Quick-Fixing: Near-Rationality in Consumption and Savings Behavior

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Abstract

The near-rationality hypothesis holds that even very small costs of optimization may lead people to act suboptimally. We embed this idea in a standard model of consumption-savings decisions: households pursue simple *quick-fix* consumption policies unless they pay a cost to optimize. We design a novel survey to explore this theory. The survey elicits households' hypothetical consumption responses to a large number of unanticipated income shocks, allowing us to estimate household-level consumption policies. Consistent with the theory, 68% of households follow one of four simple quick-fix consumption rules that either fully consume or fully save out of small shocks before abruptly switching to similar consumption policies for large shocks. Households' quick-fixing types account for 49% of the variance in MPCs across households, despite not being predictable by other demographic and economic information. Quantitatively, an incomplete-markets model calibrated to our survey findings generates more than three times as much size-dependence in the aggregate consumption response to government transfer shocks as the nested rational model. This large difference in behavior arises while households experience consumption-equivalent welfare costs of near-rationality of at most $65 per quarter.

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1 Introduction

A long-standing hypothesis in economics is that decision-makers may behave suboptimally because the gains from making better decisions are small and not worth the required effort. Akerlof and Yellen (1985b) define such *near-rational behavior* as "behavior that is perhaps sub-optimal but that nevertheless imposes very small individual losses on its practitioners relative to the consequences of their first-best policy."

Households' consumption and savings behavior is an important and natural candidate for near-rationality. Their consumption decisions and, in particular, their marginal propensities to consume (MPCs) are critical determinants of aggregate demand in standard macroeconomic models. However, optimizing consumption levels to keep up with frequent changes in economic circumstances, as required by benchmark rational models of household behavior, is challenging. And the losses from failing to do so may be very small. For example, Cochrane (1989) shows that if a representative household simply sets its consumption equal to aggregate income in the US, then its welfare losses would be less than $1 per quarter.

However, we lack both theory and evidence to understand the nature and implications of near-rationality in households' consumption-savings decisions. Is there evidence for near-rationality in households' behavior? If so, which forms does near-rationality take? And what are the macroeconomic consequences of this behavior?

This paper investigates these questions in three steps. First, we develop a simple theoretical framework for near-rational consumption-savings behavior. Instead of costly optimization, households can also rely on *quick-fixes*, simple near-rational policy functions that avoid the cost of optimization. Second, we design a survey to evaluate this theory and uncover evidence that the majority of households rely on quick-fixes to respond to income shocks. Finally, we use a quantitative model to study the macroeconomic implications of the near-rational household behavior implied by our survey results.

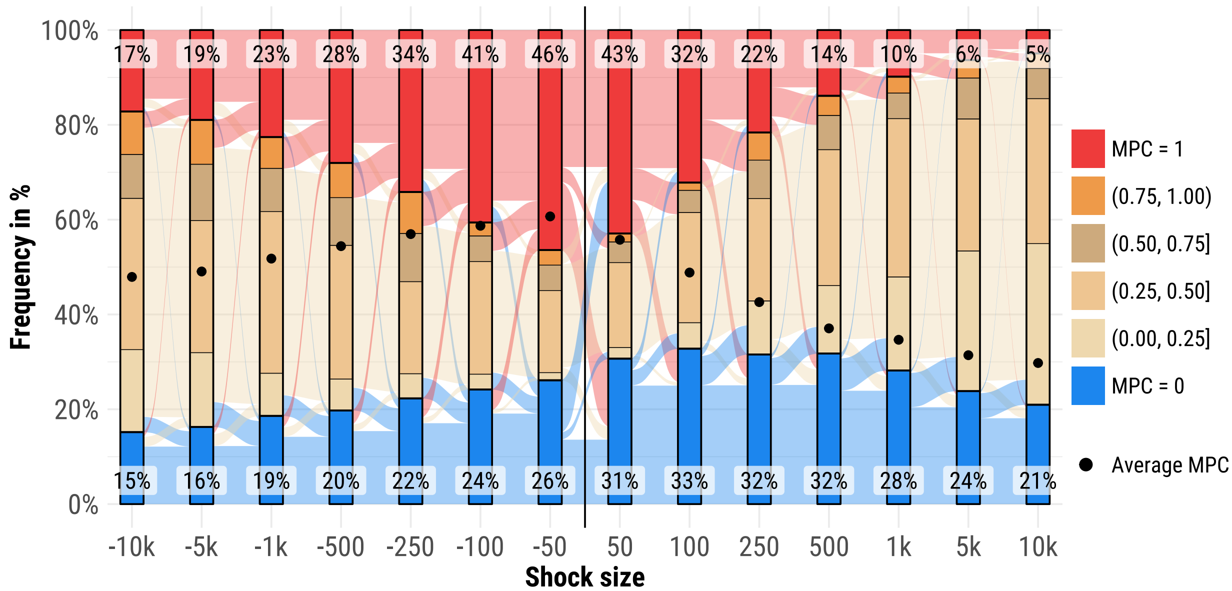
A Simple Model. We first formulate the near-rationality hypothesis in the simplest possible model of consumption and savings decisions. Households have "default" consumption policy functions which may not coincide with the optimal consumption function. We say that households *quick-fix* in a given state if they follow their default policy. Otherwise, they may choose to optimize and take the optimal action at some fixed utility cost, which captures the effort required to contemplate their circumstances and/or deliberate about what policy function to follow. Consistent with the idea of Akerlof and Yellen (1985b), even small optimization costs are sufficient to sustain large deviations from rational behavior. For example, a household with logarithmic preferences would be willing to tolerate a 5% deviation from the rational consumption level even if the cost of switching to the rational policy function is as little as 0.25% of consumption. The simple theory implies that: (i) quick-fixes govern households' responses to small income shocks, (ii) households abruptly change their behavior at critical shock thresholds when they switch from their quick-fix to rational behavior, and (iii) households behave in the same way conditional on having optimized, regardless of the nature of their quick-fix.

Quick-fixes are hence crucial to understanding households' MPCs and consumption-savings behavior, but the precise implications of the model clearly depend on *which* quick-fixes households use. This is an empirical question. However, the model implies that observational data are insufficient for characterizing quick-fixes. Even absent noise in measurement and the consumption process, observational data can reveal how a household responds to only a single shock at a given time. Absent strong structural assumptions, this cannot reveal how they would have reacted to different shocks of different sizes. This necessitates a survey-based research design that elicits household consumption and savings responses to many shocks of different sizes, from which their policy functions can be recovered.

Empirical Evidence. We therefore design a survey to elicit household consumption policy functions. We administered this survey to about 5,000 US households in October and November of 2023. The sample is balanced to approximate the US adult population in terms of gender, age, income, education, and region. We ask respondents how they would adjust their spending and saving over the next three months in response to *multiple* hypothetical shocks in random order: seven unexpected one-time payments ranging from \$50 to \$10,000 and seven unexpected one-time income losses of the same amount. Relative to existing work collecting survey measures of the marginal propensity to consume (see *e.g.,* Parker and Souleles, 2019; Jappelli and Pistaferri, 2020; Fuster, Kaplan and Zafar, 2021; Colarieti, Mei and Stantcheva, 2024), our survey collects detailed *within-respondent* information on consumption and savings responses to a wide range of shocks, as required by the theory. Specifically, the theory predicts that responses to small shocks can reveal households' quick-fixes, while responses to larger shocks reveal when and how households begin optimizing.

We document five new facts. Figure 1 visualizes the first fact, which we refer to as the "bowtie" shape of the joint distribution of MPCs and shock sizes. For small shocks, households frequently report a marginal propensity to consume of 0 (*i.e.*, fully saving a gain or drawing from savings after a loss) or 1 (*i.e.*, fully consuming a gain or cutting back consumption after a loss). As shocks get larger in absolute value, the fraction of extreme responses declines, and the fraction of interior responses increases. This transition from extreme to interior MPCs generates the "bowtie" appearance of Figure 1. This fact is at odds with the predictions of standard consumption-savings models. For example, we find that as shocks become *more* negative, *fewer* households report having a high MPC.

Figure 1: The "bowtie" MPC distribution across shock sizes



Notes: The alluvial graph summarizes the MPC data of the 4,981 US households in our sample. Each of the 14 columns displays the distribution of MPCs for one particular shock size, with colors indicating the size of the MPC. The streams between bars indicate how households' MPCs transition between two neighboring shocks (here, we only distinguish between MPCs of 0, MPCs of 1, and interior MPCs to keep the figure readable). Black dots depict the average MPCs for each shock.

Our second fact is that the distribution of MPCs is well described by a decomposition of households into four *quick-fixing types* who use extreme MPCs of 0 or 1 as quick-fixes for small shocks but abandon them for larger shocks. To tie our hands, we use only information from how households respond to the smallest shocks, the $50 loss and gain, to define these types. We say that households are *consumption fixers* if they have a zero consumption response to both shocks; *savings fixers* if they have a zero savings response to both shocks; *consumption prioritizers* if they only increase consumption after windfalls but only cut savings after losses; and *savings prioritizers* if they only increase savings after windfalls but only cut consumption after losses. These quick-fixing types span 68% of our respondents. These households: (i) adopt categorically different policies for small shocks, (ii) eventually and abruptly transition to interior MPCs for large shocks, and (iii) have similar MPCs across quick-fixing types conditional on transitioning to an interior MPC. This generates the "bowtie" shape of Figure 1 and validates the three core predictions of the near-rational model. This pattern of *within-household* responses is consistent with our idea of quick-fixing from the simple model. We call the remaining 32% of respondents "uncategorized." These respondents usually report an interior MPC that is relatively stable for different shock sizes.

Our third and fourth facts suggest that quick-fixing goes a long way to resolving the empirical puzzle that MPCs are only weakly predicted by households' financial situation and demographics. Specifically, in our data, cross-household variation in spending, income, income risk, liquid and illiquid wealth, debt, education, age, gender, and household size explain only 11% of the cross-household variation in MPCs. This result, consistent with previous findings in the literature (Lewis, Melcangi and Pilossoph, 2024; Fuster et al., 2021), poses a challenge for standard models in which such variables should explain *all* MPC variation. By contrast, our categorization of quick-fixing types accounts for 49% of the variation in MPCs (Fact 3). This comes while quick-fixing types are essentially unpredictable: the same economic and demographic characteristics of households predict quick-fixes with R^2 values between 2% and 6% (Fact 4). Thus, quick-fixing types partially open the "black box" of latent heterogeneity in the MPC that standard models fail to explain.

Our fifth and final finding supports the mechanism behind quick-fixing: quick-fixes require less deliberation. In an additional survey, we elicit households' responses to shocks alongside how carefully they would consider their decisions, how likely they are to assess their overall financial situation when making a decision, and how likely they are to consult another household member. When households quick-fix and have extreme MPCs, they are substantially less likely to report deliberating than when they have interior MPCs. Thus, our findings are consistent with the mechanism that underlies near-rationality: households quick-fix to avoid the deliberation costs of optimization.

Quantitative Model. In the final part of the paper, we gauge the potential macroeconomic implications of the near-rationality hypothesis when it is disciplined by these empirical findings. To do so, we integrate quick-fixing into a standard incomplete-markets consumption-savings problem with income risk and borrowing constraints. Motivated by our observation that household characteristics are poor predictors of quick-fixing types, we assume that the population consists of discrete types who adopt each of the four quick-fixes and a fifth group that is rational. We calibrate the model to match standard external targets for preferences and the stochastic earnings process. From the survey, we directly match the measured frequency of each quick-fixing type and calibrate optimization costs to match households' propensities to quick-fix and reoptimize.

