagel (2018) use Icelandic data and find evidence for excess sensitivity of spending to receiving one's income ("payday response"), even among individuals with high liquidity. In addition, Kueng (2018) find statistically and economically significant MPCs out of the Alaska Permanent Fund Dividends, with households in the highest income quintile having MPCs five times larger than those in the lowest quintile. These earlier empirical findings are borne out in our data too, as shown in Panel A of Figure 5, which plots the MPCs and MPDs by quintiles of liquid wealth. Even high liquidity households have positive MPCs. Impact MPCs are in fact almost identical in all quintiles (0.16 both in the lowest and in the highest quintile), while cumulative MPCs are almost double at high liquidity levels as compared to low ones (0.33 in the lowest and 0.55 in the highest quintile). On the contrary, the MPDs show the inverse patterns and are systematically much higher for low-liquidity groups, both on impact and cumulatively. These findings suggest that even highly liquid households often exhibit large spending propensities out of transitory income changes, which we can label the *liquidity puzzle*.

Panel A of Figure 10 shows a more detailed picture of impact and cumulative MPCs for the groups of HtM (wealthy and poor) and non-HtM, as defined in Kaplan et al. (2014). In our sample, 65% are non-HtM, 9% are poor HtM, and 26% are wealthy HtM.[34] The impact MPCs are similar for these groups, and cumulative MPCs are somewhat larger for Non-HtM households. The key difference again lies in the MPDs (panel B), both on impact and cumulatively, with non HtM households having the lowest propensities to repay debts and wealthy HtM the highest.

Panels C and D show the reactions to positive shocks by groups classified by liquid and illiquid assets. While MPCs on impact are again quite similar across these groups, the cumulative MPCs

[34] Our estimates are close to Kaplan et al. (2014), where poor HtM represent 14%-21% and wealthy HtM 20%-25% of the U.S. population (data from SCF and PSID).

are largest among those with high liquid and illiquid assets. On the contrary, the MPDs are monotonically rising when we go from households with high liquid and illiquid assets, to those with low assets of both types.

To better understand why households spend a transitory shock even if they have high liquidity, we can leverage our clusters and data on rationales. Figure 11 shows the share of households in different HtM and liquidity groups who are in one of the four clusters identified above. There is a mix of different clusters represented in all HtM groups, which confirms once again that it is difficult to pinpoint households' behavior models from economic or financial characteristics only. Nevertheless, among the poor HtM, a disproportionate share are of the strongly constrained type. The non-HtM are more likely to be quasi-smoothers and precautionary households. Similarly, among households with high liquid wealth, those with high illiquid wealth tend to be spenders, while among those with low illiquid wealth, there are disproportionately more quasi-smoothers and precautionary households.

Recall that household liquidity at any given time is merely a snapshot of their economic situation. But households may have low liquidity for very different reasons, as explained in Section 4.3: they may have either experienced negative recent shocks, have generally low income, or be impatient and lack self control. The final set of rows in Figure 11 shows that among households with low liquidity, those with a negative recent experience, are more likely to be of the Strongly constrained type than those who are impatient or have low risk-aversion. Figure 5 showed that, among low liquidity households, those with impatience and low self-control have much higher MPCs than those who are illiquid and have recently experienced a negative shock.

Figure 12 plots the reasons for increasing spending and the related reasons for not repaying debts (by more or at all) and not saving (by more or at all) and detailed spending responses. Panel A focuses on the Kaplan et al. (2014) groups and Panel B splits households by combinations of liquid and illiquid wealth. The reasonings align with the clusters that these households fall into. The poor HtM and the low (liquid and illiquid) wealth households resemble the strongly constrained types in their spending and reasons. The non-HtM and those with high (liquid and illiquid) wealth resemble the quasi-smoothers. The wealthy HtM and the high illiquid, low liquid asset households resemble both spenders and strongly constrained households depending on the dimension. Thus, for instance, the wealthy HtM will spend because they like to splurge or because they are term liquidity constrained, but not because they have needs. They will not try to save more because they feel like they do not need to and do not have debts in need of faster repayment. The Poor HtM will spend on necessities and because they have needs, even though they would like to have more savings and have debts in need of repayment.

This analysis showcases again why the types can be useful – they characterize people through the reasoning, not only by observable economic characteristics or (identical) observed behaviors. Our analysis suggests that the decision of spending an income shock does not depend only on the liquidity or total assets positions of agents, but also on the reasoning model adopted by individuals. For instance, a wealthier household might spend for splurging and long-term savings reasons, while a less wealthy one spends out of need for essential items.

6.3 The asymmetry puzzle

Empirical evidence suggests that MPCs out of negative income shocks are larger than those out of positive ones, as recently discussed in the review article by Kaplan and Violante (2022) and shown by Bunn et al. (2018), Christelis et al. (2019), and Fuster et al. (2021). The sign asymmetry in MPCs is not a puzzle *per se*. Traditional macro models predict that, taking into account second-order effects of income shocks, an income fall has larger MPCs than an income gain due to the concavity of the consumption function. Furthermore, higher-income or more liquid households should exhibit more symmetric spending behavior for shocks of different signs, as they operate on a less concave portion of the consumption function. However, in our data we find evidence of a large fraction of liquid and high income households that behave asymmetrically, even on the extensive margin.

Figure 14 shows the share of symmetric and asymmetric households in our data. There are two types of symmetric responses (spending the positive shock and cutting spending after a negative one ("Symmetric 1"), and smoothing consumption ("Symmetric 2")) and two types of asymmetric responses (spending more after a positive shock but smoothing the negative one ("Asymmetric 1") and smoothing the positive shock but cutting spending after the negative one ("Asymmetric 2")). The most common type in the data, accounting for 60% of all respondents is the symmetric 1 type. Smoothers are rare. On the asymmetric side, 20% of the sample are of type asymmetric 2 and around 10% are asymmetric 1.

The figure also shows what type of responses different clusters of households have. The asymmetric clusters are predominantly composed of precautionary and strongly constrained households (who tend to smooth a positive shock but to cut spending after a negative one, i.e., asymmetric type 2) and the quasi-smoother households who do the opposite (asymmetric type 1). Symmetric 2 households are essentially the quasi-smoothers, with some precautionary households; while symmetric 1 households are predominantly spenders and some strongly constrained ones.

Figure 13 considers the reasons most frequently mentioned by each type of household, which are aligned with the clusters that they are best represented by. Thus, the asymmetric type 2 households provide reasons for their behaviors akin to those of the Precautionary households from our clusters. They mention having concerns about the future, wanting to smooth consumption, and not needing anything additional as reasons for why they do not increase spending after a positive shock. They cut spending in response to an unexpected expense, also because of concerns about the future. Asymmetric type 1 households mention reasons for increasing spending after the positive shock to be term savings, the wish to minimize the cognitive burden, and the wish to splurge, akin to what Quasi-smoothers would report. Their reasons for not cutting spending after an unexpected expense are the wish to smooth consumption and the existence of spending commitments.

6.4 The co-holding puzzle

A significant share of credit-card holders revolve outstanding balances over time and, at the same time, hold (low-interest) liquid assets that are sufficient to repay these (high-interest) credit card debts. First discussed in Gross and Souleles (2002), according to Gomes et al. (2021) about 30% of U.S. card holders in the Survey of Consumer Finances data who revolve debt behave this way, i.e. they have liquid assets exceeding their outstanding balances. Different explanations have been suggested in the literature. More in line with classical models, households might need cash to purchase some items, since not all purchases can go through credit cards. Therefore they hoard cash and do not repay credit card balances (Telyukova and Wright, 2008). In addition, concerns about future access to credit motivate households to hold liquid assets and not to repay credit card balances (Fulford, 2015; Druedahl and Jørgensen, 2018; Gorbachev and Luengo-Prado, 2019). In fact, in this context, the interest cost of holding credit card debt may be smaller than the benefit of ensuring future access to credit. A final behavioral hypothesis explains the puzzle as a function of decision making within a household (Bertaut et al., 2009). An "accountant" member knows that the "shopper" member (who is more impatient) will spend and accumulate credit card debt. Therefore, the accountant preserves liquid assets instead of using them to repay the debts.

In our sample we define co-holders those households who i) have a credit card, ii) strictly positive credit card balances, and iii) checking or short-term savings accounts balances in excess of credit card outstanding balances. We find that co-holders represent 21% of the entire sample and 25% of the sample that owns a credit card, in line with earlier estimates.[35] We then ask respondents identified as co-holders why they behave this way. For the full sets of questions see A-7.7.

An important methodological point is worth noting. One difficulty in identifying co-holders is that most datasets are snapshots at a moment in time and may paint the wrong picture of the overall financial situation. To circumvent this issue, we asked respondents explicitly how much of the credit card balance will be left over after they pay their bill. Of course, some respondents might have just reported their current credit card balance. Therefore, once we get to the block of questions about co-holding, we repeat to respondents their outstanding balance as well as their liquid assets that they reported earlier and ask them whether these amounts look correct to them. If not, they can update them. We then explicitly explain the puzzle we are looking into by writing: "*Based on your previous answers, it seems like your household could repay some of your outstanding credit card debt with money in your checking and short-term saving account(s). How relevant is each of the following reasons for rolling over credit card balances rather than at least partially repaying them?*"

Figure A-51 shows the share of co-holders in each cluster, and, among co-holders in each of the

[35] This part is prone to measurement errors, either due to respondents' inattention, confusion between current credit card balance and debt to be rolled over, a lack of agreement between what constitutes liquid and illiquid assets (we consider checking and short-term savings account). We address this issue by asking respondents for a second time whether the amount that they have selected (corresponding to the median of the brackets they selected) is correct. In case they misreported, they can insert the correct amount. In our sample, around 19% of respondents correct the amount previously reported in liquid accounts or credit card debt, while 3% correct it in both accounts.

four clusters, the share that reports a reason for co-holding as being very relevant to them. Co-holders are by far more frequent in the Spenders cluster, and least frequent among quasi-smoothers. There is a large heterogeneity in the reasons for co-holding. Among strongly constrained households, the primary reason is that they like to keep some cash on hand, including for unexpected expenses. They also report wanting to use that cash to repay other debts first. Spenders report that they already have plans to cover the outstanding balance (but not in this monthly cycle), but also that they like to keep cash on-hand, that these accounts are managed by different people in the households, and that their checking account rate is higher than their credit card rate. Among precautionary households, the most common reasons are that they like to keep some cash, for both planned and unexpected expenses and that they have already planned to cover outstanding balances.

7 Conclusion

In this paper, we examined the dynamics of household financial behaviors—specifically spending, saving, and borrowing—in the face of transitory financial shocks, with a focus on understanding both the mechanisms and the motivations behind these adjustments. Leveraging large-scale survey data, we first quantified household-level intertemporal marginal propensities to consume and deleverage, revealing substantial heterogeneity in these responses. In a second step, we explored the underlying reasons for these financial behaviors, identifying distinct motivations that drive households' decisions to spend, save, or deleverage. Through a detailed examination of survey responses, we categorized households into four groups based on their financial decision-making processes, revealing a complex landscape of motivations that extend beyond mere socioeconomic factors to include personal concerns, commitments, and expectations.

Exploring the reasons behind households' financial behaviors marks a shift toward a more structural analysis rather than relying solely on reduced-form responses. This approach enables us to distinguish between different models of household behavior that might otherwise appear identical in terms of their MPCs and MPDs; that is, it becomes clear that households may undertake similar financial actions for diverse reasons. While observational data that tracks adjustments in spending, debt, or savings can offer some insights, it falls short of fully explaining the models guiding household behavior. Detailed information on how households manage their finances, such as choosing to use credit card debt over leaving bills unpaid, allows for a more accurate identification of household types, yet still does not fully capture the complexity of household decision-making. The magnitudes of the MPCs and MPDs add another layer of detail, but alone are insufficient to definitively classify household types. Knowing the underlying models would allow us to perform better counterfactual analysis that cannot easily be done with reduced-form estimates only.

By integrating quantitative estimates of financial adjustments with qualitative insights into household motivations, we can offer a more comprehensive view of the decision-making processes and cognitive frameworks guiding household finances. Furthermore, our method of cross-validation confirms the reliability of survey data for capturing these behaviors accurately, supporting the continued use of such methodologies in future research. Nevertheless, more research on when survey responses are valid estimates of real-world behaviors would be very valuable – it is likely that the reliability of self-reported reactions varies with the setting.

This paper represents only an initial foray into using specially-designed surveys to enhance our understanding of the diverse decision-making models employed by households. There are likely numerous additional factors and characteristics that could be explored to more accurately distinguish between household types, beyond the four primary categories we have delineated. It was also beyond the scope of this paper to develop a formal model that can nest the behavior of each identified type – an interesting and promising avenue for further work lies in integrating these varied models and their prevalence within the population into a cohesive, aggregate, structural framework. Such an approach could potentially lead to more precise forecasting and policy analysis by accurately capturing the aggregate responses of households in the economy.

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FIGURES and TABLES

Table 1: Sample Statistics

	U.S. Population	Survey
Male	.53	.53
25-29 years old	.13	.13
30-39 years old	.28	.28
40-49 years old	.25	.25
50-59 years old	.24	.24
60-65 years old	.1	.1
\$0-\$19999	.04	.04
\$20000-\$39999	.11	.11
\$40000-\$69999	.2	.2
\$70000-\$124999	.29	.29
\$125000+	.36	.36
White	.61	.73
Black/African-American	.12	.12
Hispanic/Latino	.18	.13
Asian/Asian-American	.07	.03
Full time employed	.78	.79
Part time employed	.09	.08
Self-employed	.1	.08
Unemployed	.03	.05
U.S. total population	260329	–
U.S. labor force, age 25-65	129923	–
Sample size	–	2923

Notes. This table displays statistics for the overall U.S. population (column 1) and compares it to the characteristics of our sample (column 2). National statistics on gender, age, income brackets, race, and employment status are from the CPS-ASEC dataset for March 2022. Numbers for "U.S. total population" and "U.S. labor force, age 25-65" are in thousands. See Appendix A-1.2 for details on how the summary statistics are constructed.

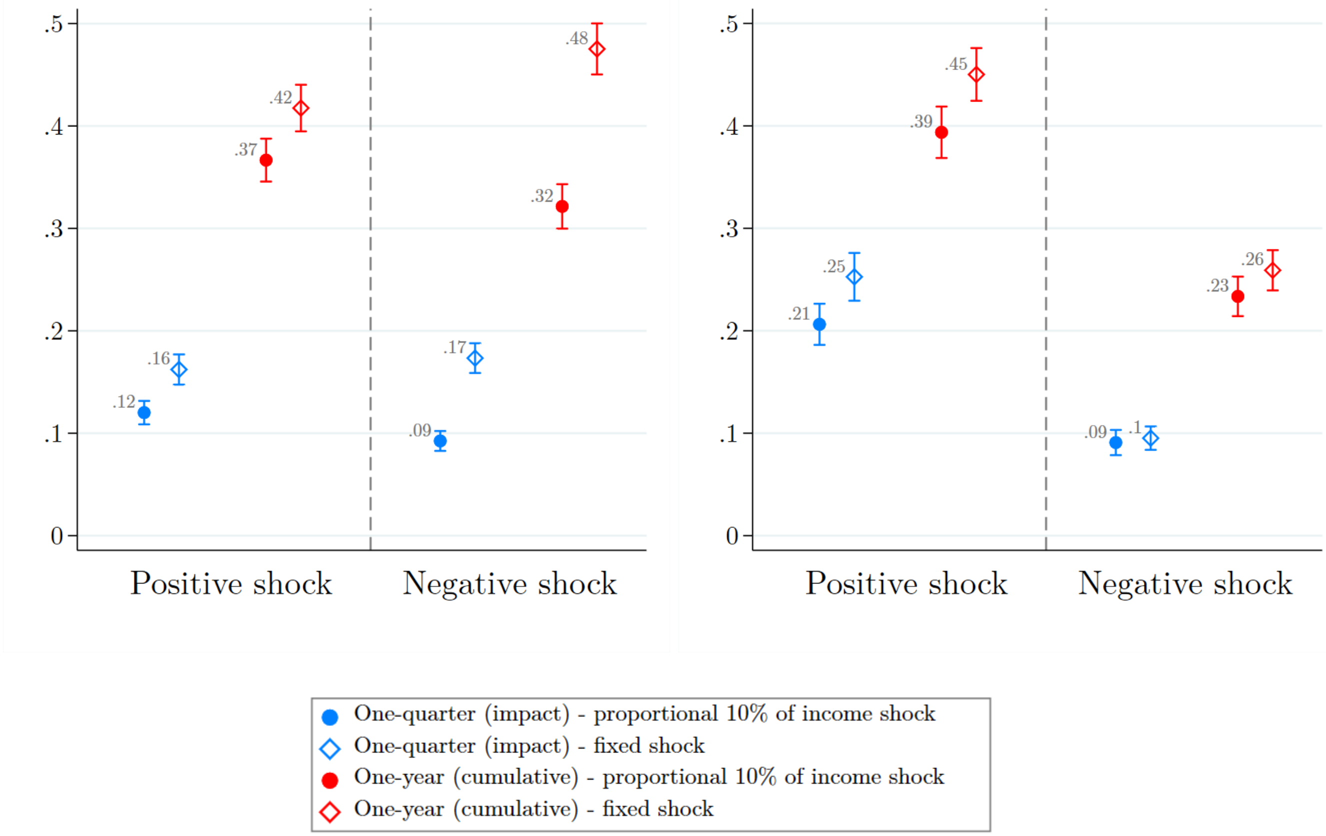
Table 2: Cross-validations

Paper	Estimate	Sample	Value	Our estimate
Patterson (2023)	**MPC** out of income loss due to unemp.	CEX, PSID	.53	.59 (.024)
Kaplan et al. (2014)	Share of HtM households	SCF	.31	.31 (.013)
	Share of wealthy HtM out of total HtM		.62	.64 (.036)
Chetty and Szeidl (2007)	Share of committed expenditures	CEX, PSID	0.5 (update: 0.6)	.62 (.005)
Baugh et al. (2021)	**MPC** out of tax refund, 30 days before receipt	Admin data, account aggregator	.001	.01 (.002)
	MPC out of tax refund, 30 days after receipt		.07	.091 (.009)
	MPC out of tax refund, 30-60 days after receipt		.03	.096 (.009)
Baugh et al. (2021)	**MPC** out of tax payment, 30 days before due	Admin data, account aggregator	.001	.044 (.007)
	MPC out of tax payment, 30 days after due		.001	.026 (.004)
	MPC out of tax payment, 30-60 days after due		.01	.02 (.004)
Di Maggio et al. (2017)	**Car spending/initial mort. paym.** out of cuts in mort. paym.	BlackBox Logic, Equifax	.043	.065 (.02)
	Repaym. of mortgage debt/initial mort. paym. out of cuts in mort. paym.		.043	.059 (.008)
Karger and Rajan (2021)	**MPC** out of the first EIP	Facteus bank-account data	.46	.5 (.024)
Misra et al. (2022)	**MPC** out of the first EIP	Facteus data, ZIP code level	.51	
Chetty et al. (2023)	**MPC** out of the first EIP	Affinity Solutions, aggregated data	.37-.61	