Our quantitative findings formalize that small costs of optimization are consistent with large and macroeconomically important differences in household behavior. First, we estimate the one-time cost of optimization as ranging between \$1.50 to \$150 depending on type. The loss from near-rationality, defined as the lifetime payoff loss from living as a quick-fixer versus an agent with zero optimization frictions, is between 50 cents and \$62 per quarter. This explains why quick-fixing behavior may persist in spite of its suboptimality: households lose so little from near-rationality that the scope for learning or "selection pressure" to instill rationality is naturally limited.

Second, consistent with our empirical finding that households' quick-fixing types are essentially unpredictable, we find that the stationary joint distribution of wealth and income is almost undistinguishable across types. This occurs because consumption mistakes "wash out" over time and across agents.

Third, our model generates considerable variation in MPCs that is unexplained by assets and income, as in the data. Such variation is absent by construction in the nested rational model. In this way, the quick-fixing model helps rationalize why empirical heterogeneity in the marginal propensity to consume is not perfectly explained by financial status or income.

Fourth, our model generates considerably more *size-dependent* responses to transfers than the standard incomplete-markets model with rational consumers. In our model, the aggregate quarterly MPC out of a \$100 transfer is 0.28 higher than that out of a \$1,200 transfer, which is more than three times larger than the difference of 0.08 in the quarterly aggregate MPCs to these shocks in the nested rational model. We moreover show that the corresponding dynamic responses or *intertemporal marginal propensities to consume* (Auclert, Rognlie and Straub, 2024) are systematically more *front-loaded* for small shocks and *back-loaded* for large shocks. The key mechanism driving this is the high incidence of quick-fixers who transition from a unitary to an intermediate MPC. Our results imply a delicate balance for policymakers who want to use stimulus checks to increase aggregate consumption: small checks will yield a smaller aggregate response but feature much greater and more immediate bang for their buck on impact.

This strong size-dependence highlights a quantitatively important manifestation of the Lucas critique in the use of MPCs in quantitative work: caution should be applied to direct extrapolation of empirical estimates of MPCs that average over shocks of different sizes when the distribution of shocks under a chosen counterfactual is markedly different.

Related Literature. Within the literature that studies the near-rationality hypothesis (Akerlof and Yellen, 1985a,b), the most related work is by Cochrane (1989) and Krusell and Smith (1996). Cochrane (1989) evaluates the loss from rule-of-thumb consumption rules using aggregate data. Krusell and Smith (1996) evaluate the equilibrium loss from following a simple rule-of-thumb with the "wrong" savings rate and find that they are small. Building on the theoretical observation that near-rational behavior can have quantitatively small costs, we use survey data to characterize the near-rational model, discipline the rules that people use rather than exogenously impose them, and quantify the macroeconomic implications of the empirically implied near-rationality of households. Other related, but more theoretical, studies include Smith (1991), Lettau and Uhlig (1999), and Ilut and Valchev (2023, 2024).

The most related papers that use surveys to understand heterogeneity in the marginal propensity to consume are Fuster et al. (2021) and Colarieti et al. (2024). Fuster et al.

(2021) identify one similar regularity in their data, the mass of agents with MPC $= 0$, and rationalize this behavior via a fixed "menu cost" of adjusting consumption. Colarieti et al. (2024) use qualitative survey questions and a clustering approach to shed light on the motives and considerations behind households' responses to large income shocks. In contrast to both, we investigate the near-rational model and, to do so, elicit multiple MPCs for each household, varying the sign and magnitude of the shock over a large set of scenarios. Our analysis builds on Fuster et al. (2021) by using more fine-grained variation in shock sizes within respondents. This is what allows us to uncover richer variation in households' policy functions beyond fixing consumption. More conceptually, the behavior of households in our near-rational model is fundamentally different from behavior with "menu costs" of adjusting behavior. In such models, agents cannot change their behavior without paying an adjustment cost. By contrast, in our model, households do change their behavior when they quick-fix — they simply may do so sub-optimally and heterogeneously. That is, the cost is an optimization cost of changing how one's actions respond to shocks and not a menu cost of changing one's action itself.

Our empirical results are consistent with the near-rationality hypothesis. By contrast, we argue that no existing consumption-savings model of which we are aware is consistent with our empirical findings (see Section 3.7 for more details). These include: (i) incomplete markets models (Bewley, 1979; Deaton, 1991; Carroll, 1997), (ii) incomplete markets models with *ex ante* heterogeneity in preferences (Carroll, Slacalek, Tokuoka and White, 2017; Aguiar, Bils and Boar, 2024) or investment opportunities (Kaplan and Violante, 2022), (iii) incomplete markets models with multiple accounts (Kaplan and Violante, 2014; Kaplan, Moll and Violante, 2018), (iv) models with durables or consumption commitments (Barsky, House and Kimball, 2007; Chetty and Szeidl, 2016), (v) models with consumption mistakes arising from present bias (Laibson, Maxted and Moll, 2021), temptation (Krusell, Kuruşçu and Smith, 2002), finite planning horizons (Boutros, 2022), sparsity (Gabaix, 2014), or misperceptions in wealth (Lian, 2023), (vi) models with infrequent optimization (Gabaix and Laibson, 2001), and (vii) models with incomplete information or rational inattention (Sims, 2006).

Outline. Section 2 introduces a simple model to formalize the near-rationality hypothesis. Section 3 presents the survey and empirical results. Section 4 presents the quantitative model and calibration. Section 5 presents the quantitative results. Section 6 concludes.

2 A Simple Theory of Quick-Fixing and Near-Rationality

We begin our analysis by laying out the simplest possible consumption-savings model in which our hypotheses of quick-fixing and near-rationality can be formalized. We characterize the implications of the theory for the profile of household consumption responses to unanticipated income shocks of different sizes, which will motivate our empirical strategy.

2.1 The Model

The Environment. A continuum of households is indexed by $i \in [0,1]$ and lives for two periods $t \in \{1,2\}$. The household is born at period $t=1$ with assets a_i and receives income $y_{i,t}$ in period t. We collect these household-level state variables as $z_i = (a_i, y_{i,1}, y_{i,2})$. The household can save in a risk-free bond that pays a gross interest rate of $R > 0$. The household has preferences over streams of consumption $(c_{i,1}, c_{i,2}) \in \mathbb{R}^2_+$ that are given by:

$$u(c_{i,1}) + \beta u(c_{i,2}) \tag{1}$$

where $\beta > 0$ and $u : \mathbb{R}_+ \to \mathbb{R}$ is a strictly concave function. We assume that $\beta R = 1$. Here, we use these simplifying assumptions to clarify the key ideas. Later, in the quantitative model of Section 4, we will dispense with these stylized assumptions and will consider the canonical environment with an infinite horizon, idiosyncratic consumption risk, and borrowing constraints.

Rational Behavior. We first describe *rational behavior*, which is what the household would optimally do in the absence of any optimization frictions. In this case, each household's optimal consumption follows the Euler equation:

$$u'(c_{i,1}) = \beta R u'(c_{i,2}) \tag{2}$$

Substituting the household's budget constraints into the Euler equation, we have that the household's optimal consumption function obeys the permanent income hypothesis:

$$c_{i,t} = c^*(z_i) = \frac{R(a_i + y_{i,1}) + y_{i,2}}{1+R} \tag{3}$$

That is, the household perfectly smooths its consumption.

Quick-Fixing. We now describe *quick-fixing*, which is what the household does when it does not engage in rational behavior. We suppose that each household has a "default" consumption function that may not coincide with the optimal consumption function. Concretely, we suppose that there is a set of types $\mathcal{D}$, where each household i has type d_i. A household with type d_i has a default consumption function given by:

$$c_{i,1} = c^{d_i}(z_i) \tag{4}$$

where period two consumption is given by the household's residual wealth.[1] Quick-fixing is potentially attractive because optimization incurs a cost: if a household of type d_i follows any consumption function other than its default consumption function, then it incurs an optimization cost of $\kappa_{d_i} > 0$. To the extent that such optimization costs are small, we follow Akerlof and Yellen (1985b) and call households' quick-fixing behavior *near-rational*.

2.2 The Losses from Near-Rational Behavior

We now characterize households' optimal quick-fixing decisions. We first observe that if a household pays the fixed cost of optimization, then it faces the same problem as a household that faces no optimization cost. Thus, whenever a household adjusts, it always adjusts to the optimal consumption function c^*, yielding value U^*:

$$U^*(z_i) = u(c^*(z_i)) + \beta u(c^*(z_i)) \tag{5}$$

The value function of following a default consumption function is, by contrast:

$$U^{d_i}(z_i) = u(c^{d_i}(z_i)) + \beta u(R(a_i + y_{i,1} - c^{d_i}(z_i)) + y_{i,2}) \tag{6}$$

A household therefore optimizes and behaves rationally in state z_i if and only if:

$$\mathcal{L}^{d_i}(z_i) \equiv U^*(z_i) - U^{d_i}(z_i) \geq \kappa_{d_i} \tag{7}$$

and otherwise quick-fixes. By applying a state-dependent second-order approximation, we obtain the following result that describes the losses involved in quick-fixing:

Proposition 1 (Second-Order Losses from Near-Rational Behavior)**.** *The loss from following a default consumption rule indexed by d_i when the asset-income state is z_i is:*

$$\mathcal{L}^{d_i}(z_i) = \frac{1}{2}(1+R)|u''(c^*(z_i))|(c^{d_i}(z_i) - c^*(z_i))^2 + O(|c^*(z_i) - c^d(z_i)|^3) \tag{8}$$

Proof. See Appendix A. □

[1] As a technical matter, if this implies that $c_{i,2} < 0$, then we set the household's payoff equal to $-\infty$. This ensures that the household will only quick-fix if it is feasible to do so.

This result formalizes that the losses from following default consumption rules are at most *second-order*, thus satisfying the Akerlof and Yellen (1985b) criterion for there being small losses from near-rational behavior. There is no first-order loss from deviations from rational behavior by the envelope theorem: when the household makes a small consumption mistake, their first-order condition implies that the slope of its lifetime utility is close to flat in the mistake. When consumption mistakes are large, higher-order terms may matter for the loss. This notwithstanding, we will later find that this simple approximation is extremely accurate in our empirically calibrated quantitative model (see Figure 6), suggesting that it provides a quantitatively realistic guide to near-rational behavior.

This result also implies that it is more costly to follow a default consumption rule whenever $|u''(c^*(z_i))|$ is high. How the losses from near-rationality vary across states therefore depends on the prudence of the household, *i.e.,* the third derivative of its instantaneous utility. Under quadratic utility, $|u''(c^*(z_i))|$ is constant across economic states. When the household is prudent, *i.e.,* when $u''' > 0$, the loss is high whenever the household has a low level of optimal consumption, *e.g.*, due to low wealth or income. Thus, this result highlights that whether quick-fixing is more or less costly for different households depends on their preferences and is, therefore, theoretically ambiguous.

Because of this basic envelope logic, even the presence of small optimization costs may motivate a household to follow a quick-fix. To substantiate this, we provide a simple example of how the second-order losses from near-rationality implied by Proposition 1 can lead small optimization costs to generate large differences in behavior.

Example 1 (Small Costs Allow for Large Mistakes)**.** Suppose that households have logarithmic preferences $u(c) = \log c$ and $R = 1$. Proposition 1 implies that the payoff loss from following a sub-optimal quick-fix is approximately equal to $([c^{d_i}(z_i) - c^*(z_i)]/c^*(z_i))^2$, which is the square of the proportional absolute deviation of consumption from the rational level. We now ask: what is the smallest optimization cost in consumption-equivalent units that can rationalize a household making a consumption mistake of a given size? Letting the consumption mistake be $m = [c^{d_i}(z_i) - c^*(z_i)]/c^*(z_i)$, it follows that the smallest utility cost that rationalizes such a mistake is $\kappa(m) = m^2$. Putting this into consumption-equivalent units of a one-period proportionate loss in consumption τ, we have that:

$$\begin{aligned} 2\log(c^*(z_i)) - \kappa(m) &= \log((1-\tau)c^*(z_i)) + \log(c^*(z_i)) \\ \implies \tau &= 1 - e^{-m^2} \end{aligned} \tag{9}$$

This is the maximum percentage of consumption that a household would be willing to give up to prefer quick-fixing to optimization when quick-fixing would lead to a relative consumption

Table 1: Small optimization costs can lead to large errors in consumption

Consumption mistake, m	1%	5%	10%	15%	20%
Consumption-equivalent optimization cost, $\tau(m)$	0.01%	0.25%	1.00%	2.22%	3.92%

Notes: This table reports the maximum percentage of consumption that a household would be willing to give up to prefer quick-fixing to optimization when quick-fixing would lead to relative consumption mistake of size m: $\tau(m) = 1 - e^{-m^2}$ (see Equation 9).

mistake of size m. The approximation $\tau \approx m^2$ is a good rule-of-thumb that is accurate to one decimal place even for a 20% shock. In Table 1, we report this optimization cost for consumption mistakes ranging from 1% to 20%. Surprisingly, if a household were to have to pay anything less than 0.25% of consumption in order to optimize, then it would be unwilling to optimize even when making a 5% consumption mistake. In this sense, even very small costs of optimization can lead to large differences in behavior from the rational model. $\triangle$

2.3 The Near-Rational Response to Income Shocks

If households are willing to tolerate large consumption mistakes, then they may quick-fix in response to even large income shocks, making quick-fixes central for understanding households' MPCs. To assess the implications of near-rational behavior, we therefore apply this simple framework to study how households respond to unanticipated income shocks of different sizes.

To this end, suppose that a household is informed that its first-period income will be $y_{i,1}(x) = y_{i,1} + x$ for some income shock $x \in \mathbb{R}$. What is the optimal near-rational response? By a simple application of Proposition 1 and defining the agent's state after the income shock as $z_i(x) = (a_i, y_{i,1} + x, y_{i,2})$, we obtain that:

Corollary 1 (When to Quick-Fix)**.** *Up to a second-order approximation, a household with asset-income state z_i with default type given by d_i quick-fixes following an income shock x if and only if:*

$$|c^{d_i}(z_i(x)) - c^*(z_i(x))| \leq \sqrt{\frac{\kappa_{d_i}}{\frac{1}{2}(1+R)|u''(c^*(z_i(x)))|}} \tag{10}$$

and otherwise pays the optimization cost and follows the rational policy $c^*(z_i(x))$.

That is, the household quick-fixes if and only if its consumption mistake from doing so is sufficiently small. Households tolerate larger mistakes if the optimization cost is larger or the curvature of its utility is smaller. Of course, the scope for absolute consumption mistakes will generally increase with the size of the shock. Therefore, to the extent that quick-fixes generate larger mistakes for larger shocks, this simple theory has three predictions for households' MPCs, which we will shortly investigate in the data: (i) households will quick-fix in response to small shocks, (ii) households will abruptly abandon their quick-fix once the shock crosses a certain threshold, and (iii) households will behave the same way conditional on optimizing, regardless of differences in the quick-fixes that they use.

Quick-fixes may therefore be essential for understanding households' MPCs and consumption-savings decisions. However, the specific effects of the model largely hinge on *which* quick-fixes households adopt. This is an empirical question.

The model also highlights a fundamental challenge for measuring near-rational behavior: there is no *ex ante* discipline that can be placed on households' quick-fixing behavior. Thus, households' default policy functions represent a latent, non-parametric type that cannot be directly observed by an econometrician. As a consequence, there is no way to recover or test for near-rational behavior in observational data. This is because a household is subject only to one shock of a given size at any given time, providing only one point on a household's policy function. This motivates the necessity and design of a novel survey to elicit households' policy functions and detect both the existence and nature of near-rational behavior.

3 Empirical Evidence from a Novel Survey

It is an empirical question whether households quick-fix and exactly what quick-fixes they employ. To answer these questions, we need to study how the same household responds to shocks of different sizes, tracing out their consumption policy functions. Specifically, the model predicts that responses to small shocks are informative about households' quick-fixes while responses to larger shocks are informative about when and why households reoptimize. This calls for a survey-based approach. In a survey, households can think about multiple precisely described income shocks, the shocks can be described in a comparable manner, and households can directly indicate how they would respond to each shock.[2]

This section presents the design and results of a novel, large-scale household survey tailored to uncover households' policy functions. We find that the majority of households quick-fix by applying simple rules of full consumption or savings responses (MPCs of 0 or 1) to sufficiently small shocks. Quick-fixing behaviors are heterogeneous in the population, poorly explained by financial and demographic characteristics, and highly explanatory of MPC heterogeneity across households and shocks. Moreover, we find that households deliberate

[2] By contrast, with consumption data deduced, *e.g.*, from banking or administrative data, it is virtually impossible to distinguish an individual's response to a shock from the inherent noise in her consumption process — not to speak of identifying multiple MPCs per household, which would require strong structural assumptions. Moreover, previous analyses find that survey-based MPC measures yield estimates that are very similar to those obtained from consumption data (Parker and Souleles, 2019; Colarieti et al., 2024).

less about quick-fix consumption decisions. We argue that these patterns are in line with the near-rational model (as described in Section 2) but not with leading alternatives.

3.1 Survey Design and Sample

We collect data from 4,981 US households in October and November 2023, collaborating with the survey company Bilendi. The sample approximates the adult US population in terms of gender, age, income, education, and region, and broadly captures the wealth distribution across the country.[3] Appendix C.1 presents further details on the sample.

We follow a standard procedure to measure households' marginal propensity to consume out of unexpected, one-time income changes (*e.g.*, Jappelli and Pistaferri, 2014, 2020; Christelis, Georgarakos, Jappelli, Pistaferri and Van Rooij, 2019; Fuster et al., 2021). First, we provide households with short definitions of consumption and saving. We refer to consumption as "spending" to follow common parlance, and we explicitly stress that we consider debt repayment as part of saving. Next, households are asked to think about an unexpected one-time income gain or loss. For example, respondents read:

> Consider a hypothetical situation where your household unexpectedly receives a one-time payment of $1,000 today.

Then, households answer how they would increase their spending and saving in response to the income shock. They can respond in two numeric open response fields, and we calculate their MPC by dividing their spending response by the income shock.[4]

> How would this one-time extra income cause your household to change its spending and saving over the next three months?
>
> Increase in spending:
>
> (By how much) would your household increase its monthly spending over the next three months? $__________
>
> Increase in saving:
>
> (By how much) would your household increase its monthly saving (which includes increases in debt repayment or <u>de</u>creases in debt-taking over the next three months)? $__________

[3] We slightly oversample respondents with a college education and respondents with lower total debt and lower illiquid wealth, but our results are robust to re-weighting and correcting for these imbalances (Appendix Figure B.1).

[4] Households' changes in spending and saving need to add up to the income gain. We elicit increases in spending and saving for income gains and decreases for income losses. We explain to respondents that they can enter negative numbers to indicate changes in the reverse direction.

The key feature of our survey is that we measure *multiple* MPCs for each household, fourteen in total. For both income gains and losses, households consider shocks of various sizes. Specifically, we include gains and losses with a magnitude of \$50, \$100, \$250, \$500, \$1,000, \$5,000, and \$10,000. We ask households' responses to *very small* shocks, such as \$50 or \$100, to isolate their near-rational behavior.

We randomize both whether respondents first face gains or losses and the order of shock magnitudes. This guards against any framing bias from the order in which respondents are faced with shocks.

The survey closes with a series of demographic and economic background questions, including questions on income, income risk, future income expectations, and wealth. Appendix C.2 presents the key instructions.[5]

3.2 The "Bowtie" Pattern in MPCs

We first describe the aggregate properties of the survey data. Figure 1, introduced earlier, plots the full distribution of consumption responses to each shock. Each bar presents the distribution of marginal propensities to consume for one particular shock, calculated as the ratio of households' "change in spending" response to the size of the shock. Black dots display the average MPC for each shock.

The figure reveals four broad patterns that are familiar in the literature in both observational and survey data (see *e.g.,* Parker and Souleles, 2019). First, the average MPC (0.47) is high. Second, MPCs decline with larger shocks: for example, they fall from 0.56 for a \$50 gain to 0.30 for a \$10,000 gain. Third, the average MPC is larger for losses (0.54) than for gains (0.40). Fourth, a significant fraction of households report an MPC of 0 or 1 (see *e.g.*, Jappelli and Pistaferri, 2014). Appendix C.4 compares our cross-sectional results to related work in further detail. Our broad conclusion is that our aggregate results on the MPC distribution *conditional on specific amounts* are in line with previous survey findings.

A key new finding is the "bowtie" pattern in the distribution of MPCs across shocks: extreme MPCs of 0 and 1 are common for small shocks but rare for large shocks. Thus, the mass of households with an "interior" MPC strictly between 0 and 1 gives a bowtie-like appearance to Figure 1. This observation is possible because our survey elicits responses to a much wider range of shocks than existing work.

To quantify this bowtie pattern, we measure how many households "transition" from extreme MPCs of 0 and 1 to an interior MPC as the shock size increases in absolute value. Since the questions for different amounts are asked in random order, households would not

[5]The full instructions are available online at https://osf.io/2s7cf.

necessarily perceive these "transitions" when taking the survey. We visualize these as the shaded flows between bars in Figure 1. For an unexpected \$50 income gain, 43% of households consume every dollar (MPC = 1), while 31% save every dollar (MPC = 0). Likewise, for an unexpected \$50 income loss, 46% of households only reduce their consumption (MPC = 1), while 26% only reduce their savings (MPC = 0). Starting from these numbers, from one shock to the next larger shock, an average net share of 7% of households transition from an extreme MPC to a more moderate interior MPC. In fact, most households — namely 68% for gains and 67% for losses — switch to an interior MPC at most once and stick to interior MPCs thereafter. Only 14% (for gains) and 16% (for losses) of households deviate from this pattern more than once.[6] Consequently, very few households still consume or save every dollar for the largest shocks.

We summarize these findings below:

> **Fact 1** (The Bowtie): Many households respond with extreme MPCs of either 0 or 1 to small shocks and transition to interior MPCs for larger shocks.

Statistical Precision and Robustness. Due to the large sample of nearly 5,000 respondents and 70,000 MPCs, our estimates are highly precise. For instance, the 95% confidence interval for the estimated average MPC ranges from 0.465 to 0.478. Likewise, the margin of error for population share estimates is 1.4 percentage points, meaning that for any given percentage share (X%) of respondents, a (conservative) 95% confidence interval would be [X% − 1.4%, X% + 1.4%]. All contrasts we mention below achieve statistical significance well above conventional levels. To enhance readability, we often do not further elaborate on statistical significance in the main text. We present the detailed significance tests in Appendix Table B.1. Likewise, we present detailed sensitivity tests in Appendix Figure B.1. The results are not sensitive to the random order of shock sizes, losses, and gains. We also find similar results if we exclude respondents who "speed through" the survey or restrict the analysis to only the first decisions that each respondent makes.