Notes. Cross-validations are taken from the first survey wave (May - October 2021), except Baugh et al. (2021), Di Maggio et al. (2017) that are based on the second cross-validation survey (February 2024). Karger and Rajan (2021) estimate the MPC out of the first EIP over an horizon of 14 days. They also show that spending responses are concentrated in the first week after the transfer receipt, while the response flattens already in the following week. Misra and Surico (2014) estimate the MPC over the first 4 days after the first EIP receipt. They also show that the spending response is flat after the first 6 days. Chetty et al. (2023) estimate the MPC over one-month after first EIP receipt separately for income quartiles. Their MPC ranges between 0.37 and 0.61 corresponding respectively to the MPCs in the lowest and highest quartile. Standard errors in parentheses.

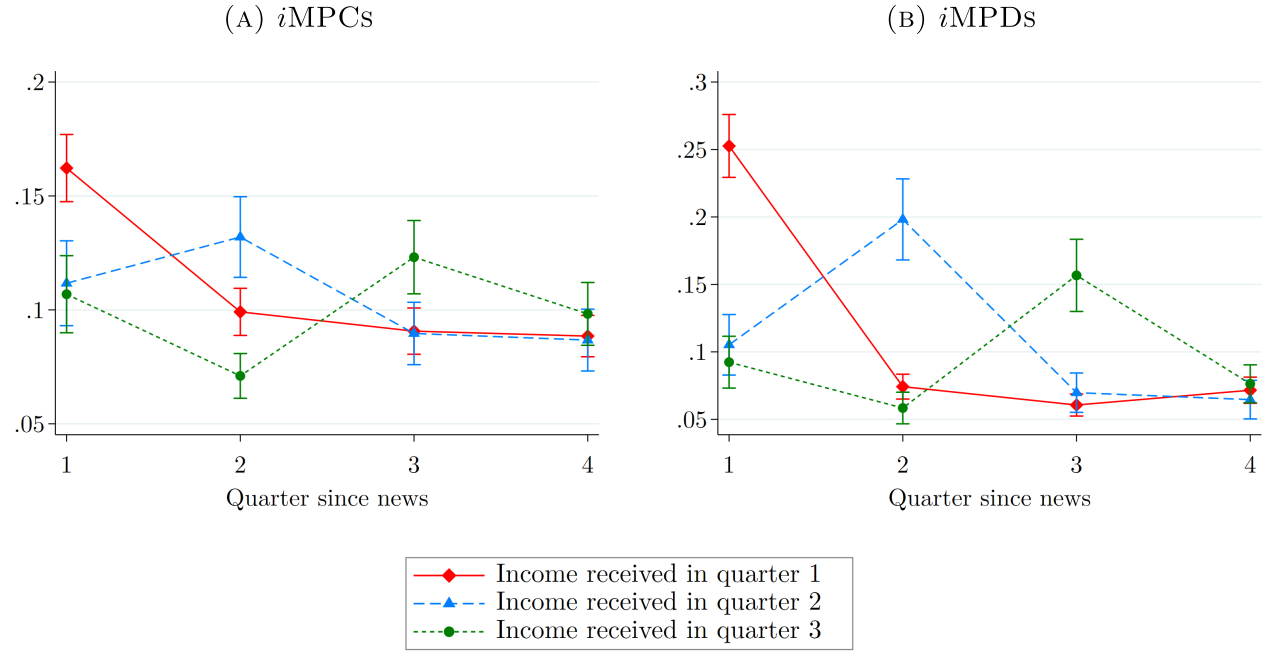
Figure 2: *i*MPCs and *i*MPDs

(a) *i*MPCs (b) *i*MPDs



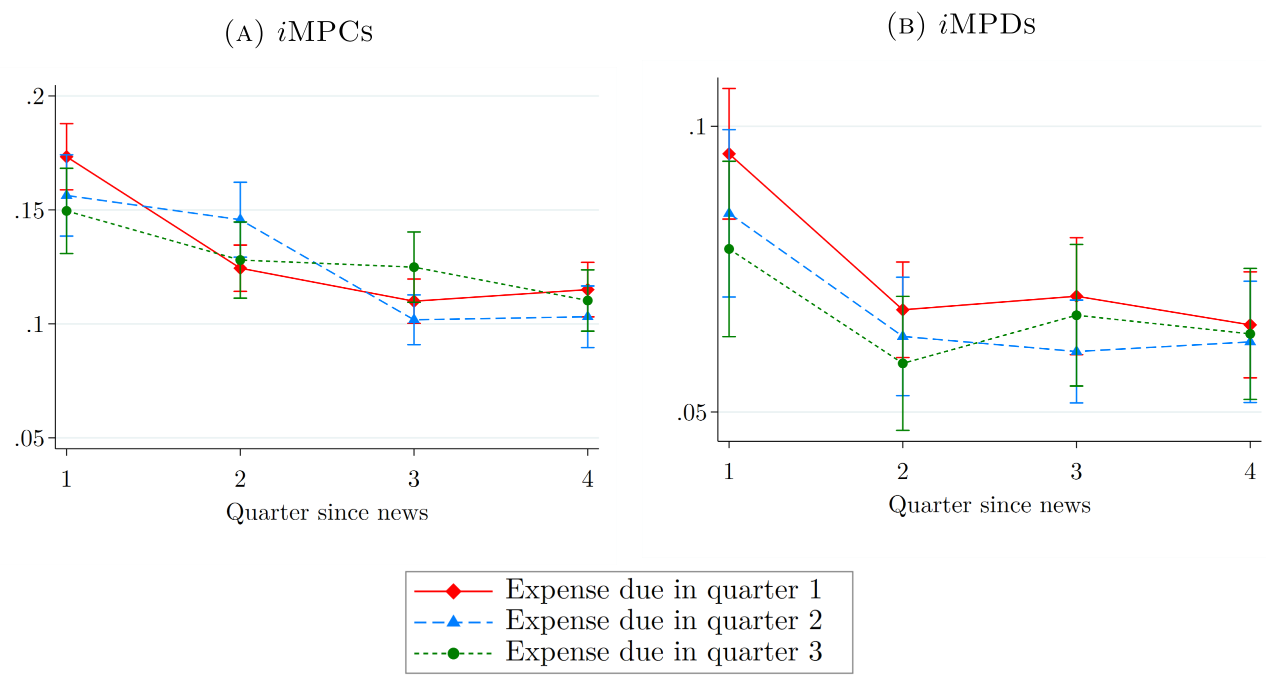
Notes. These figures report impact (blue) and cumulative (red) *i*MPCs (Panel A) and *i*MPDs (Panel B) out of a proportional 10% of income shock (dots) and out of a fixed income shock worth \$1000 (diamonds). Within each panel, positive shocks are reported to the left and negative shocks to the right. Confidence intervals are at the 90% level.

Figure 3: *i*MPCs and *i*MPDs out of a positive fixed income shock



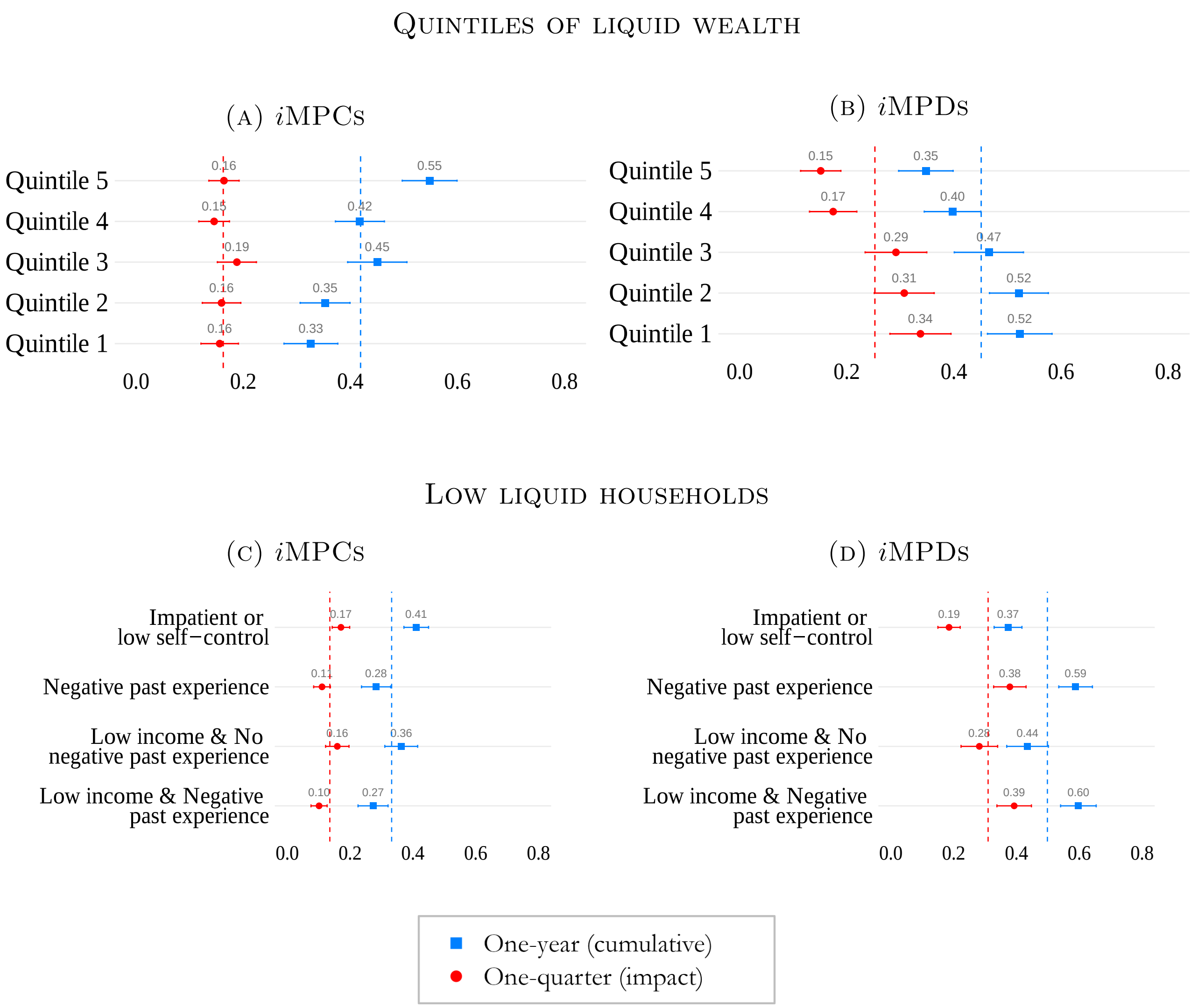
Notes. These figures report *i*MPCs (Panel A) and *i*MPDs (Panel B) over the 4 quarters out of a positive fixed income shock worth $1000, received in the same quarter of the news, in the following one, and in two quarters from the news. Confidence intervals are at the 90% level.

Figure 4: *i*MPCs and *i*MPDs out of a negative fixed income shock



Notes. These figures report *i*MPCs (Panel A) and *i*MPDs (Panel B) over the 4 quarters out of a negative fixed income shock worth $1000, received in the same quarter of the news, in the following one, and in two quarters from the news. Confidence intervals are at the 90% level.

Figure 5: iMPCs and iMPDs and liquid wealth



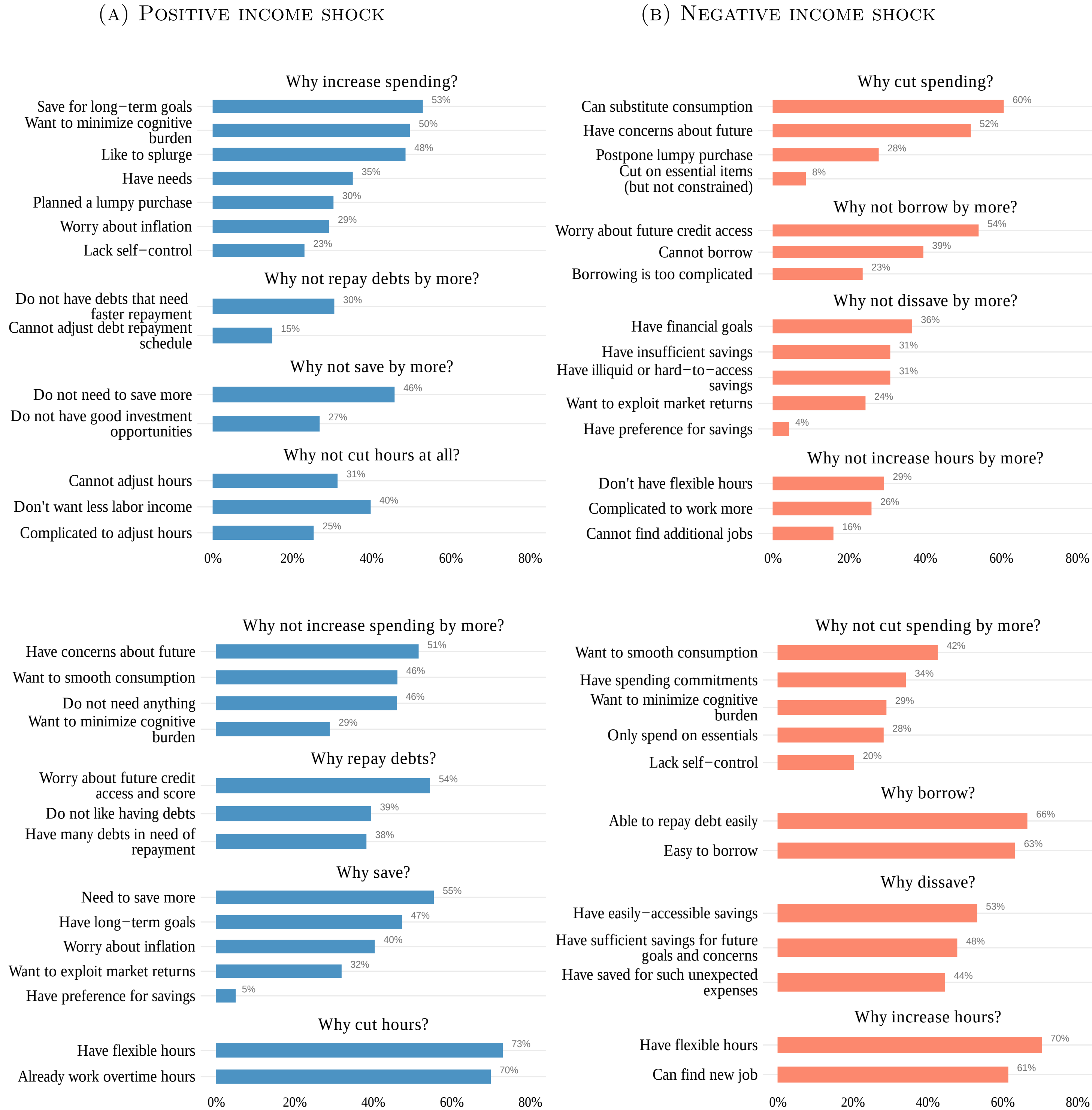
Notes. These figures report impact and cumulative iMPCs (Panel A and Panel C) and iMPDs (Panel B and Panel D) out of a positive income shock. The dashed lines represent the sample mean. Panel A and Panel B compare households by quintiles of liquid assets (defined as the sum of checking and short-term accounts) and consider a positive fixed income shock worth \$1000 (see Figure A-49 for the proportional income shock). Households are divided in 5 groups by their liquid assets: Quintile 1 (liquid assets $<$ \$ 1000), Quintile 2 (\$ 1000 $<$ liquid assets $<$ \$5150), Quintile 3 (\$ 5150 $<$ liquid assets $<$ \$ 24150), Quintile 4 (\$ 24150 $<$ liquid assets $<$ \$ 70000), Quintile 5 (liquid assets $>$ \$ 70000).
Panel C and Panel D consider low liquid assets households (i.e., liquid assets $<$ \$13500, corresponding to the bottom 50% of the distribution of liquid assets). We compare individuals who are impatient or have low self-control to those who had a negative past experience. We define impatient or low self-control individuals as those who either are "low self-control" or fall within the 35% most impatient individuals according to the self-reported [scale 0-10] measure of impatience. We define individuals who had a negative past experience as those who self report that their economic and financial situation worsened significantly or slightly over the previous two years [exact question "Do you think that your and your household's overall economic and financial situation has worsened or improved over the past 2 years?" (*Significantly worsened; Slightly worsened; Stayed the same; Slightly improved; Significantly improved*)]. We exclude individuals who are classified as both impatient or have low self-control and having a negative past experience. We also plot individuals who are low income (bottom 50% of income distribution) comparing those who did not have a negative past experience to those who had a negative past experience. From this last tabulation, we exclude individuals who are also classified as impatient or have low self-control. Confidence intervals are at the 90% level.