3.3 Household Behavior is Consistent with Near-Rationality

The prevalence of extreme (0 or 1) values in the raw MPC distribution is suggestive of near-rational behavior, insofar as these seem like simple but approximate "rules of thumb." But,

[6] Response error is inevitable in survey data, and simulation results illustrate that a reasonable degree of response error could generate a good share of the deviations we see in the data. To quantify this, we run a simple simulation. We assume that all households would want to switch to an interior MPC at most once and stick to interior MPCs thereafter. But households have "trembling hands" and deviate from their desired extensive margin response with an i.i.d. 10% error rate. In this case, 11% would deviate from the pattern more than once.

to more formally evaluate whether a near-rational model can rationalize this behavior, we need to measure the within-household responses to shocks and then test for the characteristics of near-rational behavior implied by the model.

Our model implies that, for very small shocks, household behavior is entirely determined by the quick-fix that they employ (see Corollary 1). Thus, to measure quick-fixes, we use the information about households' responses to the smallest shocks of \$50 and −\$50. In the survey, 68% of respondents report an extreme MPC for *both* of these shocks, indicative of quick-fixes that feature such extreme MPCs.

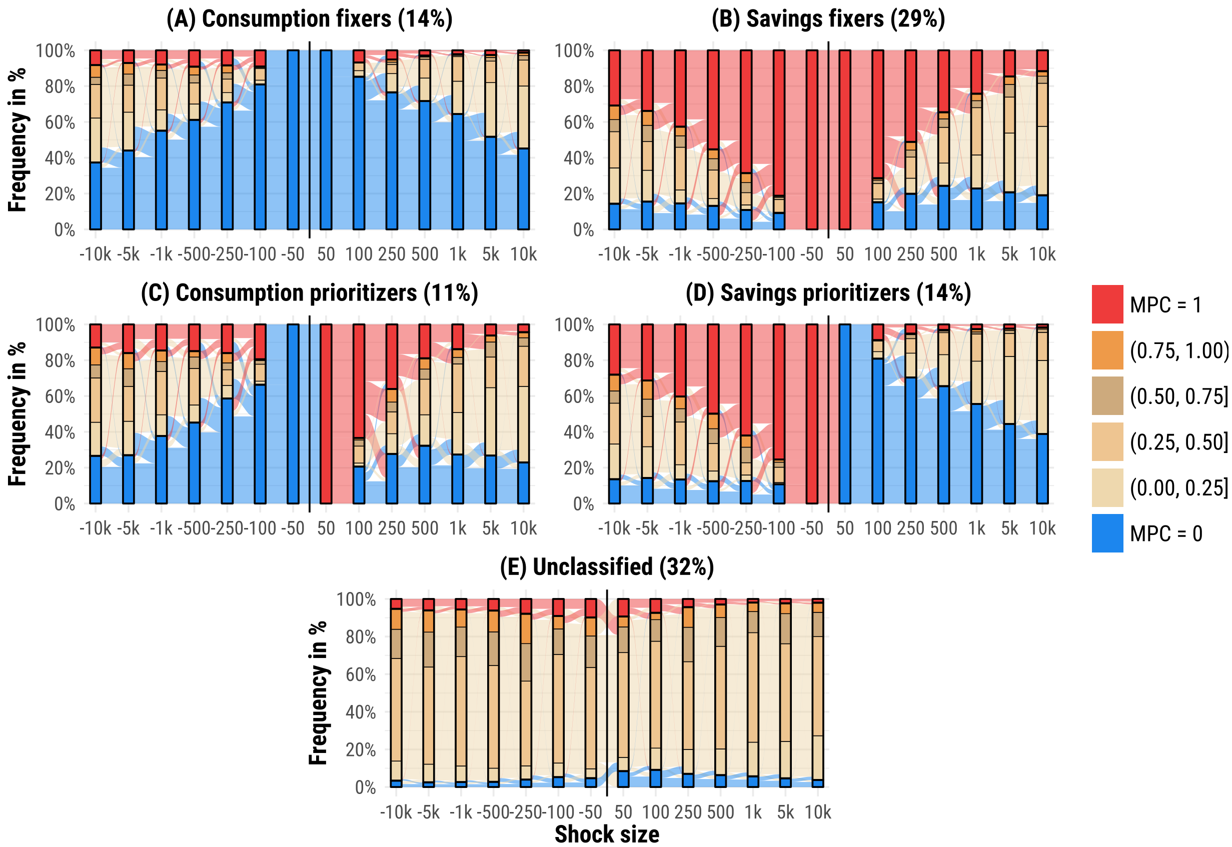
Motivated by this, we exhaustively categorize these 68% of households into four quick-fixing types based on whether they respond by consuming or saving all of these small shocks.

> **Consumption fixers (14% of households)** default to an MPC of 0 for gains and losses. Their consumption is fixed, and they absorb small shocks — gains or losses — with their savings.
>
> **Savings fixers (29% of households)** default to an MPC of 1 for gains and losses. Their saving is fixed, and they absorb small shocks — gains or losses — with their consumption.
>
> **Consumption prioritizers (11% of households)** have a quick-fixing policy that prioritizes their consumption. They only draw on their savings (MPC = 0) when they face a small loss, but they increase only their consumption (MPC = 1) when they face a small gain.
>
> **Savings prioritizers (14% of households)** have a quick-fixing policy that prioritizes their savings. They cut back only consumption (MPC = 1) when they face a small loss, but they increase only savings (MPC = 0) when they face a small gain.

The remaining group of **unclassified households (32%)** cannot be assigned to either of the four groups above because they respond with an interior MPC to even the smallest income gains or losses.

To help visualize the behavioral differences between these types, Figure 2 decomposes the aggregate MPC data and its "bowtie" pattern for each group. For example, Panel A plots the MPCs of consumption fixers for all fourteen shocks. By construction, 100% of consumption fixers start with an MPC of 0 for \$50 income gains or losses. For larger shocks, more consumption fixers adopt and then stick to an interior MPC. Panel B plots the MPCs of savings fixers and reveals a similar logic. Savings fixers respond with an MPC of 1 to small shocks but transition and then stick to interior MPCs for larger shocks. The same story emerges for consumption prioritizers and savings prioritizers: starting from extreme MPCs, they eventually move to interior MPCs. Of course, Figure 2 also reveals that not all

Figure 2: Responses to income shocks for different quick-fixing types



Notes: The alluvial graphs summarize the MPC data of four different quick-fixing types, which we define on page 14, and unclassified respondents. In each panel, each of the 14 columns displays the distribution of MPCs for one particular shock size, and the streams between bars indicate how households' MPCs transition between two neighboring shocks.

households follow their measured type perfectly. For example, moving from \$50 to \$100 and from \$100 to \$250, a minority of 8% of households move from an MPC of 0 to 1 or vice versa. But, in light of the inherent response noise in survey data, we do not want to over-interpret this pattern.

Do the data reveal additional candidates for quick-fixes? Encouragingly, this classification appears to capture most of the extreme behavior in the data: unclassified households almost never choose extreme MPCs and instead immediately adopt relatively stable interior MPCs. Moreover, the third most common response to the smallest income shocks is an MPC of 0.5, which 12% of households adopt. However, most of these households also choose an MPC close to 0.5 for larger shocks. This means that we do not observe a clear transition pattern as we do for the four quick-fixes we have identified. No other consumption response is chosen by more than 5% of households, implying that other quick-fixes — to the extent that they exist — are not very prevalent.

Household Behavior is Consistent with Near-Rationality. These four widespread response types in our data are plausible quick-fixes: they prescribe simple, extreme responses to sufficiently small shocks. But, to more formally evaluate whether a near-rational model can rationalize this behavior, we now test for the characteristics of near-rational behavior. We observe that all four of these simple consumption policies would generate larger consumption mistakes for larger shocks in our model. Thus, we test the near-rationality hypothesis for these types by evaluating the three predictions of Corollary 1.

First, households are more likely to apply quick-fixes for smaller shocks than for larger shocks. This is apparent from Figure 2: within each type, the fraction of extreme responses declines as the shock size increases. Moreover, within each type, households tend to transition from extreme to interior MPCs, as visualized by the flows in Figure 2.

Second, quick-fixes are abruptly abandoned once a household-dependent critical shock size is reached. In the survey, shifts from extreme to interior MPCs rarely occur gradually. Households who start with an MPC of 1 tend to immediately jump from this extreme MPC to an interior MPC that is typically around 0.25 to 0.60 (the 20%-80% quantile range). Their first interior MPCs are thus not unlike those of households who start from the opposite MPC of 0, whose 20%-80% quantile range ranges from 0.20 to 0.50. Moreover, households rarely (if at all) transition *back* from the interior to the extremes: for only 3% of shock size increases, we observe a transition from interior to extreme MPCs, and conditional on starting from an interior MPC, households stay in the interior for 93% of shock size increases.

Third, once households abandon their quick-fixes, their consumption policies are relatively stable *within* respondent and similar *across* respondents, even if their quick-fixing type differs. In the survey, the average absolute difference between two interior MPCs of adjacent shock sizes is 0.14, while the average conditional on a transition from the extremes (0 or 1) to the interior is 0.41. Moreover, interior MPCs are highly similar across respondents compared to MPCs as a whole: the variation in interior MPCs contributes only 16% to the total variance in MPCs.

We summarize these findings below:

> **Fact 2** (Quick-Fixing and Near-Rationality): The majority of households can be categorized as one of four quick-fixing types — consumption fixers, savings fixers, consumption prioritizers, and savings prioritizers — who vary in their extensive margin response to small shocks. Households of all four quick-fixing types tend to abruptly transition from having extreme MPCs to small shocks to having similar interior MPCs for large shocks.

3.4 Quick-Fixes Account for MPC Heterogeneity

Differences in MPCs across households are notoriously hard to predict using observable characteristics of households' wealth, income, and demographics (*e.g.*, Lewis et al., 2024; Fuster et al., 2021). To test this in our data, we model respondents' average MPCs as a function of a host of observables in the following regression equation:

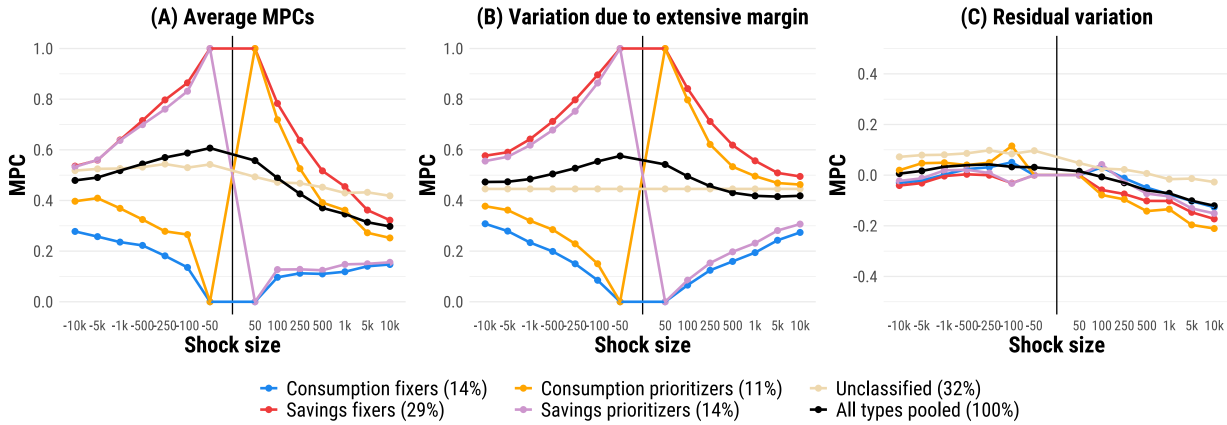
$$\text{MPC}_i = \alpha + \beta' X_i + \epsilon_i \tag{11}$$

where MPC_i is each respondent's average MPC across the 14 scenarios and X_i is a vector of variables that includes: households' monthly spending (log), income (log), and income risk; non-parametric functions of liquid wealth, illiquid wealth, and debt; and four additional demographic characteristics (a college dummy, age, gender, and household size). Echoing findings in the literature, these characteristics together explain only 11% of the cross-sectional variation in MPCs (Appendix Table B.2). Even though measurement error in our explanatory variables will somewhat attenuate the estimated R^2, this finding remains surprising since standard theories suggest that these characteristics should explain the majority (or even all) heterogeneity in MPCs.

By contrast, the four quick-fixing types account for almost *half* of the variation in MPCs by themselves. That is, when we replace X_i with four dummy variables indicating the quick-fixing types, we obtain an R^2 of 49%. This is true even though households who adopt the same quick-fix could still have very different average MPCs, depending on how quickly they abandon the quick-fix and which interior MPC they adopt. Nevertheless, taking households' quick-fixing policy into account allows us to account for a very large share of the variation. This suggests that households' quick-fixing types are a potentially major driver of MPC heterogeneity and could go a long way toward opening this "black box."

Quick-fixing types not only account for much of the cross-sectional dispersion in MPCs, they also explain variation in the aggregate MPCs out of shocks of varying signs and sizes. To demonstrate this fact, Figure 3 plots the average MPC for each shock, pooled across all households and separately for each type. Panel A shows the raw average MPCs for all respondents (black line and dots) and separately for each type (colored lines and dots). Panel B shows the portion of MPCs that is predicted by the "extensive margin" of type membership and switching to the interior via a simple calculation. Suppose that households consistently follow their estimated type: they start with the MPC prescribed by their type, and once they switch to a different MPC for the first time in the data, that they permanently switch to the average interior MPC of 0.45. Thus, MPCs only vary if households transition from extreme to interior MPCs. Panel B shows that this simple calculation accounts for many of the key

Figure 3: The extensive margin explains MPC means and heterogeneity



Notes: The left panel displays the average MPCs of four different quick-fixing types, which we define on page 14, and unclassified respondents for 14 different income shocks. The black line shows the average MPC of the full household sample. The middle panel shows the same statistics after "enforcing consistency" to isolate the effect of the extensive margin. All interior MPCs are fixed at 0.45. Households start with the MPC prescribed by their type. Once they change their MPC, they permanently switch to the interior. The right panel graphs the difference between the left panel and the middle panel.

patterns in the MPC data: (i) significant heterogeneity across the five groups, (ii) the high average MPC, (iii) the higher MPCs for losses versus gains, and (iv) the size-dependence of MPCs, that is, the decline in MPCs as shock sizes increase in absolute value.

The *size-dependence* in aggregate MPCs will play an important role when we discuss the macroeconomic implications of quick-fixing, and so we briefly explain how quick-fixing can generate size-dependence. In the raw data, the MPC out of a \$100 gain is 0.06 higher than the MPC out of a \$250 gain and 0.14 higher than that out of a \$1,000 gain. The extensive margin (Panel B of Figure 3) accounts for roughly two-thirds of these differences (0.04 and 0.08, respectively). Quick-fixing via our four types could, in principle, lead to MPCs that are decreasing or increasing in shock size. But we observe that quick-fixing *reduces* MPCs for larger shocks because our data features more savings fixers and consumption prioritizers who transition from MPC = 1 to the interior than consumption fixers and savings prioritizers who transition from MPC = 0 to the interior. Moreover, due to an average interior MPC below 0.5, abandoning an MPC of 1 has a larger impact than abandoning an MPC of 0.

Finally, Panel C of Figure 3 shows the residual variation, *i.e.*, the difference between Panel A and B, which is much smaller and similar across all quick-fixing types. This is a different way of showing that quick-fixing types behave similarly conditional on adopting an interior MPC, consistent with our model. The residual variation also illustrates what a simple framework with constant interior MPCs does not capture: (i) falling interior MPCs for higher shock sizes and (ii) lower interior MPCs for gains than for losses. Although this is not the focus of our analysis, our full model in Section 4 does not impose constant interior

MPCs and can therefore generate behavior consistent with these response patterns.

We summarize these findings below:

> **Fact 3** (Quick-Fixes Explain MPCs): The four quick-fixing types explain both a large share of variation in average MPCs across households and aggregate MPCs out of shocks of varying sizes and signs.

3.5 Household Characteristics Do Not Predict Quick-Fixing

The importance of quick-fixing for explaining MPCs raises the question: are households' quick-fixing behaviors themselves related to their economic and demographic characteristics? Theoretically, our framework in Section 2 imposes no restriction on this relationship. Empirically, we find that it is not strong.

To formally establish this, we first estimate a series of linear probability models that try to predict our type classification across households i:

$$1_{i \text{ has type } j} = \alpha + \beta' X_i + \epsilon_i \tag{12}$$

where the outcome is an indicator for being categorized as one of our four types (consumption fixer, savings fixer, consumption prioritizer, or savings prioritizer) and the regressors X_i are the same as those studied in the previous subsection, describing a number of household characteristics regarding wealth, income, and demographics. We report the results in columns 3–6 of Table B.2. The R^2 of these models ranges from 0.02 to 0.06. To mention just two positive examples of predictive relationships, liquidity-constrained households are 5 percentage points more likely to be savings fixers (MPC = 1), while high-liquidity households are 7 percentage points more likely to be consumption fixers (MPC = 0). We observe a clearer relationship between households' characteristics and whether we can classify them as quick-fixer at all ($R^2 = 0.17$). For example, households with high income risk, intermediate liquid wealth levels, low illiquid wealth, and high education are more likely to adopt interior MPCs even for the smallest shocks.

Can we predict for how long quick-fixing households stick to their quick-fix? The theoretical model has ambiguous predictions for how household characteristics should affect the losses from quick-fixing (and thereby the propensity to optimize). Nevertheless, this is an interesting question to investigate empirically. We find that households' switching thresholds — the smallest shock for which they switch from an extreme to an interior MPC — vary little across quick-fixing types ($R^2 = 0.02$). They are smaller for households of lower age, intermediate liquid wealth levels, debt, and low income, but households' economic characteristics can account only for 6% of the total variation.

A corollary to these findings is that we observe a marked transition from extreme MPCs to interior MPCs among households from *all ranges* of the socioeconomic distribution. Appendix Figure B.2 visualizes this result by showing the "bowtie" distribution of MPCs for households across the distributions of wealth (liquid and illiquid) and debt.

We summarize this finding below:

> **Fact 4** (Quick-Fixes Are Unpredictable): Quick-fixing behavior is essentially unpredictable from households' economic and demographic characteristics.

3.6 Quick-Fixes Require Less Deliberation

Our notion of quick-fixing is based on the idea that households prefer quick and simple solutions for small shocks but think harder about how to respond to large shocks. To test this behavioral mechanism, we investigate how carefully households consider their responses to income shocks of various sizes and signs. We draw on an additional survey, which we conducted with 517 additional US households in August 2024. We measure their MPC policy functions for gains or losses, following the same procedure as in the main study. In addition, we ask each respondent to rate for each shock (i) how carefully they would consider how to change their spending and saving (on a six-point scale), (ii) what is the percent chance that they would assess and consider their household's overall financial situation prior to deciding how to respond, and (iii) what is the percent chance that they would discuss their response with other household members.[7]

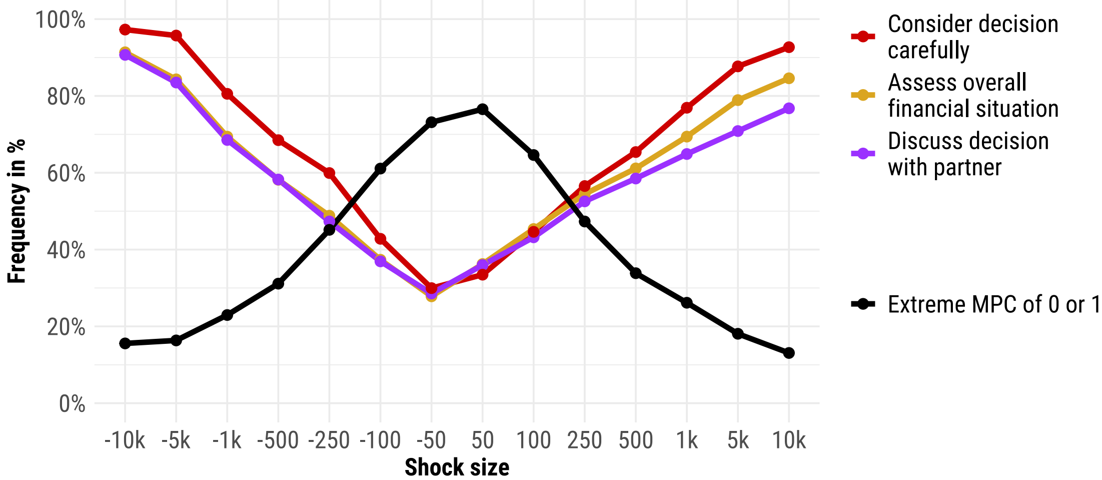
Figure 4 shows that deliberation strongly increases with shock size. For example, the likelihood that households assess their overall financial situation when deciding how to respond to an income shock is on average 32% for the smallest shocks but 88% for the largest shocks (yellow line). Likewise, the likelihood that respondents consult other household members increases from 32% to 84% (purple line).

These findings are consistent with the mechanism in the theory that quick-fixes avoid the cost of deliberation and optimization. Concretely, we find that increases in deliberation mirror the *decreasing* likelihood that households choose an extreme MPC of 0 or 1 (black line). On the household level, a one-standard-deviation higher deliberation score (on either of three measures) comes with an about 25 pp *lower* chance that a household adopts an extreme MPC of 0 or 1 (Appendix Table B.3).

We summarize these findings below:

[7] We recruit participants with the survey company Prolific. The sample is not quota-based and does not represent the US population, but we obtain identical results if we correct for sampling imbalances with post-stratification weights (see Appendix Table B.3). Appendix C.2 contains the additional survey instructions.

Figure 4: Self-reported deliberation and extreme MPCs



Notes: Data from the additional deliberation study (517 US households). For fourteen different income shocks, the figure shows the average frequency with which households report to consider their response carefully (a score of at least four on a six-point scale, red line), assess their overall financial situation (yellow line), discuss the decision with other household members (purple line), or report extreme MPCs of 0 or 1 (black line). Households either face all seven positive or all seven negative income shocks.

> **Fact 5** (Quick-Fixing Requires Less Deliberation): Households think more carefully about their consumption-savings responses when they face larger income shocks. Lower levels of deliberation come with a higher frequency of quick-fixing.

Additional Qualitative Evidence. We complement our evidence with a smaller qualitative survey to provide some first illustrative insights into why extreme MPCs may serve as convenient quick-fixes and require less deliberation. We ask households to explain in their own words why they switch from extreme MPCs for a small shock ($100) to interior MPCs for a large shock ($1,000) (see Appendix C.5 for details).