Table 3: MPCs and MPDs estimates across studies

Paper	Time period	Source	Sign	Size	Horizon	MPC Non Durables	MPC Durables	MPD
Boehm et al. (2025)	5/22	Crédit Mutuel Alliance Fédérale	+	$300	1 month	.17	.06	
Kosar et al. (2023)	6/20	NY Fed SCE	+	$2400 median check	Not specified	.3*		.32
Armantier et al. (2020, 2021)	6/20, 7/20, 3/21	NY Fed SCE	+	$2400 median check	Not specified	.25-.29*		.34-.37
Coibion et al. (2020)	7/20	Nielsen Homescan	+	$2400 median check	Not specified	.35	.07	.31
Parker et al. (2022)	EIP1 4/20	CEX	+	$2400 median check	3 months	.1	.13	
	EIP2 1/21	CEX	+	$1200 median check	3 months	.08	.16	
	EIP1 4/20	CEX	+	$2400 median check	6 months	.12	.33	
	EIP2 1/21	CEX	+	$1200 median check	6 months	.15	.45	
Fagereng et al. (2021)	Lotteries '94-'06	Norwegian admin. data	+	$1500 – 150000 win	1st year	.49	.03	.07
	Lotteries '94-'06	Norwegian admin. data	+	$1500 – 150000 win	2nd year	.2*		.01
Parker et al. (2013)	'08 tax rebate	CEX	+	$300-1.2K	3 months	.12-.3	.38-.6	
Orchard et al. (2025)	'08 tax rebate	CEX	+	$300-1.2K	3 months	-.02	.3	
Fuster et al. (2021)	2016-2017	NY Fed SCE	+	$500	3 months	.05	.02	
	2016-2017	NY Fed SCE	+	$2.5K	3 months	.06	.03	
	2016-2017	NY Fed SCE	+	$5K	3 months	.08	.04	
	2016-2017	NY Fed SCE	+	$500 in 3 months	3 months	-.01	-.01	
	2016-2017	NY Fed SCE	+	$5K in 3 months	3 months	.03	.01	
	2016-2017	NY Fed SCE	-	$500	3 months	.26	.06	
Christelis et al. (2019)	2015	Dutch National Bank survey	+	1 month of income	1 year	.2	.19	.15
	2015	Dutch National Bank survey	+	3 months of income	1 year	.14	.22	.16
	2015	Dutch National Bank survey	-	1 month of income	1 year	.24	.26	.07
	2015	Dutch National Bank survey	-	3 months of income	1 year	.24	.27	.07

Notes. Asterisk means total MPC (nondurable and durable jointly) in cases when separate estimates are not provided or cannot be recovered. For Boehm et al. (2025), MPC for durables is computed as the share of additional expenditure on durables (reported in their Table 2 for card group 1) times the overall MPC for card group 1, equal to 0.23. For Fuster et al. (2021), MPC for durables is computed as the share of additional expenditure on durables (reported in their Table A-2) times the total MPCs in their Table 3. The acronyms used are CEX (Consumer Expenditure Survey), EIP (Economic Impact/Stimulus Payment) and SCE (Survey of Consumer Expectations).

Figure 6: Distribution of reasons



Notes. We tabulate the share of respondents that select a reason for using or not using by more (or at all) a given margin. We consider a fixed income shock. Appendix Figure A-22 compares the distribution of reasons between fixed and proportional income shocks.

Table 4: Classification of households summary table

Characteristics	Strongly constrained (18%)	Spenders (33%)	Precautionary (16%)	Quasi-smoothers (18%)
MPCs/MPDs after positive shock	Low MPCs, high MPDs	High MPCs, low MPDs	Low MPCs, low MPDs	Slightly higher MPCs, low MPDs
MPCs/MPDs after negative shock	Average MPCs, high MPDs on impact only	Low MPCs, high MPDs	High MPCs, low MPDs	Slightly lower MPCs, low MPDs
Main reaction after positive shock	Deleverage	Spend more	Save	Save
Main reason	Too many debts	Minimize cognitive burden, splurging	Concerns about future and long term goals	Do not need things, have long term goals
Main reaction after negative shock	Cut spending and borrow	Mix of spending cut, borrowing and dip into savings	Dip into saving and cut consumption	Dip into savings
Main reason	Future concerns, substitute away towards lower quality & cannot borrow more	Easy to borrow, want to minimize cognitive burden	Future concerns and because they have buffer stock for such situations	Want to smooth consumption and have easily accessible savings
Decision making characteristics	Can only handle very limited unexpected expenses, unable to stick to plans because of volatility and shocks, planning horizon short	Average length planning horizon, able to withstand average unexpected expenses	Large planned investments, stick to plans in disciplined manner	Longer planning horizon, able to stick to plans, can handle large unexpected expenses
Main socioeconomic characteristics	Women, older, low income, low assets of all types	Younger, higher income and assets, with children, low income risk	Somewhat older, higher assets, lower debts, typically low income risk	Older, high assets, low debt
Other characteristics	Higher risk aversion, lots of concerns, high income risk	Low self-control, low risk-aversion	High self-control, high planned investments	High self-control, high risk aversion

Notes. This table summarizes the key features of the four types of households identified.

Figure 7: Distribution of reasons across clusters

(A) Positive income shock

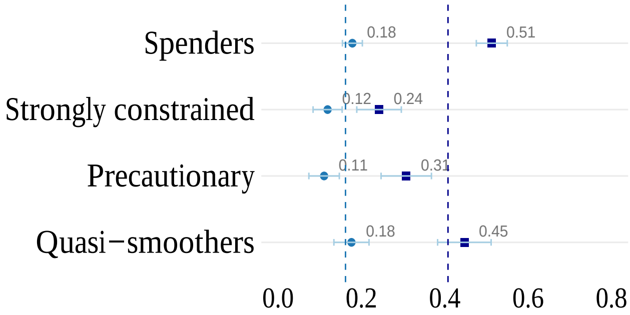
(B) Negative income shock

Notes. We tabulate the share of respondents in each cluster that select a reason for using or not using a given margin by more (or at all) in response to a fixed $1000 income shock. The gray bars represent the sample mean.

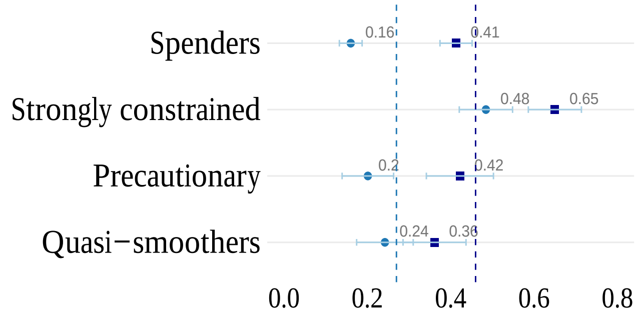
Figure 8: *i*MPCs and *i*MPDs

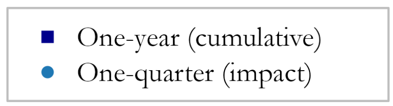
Positive income shock

(a) *i*MPCs



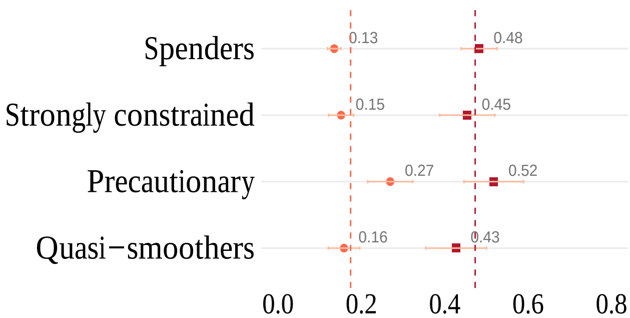
(b) *i*MPDs



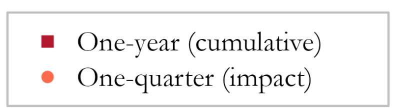


Negative income shock

(c) *i*MPCs



(d) *i*MPDs



Notes. These figures report *i*MPCs (Panel A and Panel C) and *i*MPDs (Panel B and Panel D) impact and cumulative for fixed $1000 income shock across each cluster. Panel A and Panel B refer to a positive income shock, while Panel C and Panel D to a negative income shock. The dashed lines represent the sample mean.