We summarize four patterns in these qualitative data. First, almost all households refer to the difference in shock size to explain the difference in their MPCs. Second, households mention habits and routines, *e.g.*, a fixed spending budget, a fixed monthly transfer to savings, or the goal to maximize savings, and deviating from such default rules could come at a cost. Third, for small shocks, extreme MPCs appear to be easier to imagine, evaluate, and appreciate. By contrast, interior MPCs lead to two small, seemingly imperceptible changes that are not perceived to "make a dent" in households' savings or spending. Fourth, many households recognize an income gain as a welcome opportunity to treat themselves or their families. Most balance consumption and saving for the large shock, but they approach the smaller $100 gain differently. Some conclude that they should "indulge" and spend everything, while others choose to maintain "discipline" and save everything. We relegate a more detailed discussion to Appendix C.5. Of course, it seems plausible that further psychological forces are at work, which are harder for households to explicitly articulate. For example, finding a good compromise between consumption and saving could require more computational effort.

Our model of quick-fixing captures the convenience of extreme MPCs for small shocks and the transition pattern from extreme to interior MPCs, thus providing a plausible representation of households' introspection.

3.7 Can Existing Models Rationalize These Data?

In short, we argue the answer is no. In this section, we summarize why alternative theories of consumption-savings behavior do not satisfactorily capture the transition from extreme MPCs to interior MPCs that we observe in the data. The list of models we discuss here exhausts the set of models studied in a recent review article by Kaplan and Violante (2022) and includes many additional models.

Incomplete Markets Models. The standard incomplete markets model (or "Bewley" (1979) model) cannot account for the "bowtie" pattern in Figure 1. For example, this model predicts that as shocks become more negative, the fraction of high MPC households should increase as more households become borrowing-constrained. This is the opposite of the pattern that we see in the data: as shocks become more negative, households become less likely to have high MPCs.

Incomplete Markets Models with Heterogeneity. This failure of the incomplete markets model to match the data is not remedied by the many extensions of the model that feature *ex ante* heterogeneity in preferences and investment technologies among agents. Such models account for heterogeneous discount factors (Carroll et al., 2017; Aguiar et al., 2024), elasticities of intertemporal substitution (Aguiar et al., 2024), risk aversion (Kaplan and Violante, 2022), and investment opportunities (Kaplan and Violante, 2022). Importantly, our design elicits consumption responses within-subject. The consumption fixers, savings fixers, consumption prioritizers, and savings prioritizers that we detect in the data constitute 68% of all respondents, and none of these respondents have the behavior predicted by an incomplete markets model. Thus, *ex ante* heterogeneity cannot explain our findings.

Incomplete Markets Models with Multiple Assets or Accounts. To account for the presence of wealthy agents with high MPCs, the so-called wealthy hand-to-mouth, Kaplan and Violante (2014) introduce multiple accounts of varying liquidity to the standard incomplete markets model. Variants of this model form the basis for the highly influential HANK model of Kaplan et al. (2018). While households with low liquidity in such a model may behave in richer ways than allowed by the incomplete markets model, households with high levels of liquidity still behave according to the standard incomplete markets model. In Figure B.2, we document a pronounced "bowtie" pattern of adjustment for all levels of liquid wealth. Even households who have more than \$100,000 of liquid wealth display the "bowtie" pattern. Thus, liquidity and costly reallocation of assets across accounts cannot account for the behavior of our respondents.

Models with Durables or Consumption Commitments. To account for differences in household consumption-savings decisions between durables and non-durables, many models in the literature explicitly study the role of durable consumption (see, *e.g.,* Barsky et al., 2007). In a similar vein, Chetty and Szeidl (2016) study consumption-savings decisions when households may be pre-committed to certain spending patterns, *e.g.,* because of contracts that they have previously entered into to rent or lease a good. Such models predict that any given household will be increasingly likely to undergo a large increase in consumption and have high MPCs (as households purchase a lumpy durable good) as they experience progressively larger positive shocks. This is at odds with our finding that very few households transition from an interior MPC to an extreme MPC of 1 as positive shocks get larger. These models are also inconsistent with the behavior of consumption prioritizers and savings fixers, which account for 40% of respondents.

Models with Mistakes in Consumption. To account for the high MPCs that we see in the data, many papers have introduced behavioral elements to consumption-savings problems. Five prominent such models are those with present bias (see, *e.g.,* Laibson et al., 2021), temptation (see, *e.g.,* Krusell et al., 2002), finite planning horizons (Boutros, 2022), sparsity (Gabaix, 2014), or misperceptions of wealth (Lian, 2023). While these models generate higher (or lower) MPCs than the incomplete markets model, they once again do not generate the "bowtie" pattern of responses as a function of shock size (Figure 1) or the stark and discrete heterogeneity in policy functions that we uncover.

Models with Infrequent Optimization. To explain the failure of conventional models to generate a realistic equity risk premium, Gabaix and Laibson (2001) propose a model in which agents optimize and adjust their savings accounts only every D periods. This model does not generate the substantial fraction of agents in our data that report adjusting their savings within the next three months, as Gabaix and Laibson (2001) argue that D is at least one year. Other models generate infrequent optimization through "menu costs" of adjusting behavior (see, *e.g.*, Fuster et al., 2021). In our data, quick-fixing households adjust their behavior even in response to small shocks but differ in whether they adjust along the margin of consumption or spending. This is consistent with our model with optimization costs and heterogeneous quick-fixes and inconsistent with a model with adjustment costs.

Models with Imperfect Information or Rational Inattention. Another explanation for the *ex post* suboptimality of households' behavior is that they do not perfectly know the state of the world (such as income) and may have noisy information. Fundamentally, such models feature similar policy functions as rational models, but where the arguments of the policy function are observed with noise (see, *e.g.,* Sims, 2006). Thus, such models are not compatible with both the bowtie pattern of responses and the stark and discrete heterogeneity in household consumption policies in response to small shocks.

Our Model: Quick-Fixing and Optimization. We have argued that no existing model can capture the new empirical facts that we have documented. Instead, our empirical evidence on households' policy functions is consistent with a model of quick-fixing. It suggests that extreme MPCs often constitute crude but simple quick-fixes that avoid the costs of figuring out the optimal balance between spending and savings. Our model captures such a decision-maker who prefers quick-fixes as long as the opportunity cost of not implementing the optimal response is sufficiently small.

4 Quantitative Model

To study the macroeconomic implications of our findings, we incorporate quick-fixing into a quantitative dynamic model of consumption and savings. This model enriches the framework of Section 2 with three features present in benchmark quantitative models: more than two periods, stochastic income, and borrowing constraints. In this section, we set up the model and calibrate it to match our survey evidence.

4.1 Set-up

Time is discrete and indexed by $t \in \mathbb{N}$. There is a unit measure of households indexed by $i \in [0, 1]$. Households have the same flow payoffs and face the same exogenous economic environment, but differ in their quick-fixing behaviors.

All households have expected discounted utility preferences with discount factor $\beta \in [0, 1)$. Their flow payoff is $u(c) = \frac{c^{1-\gamma}-1}{1-\gamma}$, where γ is the inverse elasticity of intertemporal substitution. In each period t, each household earns a stochastic income y_t which lies in a discrete set $\mathcal{Y} \subset \mathbb{R}_{++}$. Income follows a first-order Markov process with transition matrix P. Households can save in a risk-free bank account with gross interest rate $R \in \mathbb{R}_+$. We denote their savings as a_t. Due to incomplete markets, households cannot borrow: $a_t \geq 0$.

Rational Behavior. We first introduce dynamic optimization of rational households, whom we henceforth refer to as type "R." Their problem of optimally planning consumption and savings under uncertainty can be formulated as a recursive dynamic program. We let $V^R : [0,\infty) \times \mathcal{Y} \to \mathbb{R}$ denote the value function of a rational household as a function of the state (a, y), or the household's assets and income. This value function is defined by:

$$\begin{aligned} V^R(a,y) = \max_{a'} &\left\{ u(c) + \beta \mathbb{E}\left[V^R(a',y') \mid y \right] \right\} \\ \text{s.t. } & a' = Ra + y - c \\ & a \geq 0 \end{aligned} \tag{13}$$

where the expectation is taken over unknown income states y'. We let c^* denote the optimal consumption policy function for rational households.

Quick-Fixing Households. We now introduce households that quick-fix. As in Section 2, we associate each household i with a *default consumption function* c^{d_i} that maps the current state to a default choice and with a quick-fix-specific *reoptimization cost* $\kappa_{d_i} \in \mathbb{R}_+$.

Our survey places discipline on the set of quick-fixes that households use. We found that quick-fixing commonly takes one of four forms: fixing consumption, fixing savings, prioritizing consumption, and prioritizing savings. To describe these behaviors dynamically, it is necessary to keep track of two additional household state variables: a *reference consumption level* $\bar{c} \in \mathbb{R}_+$ and a *reference income state* $\bar{y} \in \mathcal{Y}$. Heterogeneity in quick-fixes can be summarized by four default consumption functions, indexed by $d \in \{\text{CF}, \text{SF}, \text{CP}, \text{SP}\}$, that depend on reference consumption $\bar{c}$ and an income shock $y - \bar{y}$:

$$\begin{aligned} c^{\text{CF}}(\bar{c}, y-\bar{y}) &= \bar{c} & c^{\text{CP}}(\bar{c}, y-\bar{y}) &= \bar{c} + \max\{y-\bar{y}, 0\} \\ c^{\text{SF}}(\bar{c}, y-\bar{y}) &= \bar{c} + (y-\bar{y}) & c^{\text{SP}}(\bar{c}, y-\bar{y}) &= \bar{c} + \min\{y-\bar{y}, 0\} \end{aligned} \tag{14}$$

Consumption fixers (CF) default to a fixed level of consumption. *Consumption prioritizers* (CP) default to a fixed level of consumption plus the *positive* component of income in excess of the reference ("income shocks"), while absorbing negative shocks as reduced savings. *Savings fixers* (SF) default to a fixed level of savings, $s^{\text{SF}} = y - c^{\text{SF}}(\bar{c}, y-\bar{y}) = \bar{y} - \bar{c}$. *Savings prioritizers* (SP) default to a fixed level of consumption plus the *negative* component of income shocks, absorbing the positive component as increased savings.[8]

In each period, quick-fixers decide whether to adopt their quick-fix, which we denote by $D = 0$ (D for deliberation), or to pay utility cost κ_{d_i} to reoptimize by adopting the unconstrained, rational choice, in which case $D = 1$. For each type d, this behavior is

[8]If c^d is negative, we adopt the convention that the household automatically reoptimizes.

described by the dynamic program

$$\begin{aligned}
V^d(a, y, \bar{c}, \bar{y}) = \max_{D \in \{0,1\}} & \Big\{ D \left(u(c^*(a, y)) + \beta \mathbb{E} \left[V^d(a', y', c^*(a, y), y) \mid y \right] - \kappa_d \right) \\
& + (1 - D) \left(u(c^d(a, y, \bar{c}, \bar{y})) + \beta \mathbb{E} \left[V^d(a', y', \bar{c}, \bar{y}) \mid y \right] \right) \Big\} \\
\text{s.t. } & a' = Ra + y - \left(D(c^*(a, y)) + (1 - D)(c^d(a, y, \bar{c}, \bar{y})) \right) \\
& a \geq 0
\end{aligned} \tag{15}$$

If the household reoptimizes ($D = 1$), then it pays a utility cost κ_d, adopts the rational consumption policy $c^*(a, y)$, and resets the reference consumption and income states to $c^*(a, y)$ and y, respectively. That is, today's optimized level becomes tomorrow's reference level. If the household quick-fixes ($D = 0$), then it foregoes the utility cost, adopts a consumption policy consistent with its default rule, and does not change its reference states.

Two modeling choices that are necessary in the dynamic model are the treatment of the persistence of types and households' sophistication in understanding the future consequences of near-rationality. First, we treat the identity of an individual's quick-fixing function as an immutable and idiosyncratic characteristic. This choice is motivated by our empirical finding that household wealth and financial status are poor predictors of quick-fixing types (Fact 4). Second, households reoptimize by adopting the choice of rational households, as in the simple model. That is, households are not sophisticated in the sense that their optimizations embed the best way to manipulate their future quick-fixing choices. We argue that this approach is most consistent with the idea of near-rationality. Indeed, the costs of such naivete are bounded above by the costs of near-rationality, which we will shortly find are very small. We argue that this makes the distinction quantitatively irrelevant for households' welfare.

Interpreting One-Time Income Shocks. To study a number of questions about dynamic consumption-savings behavior, it is necessary to operate in a stationary stochastic environment. But, to link to the hypothetical scenarios of our survey, we must define household behavior in response to *one-time* shocks. To do this, we assume that the household contemplates an income shock $x \in \mathbb{R}$ in an interim period after initially choosing whether to quick-fix or reoptimize in a given period, but before observing income or making decisions for the next period. In some abuse of notation, we write c^{d*}, $\bar{c}^*$, and $\bar{y}^*$ as the optimal choices in the original decision period, suppressing their dependence on the household's state

$(a, y, \bar{c}, \bar{y})$. The household's problem, when faced with an unanticipated shock x, is

$$\begin{aligned}
\max_{D_x \in \{0,1\}} & \Big\{ D_x \left(u(c^*(a, y+x)) + \beta \mathbb{E}\left[V^d(a', y', c^*(a, y+x), y) \mid y \right] - \kappa_d \right) \\
& \quad + (1 - D_x) \left(u(c^d(c^{d^*}, x)) + \beta \mathbb{E}\left[V^d(a', y', \bar{c}^*, \bar{y}^*) \mid y \right] \right) \Big\} \\
\text{s.t. } & a' = Ra + y - \left(D_x(c^*(a, y+x)) + (1 - D_x)(c^d(c^{d*}, x)) \right) \\
& a \geq 0
\end{aligned} \tag{16}$$

If a household reoptimizes, then it follows the rational, forward-looking behavior embodied in c^*. This entails an optimization cost. If the household quick-fixes, then it treats c^{d*} as its reference consumption and the shock x as the income shock (Equation 14). That is, as we observed in the survey, consumption fixers absorb the shock entirely into savings, savings fixers absorb the shock entirely into consumption, and the prioritizers do one or the other depending on the sign of the shock.

4.2 Calibration

We calibrate the model to match standard facts on US households' behavior as well as our survey findings. We proceed in four steps.

First, we choose the flow utility and income process to match external estimates. We set $\gamma = 1$ (logarithmic preferences) to be consistent with standard estimates of the EIS. We calibrate the earnings process to match the frequency and size of quarterly-frequency earnings shocks in US micro data. The process is a 5-state discretization of a Gaussian AR(1) process that targets a variance in log annual earnings of 0.70 and an expected state switch of once every five quarters.[9] We scale income such that one unit coincides with the median quarterly income reported in our survey, \$15,625. We finally set the quarterly interest rate as $R = 1.01$.

Second, we calibrate the discount rate to match the spending behavior of households who do *not* quick-fix in the survey (*i.e.,* are "unclassified"). For the "rational" or non-quick-fixing type in the model, we calculate the average MPC out of transfer shocks of size x as $\text{MPC}_x^R = \frac{1}{x} \int (c^*(a, y+x) - c^*(a, y))\, \mathrm{d}\Phi^R(a, y)$, where $\Phi^R(a, y)$ is the stationary distribution over assets and income for rational-type agents. We choose the discount factor to minimize the sum of squared residuals between these predictions and the measured MPCs

[9] This calibration matches the variance in log annual earnings estimated by Kaplan et al. (2018) using Social Security Administration data, as well as the variance in the 1-year change in log annual earnings (0.23). See Kaplan et al. (2018) (Table III) for further details.

of "unclassified" survey respondents. That is,

$$\beta^* = \arg\min_{\beta\in(0,1)} \left\{ \sum_{i=1}^{14} \left(\mathrm{MPC}^R_{x_i} - \widehat{\mathrm{MPC}}^R_{x_i} \right)^2 \right\} \tag{17}$$

This results in a calibrated value of $\beta = 0.92$.

Third, we calibrate the fraction of agents of each quick-fixing type to match the categorization in Figure 2. The fraction of rational agents is matched to the share of unclassified households in the data. As any quick-fixers outside our four types are coded as unclassified in the data, this represents an upper bound on the fraction of rational households and is therefore conservative for the near-rational theory.

Fourth, we calibrate the four type-specific reoptimization costs, $(\kappa_{\mathrm{CF}}, \kappa_{\mathrm{SF}}, \kappa_{\mathrm{CP}}, \kappa_{\mathrm{SP}})$, to match our main findings about quick-fixing behavior in the survey (Figures 1 and 2). Specifically, for each type and each shock size, we calculate in the survey the fraction of respondents who reoptimize by reporting a propensity to consume that does not coincide with the quick-fix. In the model, we calculate, for each shock x,

$$\mathrm{ReoptFraction}^d_x = \int D^{d*}_x(a, y, \bar{c}, \bar{y})\, \mathrm{d}\Phi^d(a, y, \bar{c}, \bar{y}) \tag{18}$$

where $D^{d*}_x \in \{0, 1\}$ denotes the optimal reoptimization policy for type d in response to shock x and Φ^d is the model-implied stationary distribution for those types. The optimization costs affect reoptimization behavior directly via the optimal policy and indirectly via the stationary distribution of observed and latent states. For each type, we choose the parameter κ_d to minimize the sum of squared residuals of model versus data:

$$\kappa^*_d = \arg\min_{\kappa_d>0} \left\{ \sum_{i=1}^{14} \left(\mathrm{ReoptFraction}^d_{x_i} - \widehat{\mathrm{ReoptFraction}}^d_{x_i} \right)^2 \right\} \tag{19}$$

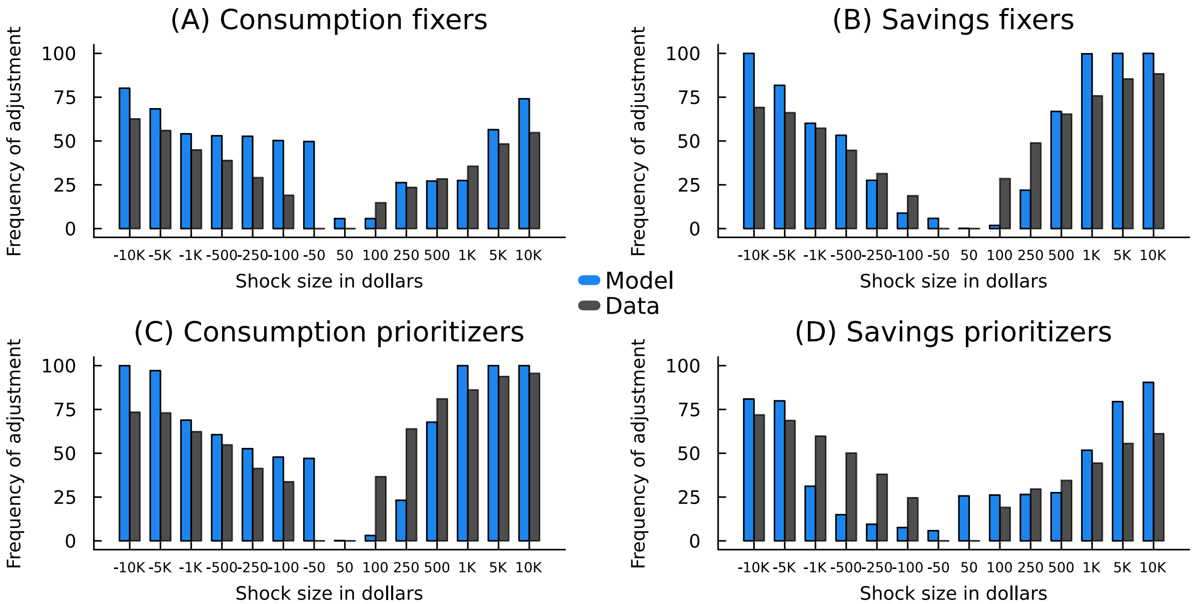
We report the calibrated values of κ_d and provide an economic interpretation of their magnitude in Table 2 in Section 5.1.

4.3 Model Fit

Reoptimization. Figure 5(i) compares the model prediction and data for the key moments that discipline the costs of reoptimization, namely the propensities to reoptimize for different shock sizes. The model fits the overall adjustment pattern quite well: as shocks get larger, considerably more individuals reoptimize. Because the model is overidentified, with 56 moments and 4 parameters for the final step of calibration, we do not exactly match

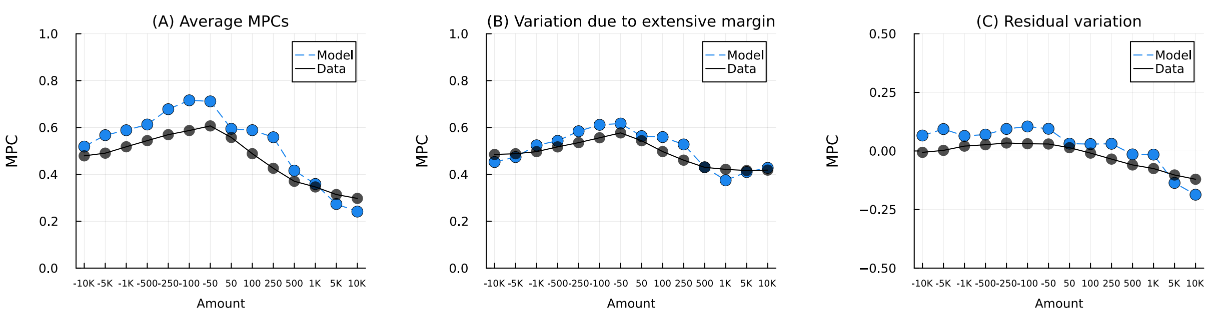
Figure 5: Quantitative model fit

(i) Reoptimization in Response to Shocks



Notes: The bar graphs compare empirical measurements and model predictions for the propensity of agents to reoptimize following unanticipated shocks. Each panel corresponds to one of the four types and therefore to the calibration of the corresponding optimization cost parameter. The blue bars denote model predictions, described in Equation 18, and the grey bars are empirical measurements, as reported in Figure 2.