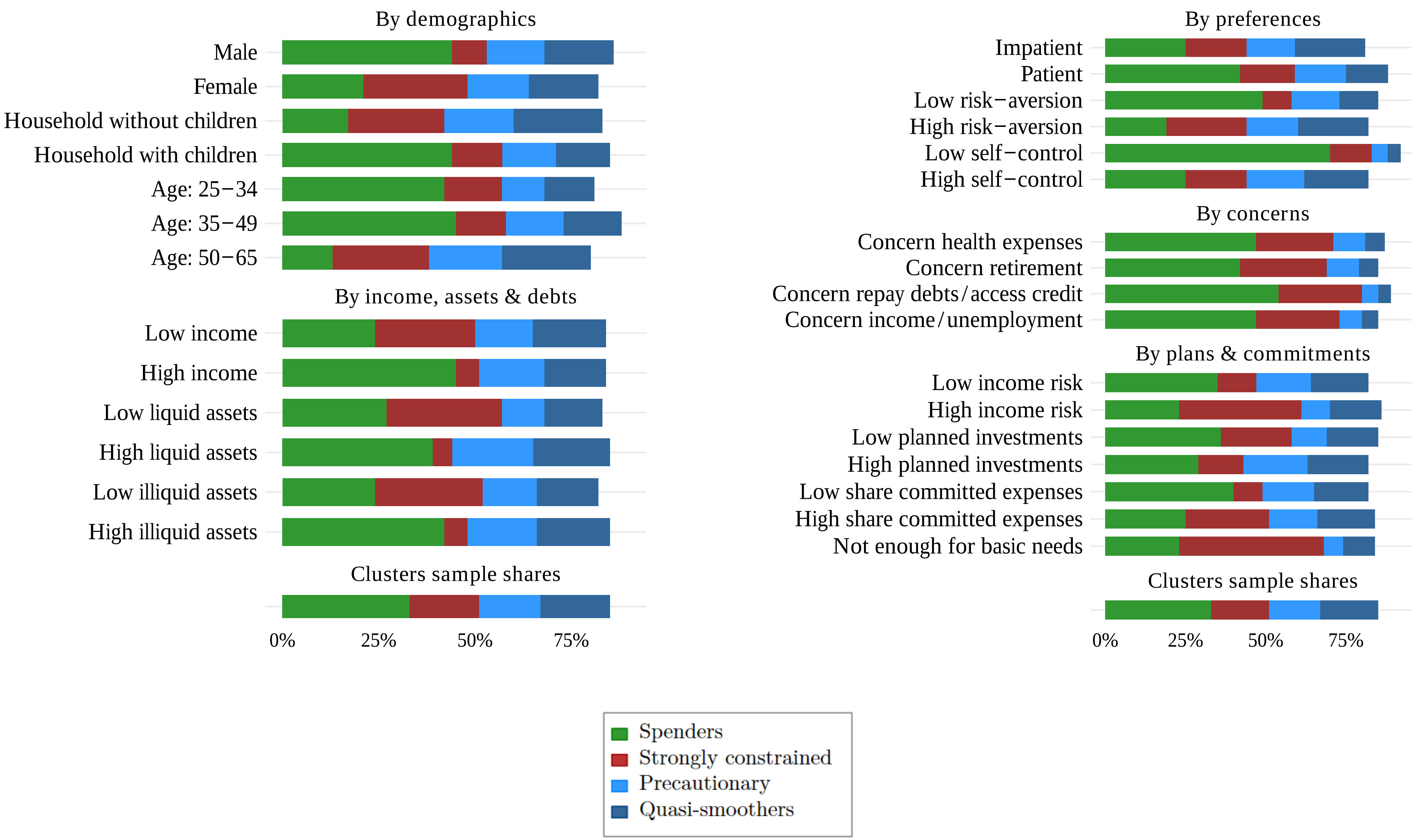
Table 5: Prediction of clusters

	Quasi-smoother households		**Precautionary households**		**Strongly constrained households**		**Spender households**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.009	-0.012	0.037	0.038	0.116***	0.092***	-0.161***	-0.118***
	(0.026)	(0.025)	(0.025)	(0.025)	(0.024)	(0.023)	(0.028)	(0.026)
Age: 35-49	0.028	0.035	0.038	0.044	0.033	0.014	-0.099***	-0.094***
	(0.032)	(0.031)	(0.031)	(0.030)	(0.029)	(0.028)	(0.035)	(0.032)
Age: 50-65	0.094***	0.072**	0.090***	0.075**	0.093***	0.027	-0.277***	-0.173***
	(0.034)	(0.034)	(0.032)	(0.033)	(0.031)	(0.030)	(0.036)	(0.035)
High education	-0.020	-0.022	0.019	0.004	-0.039	-0.010	0.040	0.028
	(0.028)	(0.027)	(0.027)	(0.027)	(0.026)	(0.025)	(0.031)	(0.029)
Household with children	-0.065*	-0.061*	-0.012	-0.022	-0.010	0.004	0.086**	0.078**
	(0.035)	(0.033)	(0.034)	(0.033)	(0.032)	(0.030)	(0.038)	(0.035)
High income	-0.027	-0.044	0.006	-0.017	-0.046	-0.025	0.067*	0.086***
	(0.032)	(0.031)	(0.031)	(0.031)	(0.030)	(0.028)	(0.035)	(0.032)
High liquid assets	0.060**	0.047	0.132***	0.098***	-0.168***	-0.116***	-0.023	-0.030
	(0.030)	(0.029)	(0.028)	(0.028)	(0.027)	(0.026)	(0.032)	(0.030)
Have credit card debt	-0.125***	-0.059**	-0.112***	-0.073***	0.111***	0.091***	0.125***	0.040
	(0.026)	(0.025)	(0.025)	(0.025)	(0.024)	(0.023)	(0.028)	(0.026)
High illiquid assets	0.076**	0.076**	-0.025	-0.046	-0.107***	-0.053*	0.055	0.023
	(0.033)	(0.033)	(0.032)	(0.032)	(0.031)	(0.030)	(0.036)	(0.034)
High illiquid debt	-0.071***	-0.061**	-0.013	-0.008	0.042*	0.040*	0.042	0.028
	(0.025)	(0.024)	(0.024)	(0.024)	(0.023)	(0.022)	(0.027)	(0.025)
Low self-control		-0.080**		-0.086***		-0.087***		0.253***
		(0.031)		(0.031)		(0.029)		(0.033)
Low risk aversion		-0.065**		-0.001		-0.064***		0.130***
		(0.027)		(0.026)		(0.024)		(0.028)
Patient		-0.074***		0.033		0.032		0.010
		(0.024)		(0.024)		(0.022)		(0.025)
Concern income/unemployment		-0.076**		-0.053*		0.046*		0.083***
		(0.030)		(0.030)		(0.027)		(0.031)
Concern repay debts/access credit		-0.039		-0.089***		0.040		0.087**
		(0.032)		(0.032)		(0.029)		(0.034)
Concern health expenses		-0.031		0.008		-0.027		0.050
		(0.034)		(0.034)		(0.031)		(0.036)
Concern retirement		-0.105***		-0.003		0.062**		0.046
		(0.029)		(0.029)		(0.027)		(0.031)
High share committed expenses		-0.009		-0.005		0.070***		-0.056**
		(0.024)		(0.024)		(0.022)		(0.025)
High income risk		0.006		-0.055*		0.085***		-0.036
		(0.030)		(0.030)		(0.027)		(0.032)
High planned investments		0.029		0.064***		0.024		-0.117***
		(0.024)		(0.024)		(0.022)		(0.025)
Not enough for basic needs		-0.087***		-0.087***		0.225***		-0.051
		(0.032)		(0.032)		(0.029)		(0.034)
Observations	1107	1103	1107	1103	1107	1103	1107	1103
Adjusted R^2	0.067	0.157	0.055	0.105	0.221	0.319	0.236	0.358

Notes. The dependent variables are indicator variables for the clusters: quasi-smoother households (columns 1 to 2), precautionary households (columns 3 to 4), strongly constrained households (columns 5 to 6) and spender households (columns 7 to 8).

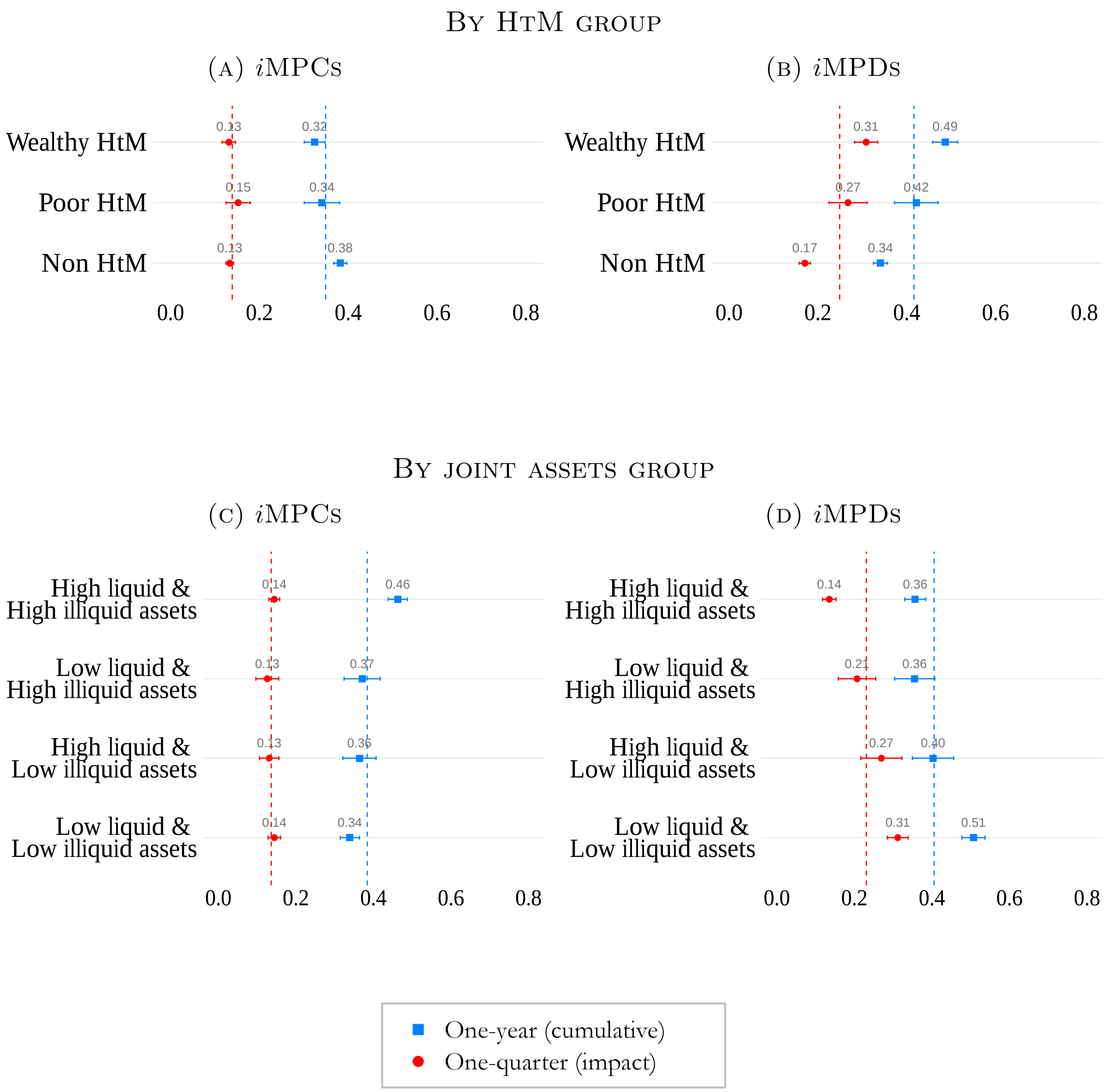
These are regressed (odd columns) on the *fixed shock* indicator, on the indicator for *individual decision making* (not shown), demographic variables (number of household members – not shown –, indicators for female, age classes 35-49 and 50-65, black and other races – not shown –, high education, household with children); income, assets, and liabilities controls (indicators for high income, high liquid assets, high credit card debts, high illiquid assets, high illiquid debts). In addition, in even columns we control for preferences (indicators for low self-control, low risk-aversion, patient); concerns (indicators for concerns about income/unemployment, repaying debts/accessing to credit, health expenses, retirement), other plans and constraints variables (indicators for high spending commitments, high income risk, high planned investments, not having enough for basic spending needs). Omitted categories are the indicator variables for age 25-34, white race. All variables are defined in more detail in Appendix A-2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 9: Distribution of clusters for each characteristic



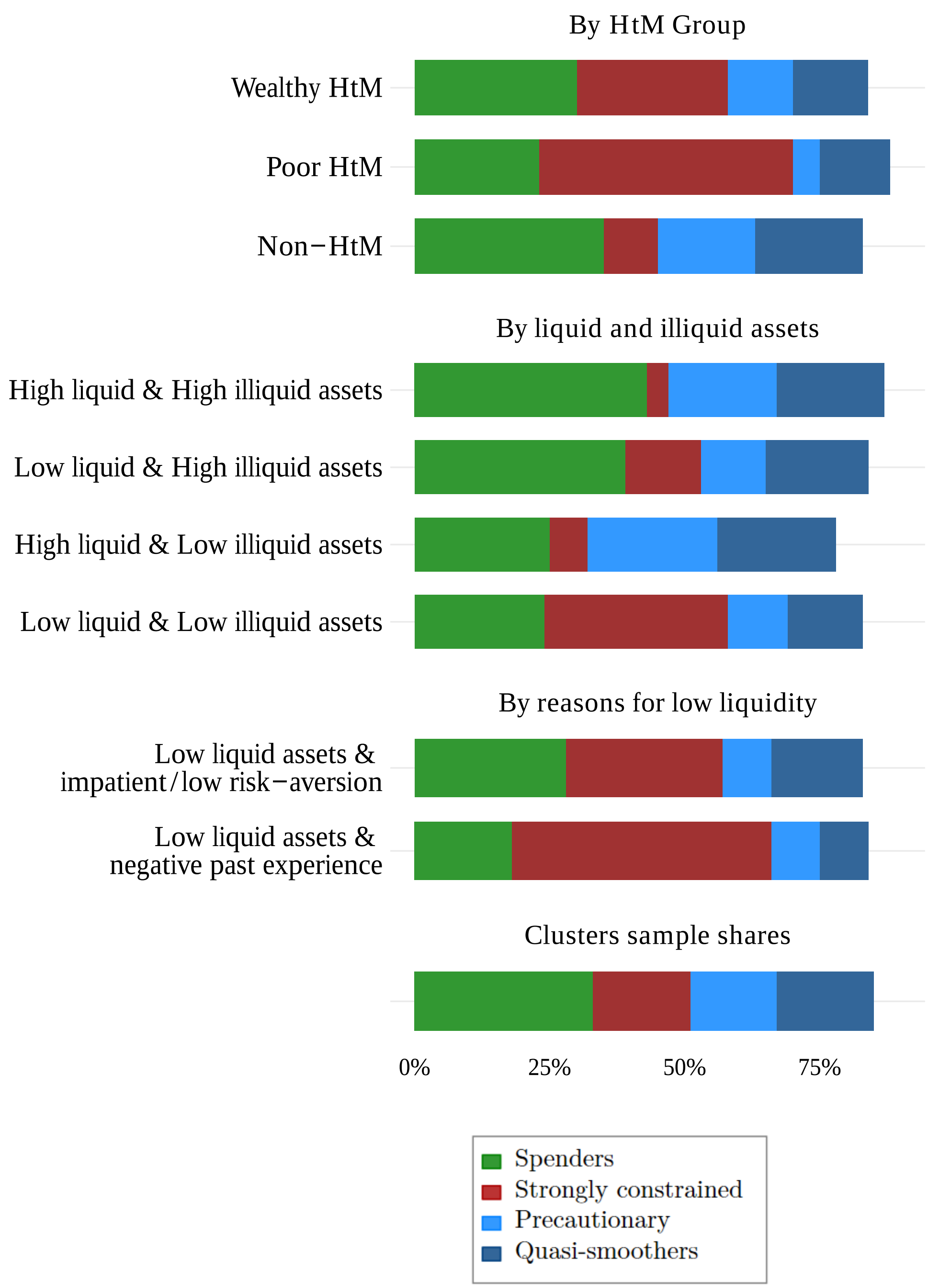
Notes. We plot the distribution of a given characteristic across clusters for a fixed $1000 income shock. Note that shares do not sum up to 100 because a minor share of respondents is not classified in any of the four clusters.

Figure 10: *i*MPCs and *i*MPDs by households' assets



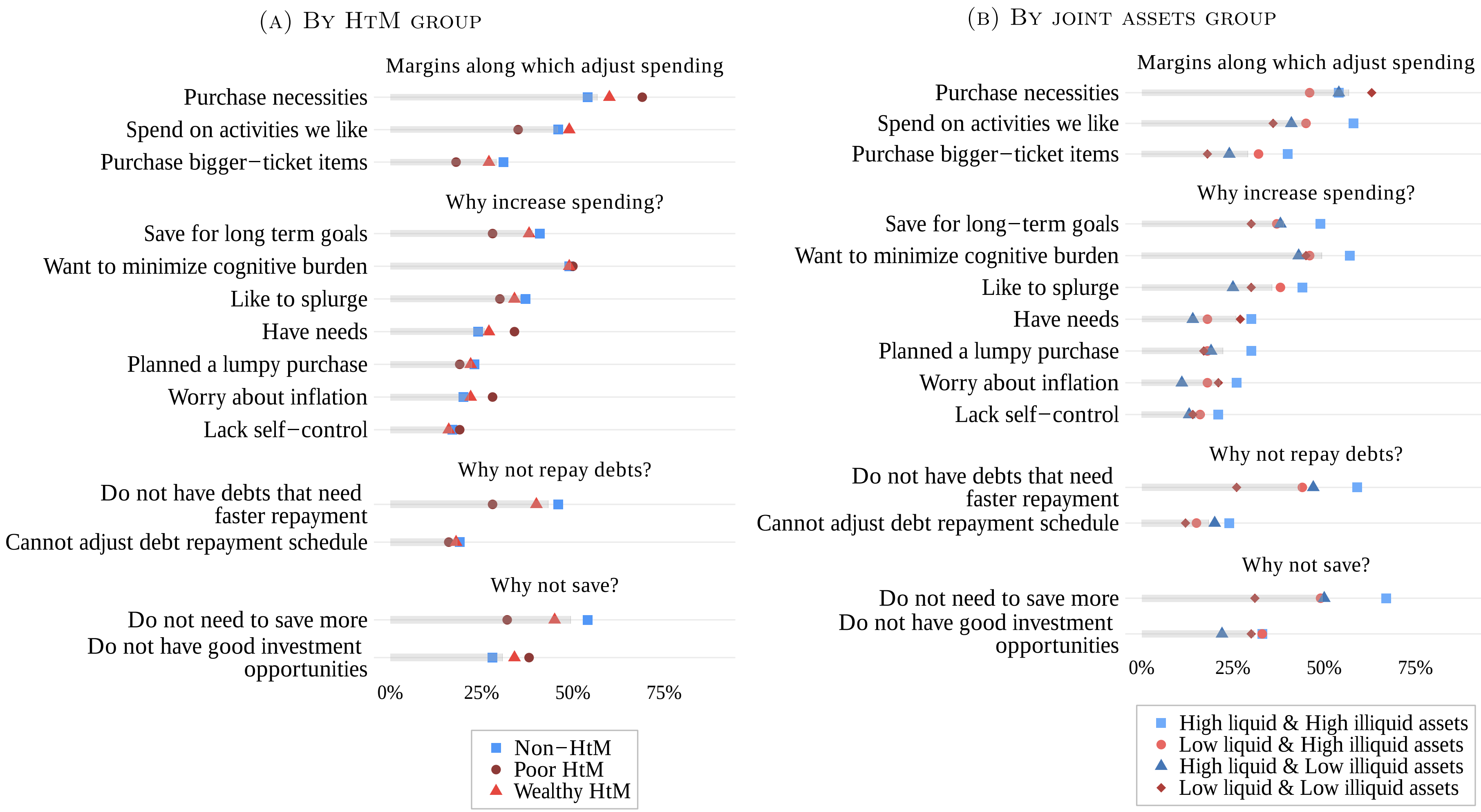
Notes. These figures report impact and cumulative iMPCs (Panel A and Panel C) and iMPDs (Panel B and Panel D) for a positive proportional or fixed income shock, received in the same quarter of the news. Panel A and Panel B compare households who are classified as wealthy hand-to-mouth (HtM), poor HtM , and non-HtM (following Kaplan et al. (2014), see Appendix A-2.4). Panel C and Panel D compare households based on the joint distribution of liquid and illiquid assets (low/high liquid or illiquid assets are defined as the bottom and top 50% of their respective distributions). Panel C and Panel D exploit also data from the first survey wave of May-October 2021. The dashed lines represent the sample mean. Confidence intervals are at the 90% level.

Figure 11: Clusters by households' assets



Notes. We plot the distribution of a given characteristic across cluster for a fixed \$1000 income shock. Note that shares do not sum up to 100 because a minor share of respondents is not classified in any of the four clusters.

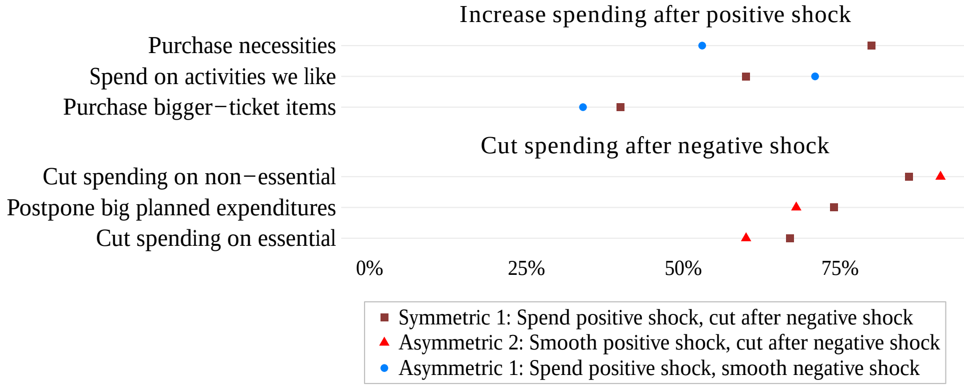
FIGURE 12: REASONS AND MARGINS BY HTM AND JOINT ASSETS GROUPS



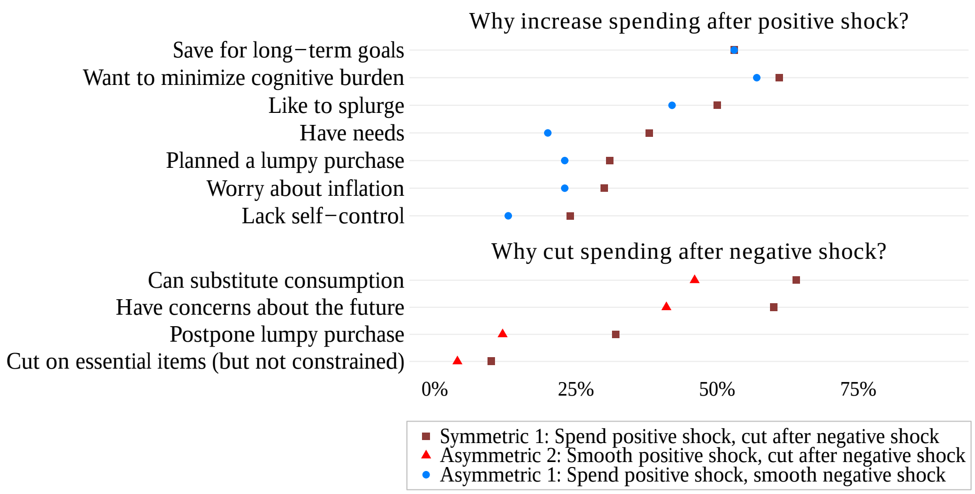
Notes. We plot the detailed margins of spending adjustment and reasons to increase spending, not repay debts by more or at all, and not save by more or at all out of a positive fixed income shock worth \$1000. Reasons are unconditional on the margin selected. Panel A compares households who are classified as wealthy HtM, poor HtM, and non-HtM. Panel B compares households based on the joint distribution of liquid and illiquid assets. The gray bars represent the sample mean.

Figure 13: Reasons and margins by symmetric/asymmetric groups

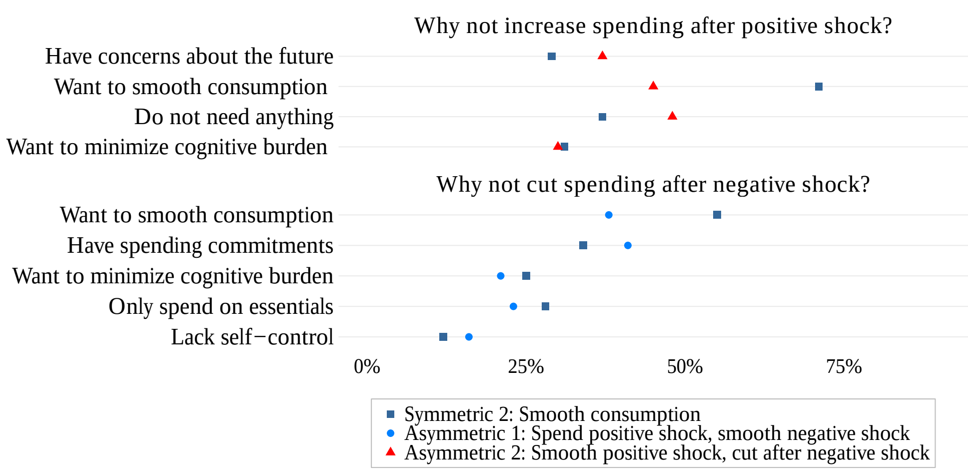
(a) Margins



(b) Reasons for increasing & cutting spending

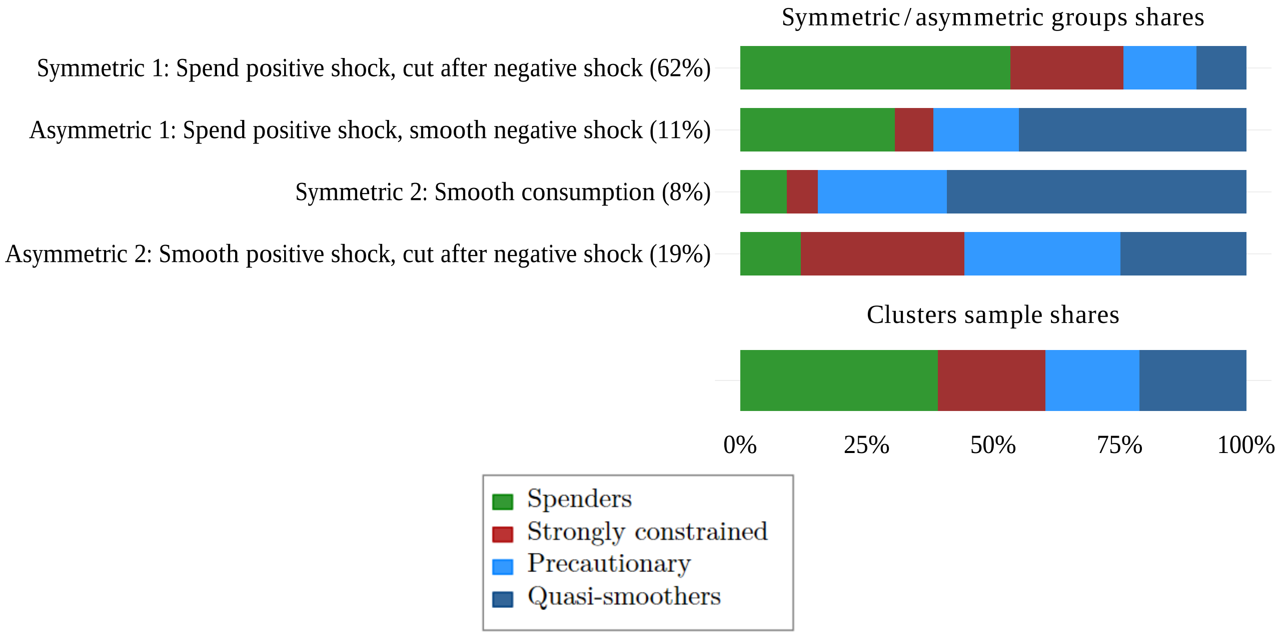


(c) Reasons for not increasing & not cutting spending



Notes. Panel A shows the detailed spending margins: we compare the two asymmetric cases (increase but not cut spending / not increase but cut spending) to the benchmark symmetric case (increase and cut spending). Panel B shows reasons to increase and cut spending: we compare the two asymmetric cases (increase but not cut spending / not increase but cut spending) to the benchmark symmetric case (increase and cut spending). Panel C shows reasons not to increase and not to cut spending: we compare the two asymmetric cases (increase but not cut spending / not increase but cut spending) to the benchmark symmetric case (not increase and not cut spending). We consider a fixed \$1000 income shock.

Figure 14: Clusters by symmetric/asymmetric groups



Notes. We show the share of each symmetric/asymmetric group that falls into each cluster for a fixed $1000 income shock. Note that for each group in brackets there is the share in the sample.