(ii) Average Marginal Propensities to Consume (MPCs)



Notes: The line graphs compare empirical measurements and model predictions for the average marginal propensity to consume out of shocks of different amounts. The decomposition corresponds exactly to that of Figure 3. Panel A shows average MPCs. Panel B shows variation due to the extensive margin, calculated by assuming that quick-fixers follow their associated quick-fix and non-quick-fixers use a reference interior MPC of 0.45. Panel C shows the residual between Panel A and Panel B. The blue dashed line and dots correspond to the model prediction, and the black solid line and dots correspond to the data (and exactly to the "All types pooled" lines of Figure 3).

all of the measurements. The largest gap between the model's fit with the data occurs in cases in which consumption adjusts and savings is fixed (all of Panel B, the positive shocks in Panel C, and the negative shocks in Panel D). In these cases, the model under-estimates adjustment for low shock sizes and over-estimates adjustments for large shock sizes. To rationalize optimization in response to relatively small shocks like gaining or losing $250, the model struggles to rationalize *not* reoptimizing after gaining or losing $10,000. This is a limitation for the model's fit to the data. But, as large shocks of $10,000 are potentially unusual and hard to think about, this is exactly where we might expect the greatest error in the survey responses.

Average MPCs. Figure 5(ii) shows how the model fits average MPCs and the decomposition of MPCs between the extensive and intensive margin. While the calibration directly targets reoptimization behavior (Figure 5(i)) and the MPC profiles of unclassified agents (see Figure B.3), it does not target the average MPCs of quick-fixing agents. The model deviation in average MPCs is small and equal to 0.13 at the maximum (Panel A). The maximum difference is attained for small negative shocks (less than or equal to $250) and can be largely accounted for by a larger residual component (Panel C). This is driven by the high estimated fraction of agents at the binding borrowing constraint (see also Figure 7). This generates the correct qualitative pattern that residual variation is largest for small negative shocks but slightly overstates the quantitative magnitude.

The MPC Distribution. We finally re-create our key empirical finding about the *shape* of the MPC distribution (Figure B.4). The model replicates the "bowtie" pattern, whereby extreme MPCs (0 or 1) are less likely in response to larger shocks.

5 Quantitative Results

Having estimated the model, we now explore its economic properties. We first show quantitatively that the near-rational model predicts large differences in behavior compared to the nested rational model, but with economically very small losses from near-rational behavior. We next use the model to decompose how quick-fixing explains latent heterogeneity in the MPC, consistent with our empirical findings. We finally use the model to gauge the model's implications for the efficacy of government transfers to stimulate aggregate consumption.

5.1 The Losses from Near-Rationality Are Very Small

What size of optimization costs can rationalize the quick-fixing behavior uncovered by our empirical analysis? In Panel A of Table 2, we verify that the calibrated costs of optimization

Table 2: The small costs of optimization and near-rationality

Panel A: Optimization costs κ_d		
Household type	% reduction in consumption	Average dollar cost
Consumption fixer	0.94	\$152.26
Savings fixer	0.007	\$1.48
Consumption prioritizer	0.006	\$1.44
Savings prioritizer	0.14	\$23.00

Panel B: Value loss due to near rationality $V^R - V^d$ (per quarter)		
Household type	% reduction in consumption	Average dollar loss
Consumption fixer	0.39	\$62.06
Savings fixer	0.004	\$0.59
Consumption prioritizer	0.003	\$0.54
Savings prioritizer	0.07	\$10.58

Notes: Panel A reports the calibrated optimization costs κ_d, in economically interpretable units. Panel B reports "costs of near rationality" defined as the change in value for rational agents were they to adopt quick-fixing, on average. See Section 5.1 for details.

are payoff-equivalent to at most a 1% reduction in consumption or \$150 one-time loss. The first column reports these losses for all types in payoff units ($100\times\kappa_d$, which can be interpreted as percent consumption reduction due to logarithmic preferences), and the second column reports these as dollar equivalents.[10] The costs are by some margin highest for consumption fixers, as this strategy features relatively little reoptimization in the survey, even for very large shocks. The losses are on the order of *one hundredth of a percent* for savings fixers and consumption prioritizers, or about \$1.50.

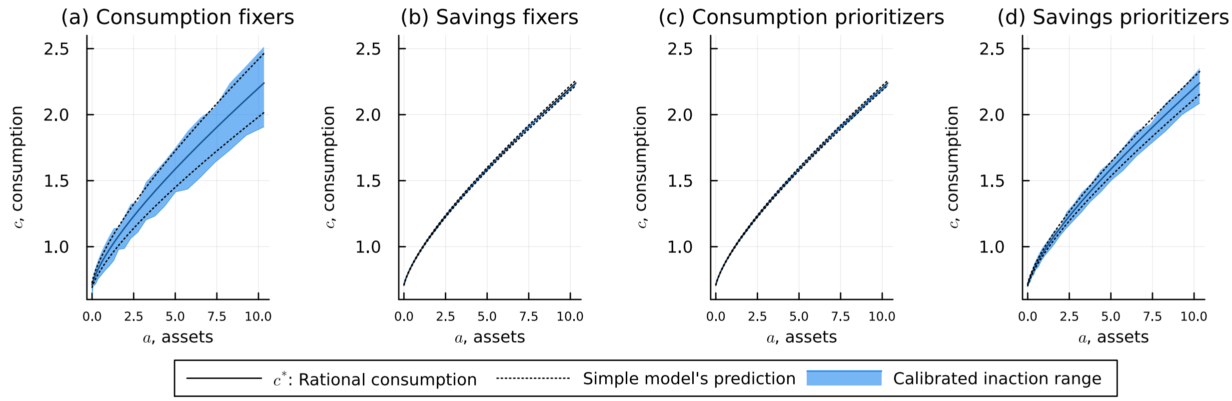
We next compute the lifetime losses from near-rationality in our stationary environment. Concretely, we compute the average lifetime loss in value for rational agents if they were to adopt the behaviors and bear the decision costs of quick-fixers:

$$\Delta V^d = \int (V^R(a,y) - V^d(a,y,c^*(a,y),y))\,\mathrm{d}\Phi^R(a,y) \tag{20}$$

Exploiting logarithmic preferences, we observe that the equivalent percentage reduction in any consumption stream $(c_t)_{t=0}^{\infty}$ solves $\sum_{t=0}^{\infty}\beta^t\log(c_t) - \sum_{t=0}^{\infty}\beta^t\log\big((1-\delta^d)c_t\big)$ and is therefore $\delta^d := 1 - e^{-(1-\beta)\Delta V^d}$. One expects this to be even lower than the optimization costs

[10] For an agent in state z, the dollar-equivalent cost of reoptimizing when consuming $c^d(z)$ solves $\log\big(c^d(z) - \Delta^d(z)\big) - \log\big(c^d(z)\big) = \kappa$, and is therefore $\Delta^d(z) = c^d(z)(e^{\kappa} - 1)$. We compute $\mathbb{E}[\Delta^d(z)|D^*(z) = 1]$, or the average dollar-equivalent cost conditional on reoptimizing.

Figure 6: Inaction regions in the calibrated quick-fixing model



Notes: Each panel corresponds to one of the four behavioral optimization types and shows that type's consumption inaction behavior as a function of assets in the median income state. If consumption and assets lie in the blue shaded area, the agent does not reoptimize their consumption level. The black line is the consumption function for rational, always-optimizing agents. The dotted lines show the boundaries of the predicted inaction region from the simple model (Proposition 1).

calculated earlier because it (i) averages over a lifetime in which reoptimizations do not always occur and (ii) accounts for the benefits from reoptimizing and obtaining higher flow payoffs.

The costs of near rationality in our calibrated model are all less than 0.5% of per-period consumption or \$65 per quarter (Panel B of Table 2). This is despite the fact that near-rational households do, in fact, frequently quick-fix (Table 3). The small loss from near-rationality helps explain why quick-fixing might persist even in a world of "selection pressure" against suboptimal strategies: the payoff cost of being a quick-fixer is extremely small.

5.2 Households Tolerate Large Deviations from Rational Behavior

We next study which deviations from rational consumption levels quick-fixing households tolerate. Figure 6 visualizes the states in which households quick-fix rather than reoptimize as shaded "inaction regions" around the rational consumption function, holding fixed income at its median state. The width of the inaction region can be interpreted in units of mean quarterly income. The inaction regions are substantial for consumption fixers and savings prioritizers, the two groups with the largest costs of optimization. In dollars, at the asset state $a = 1$ (*i.e.*, assets equal to one quarter's income), the inaction regions correspond to tolerated deviations of \$3,497 (consumption fixers), \$84 (savings fixers), \$65 (consumption prioritizers), and \$1,697 (savings prioritizers). These are all an order of magnitude larger than the equivalent dollar cost of reoptimizing (Table 2), as one would predict from the logic that losses from misoptimization are *second order* in the size of consumption deviations.

Table 3: Likelihood of quick-fixing by type

Household type	Likelihood of quick-fixing
Consumption fixer	67%
Savings fixer	53%
Consumption prioritizer	52%
Savings prioritizer	65%
Rational	0%

Notes: Each cell prints the percentage likelihood that an agent quick-fixes in a given quarter, evaluated at the stationary distribution over states. Each row corresponds to one of the four quick-fixing types or the rational type.

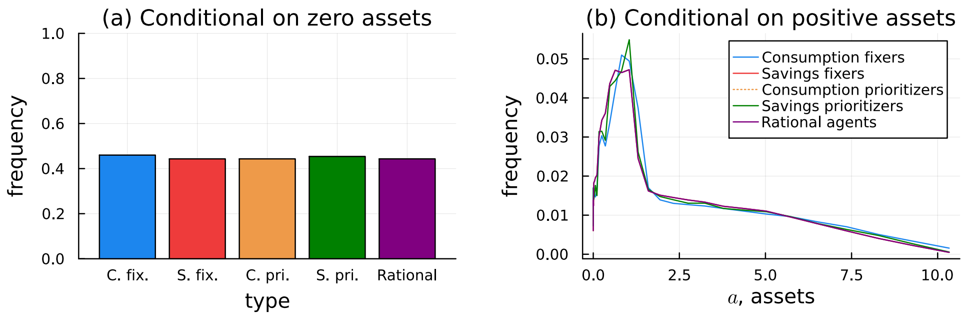
We also observe that the very different width of inaction bands across types are consistent with similar probabilities of quick-fixing, between 50% and 70% (Table 3). This reflects the fact that the quick-fixes which fix savings rather than consumption *do* allow consumption to respond to shocks. In particular, strategies which fix savings and adjust consumption one-to-one with income will achieve close to the rational response to a highly persistent income shock when away from the borrowing constraint, and they will exactly coincide with the rational response for any income shock when the borrowing constraint binds strictly.

We finally note that the approximate calculation of inaction regions from the two-period model (Proposition 1) is roughly correct in this much richer setting (dotted lines in Figure 6). Intuitively, with a persistent income state, the continuation ($t+1$) costs of keeping a default level of consumption — a force necessarily ignored in the two-period model — scale very closely with the static (t) costs. The approximation is relatively worse for lower asset households because of two forces missing in the simple model and its quadratic approximation: the changing second derivative of the utility function (prudence), which is most pronounced at lower consumption levels, and the borrowing constraint.

5.3 Quick-Fixing is Unrelated to Wealth, But Generates MPC Heterogeneity

One moment that we did not use to calibrate the model is the limited relationship between quick-fixing types and wealth (Fact 4). This is not a foregone conclusion in the quantitative model. Assets are an endogenous state variable and household savings responses to shocks differ across types. It is a reasonable conjecture, for example, that households who default to increasing saving in response to any shock (savings prioritizers) accumulate more wealth than those who default to increasing consumption in response to any shock (consumption prioritizers).

Figure 7: Wealth distributions by type



Notes: This figure shows the distribution of assets for each type. Panel (a) shows the frequency of households at the borrowing constraint, $a = 0$. Panel (b) shows the distribution of wealth conditional on $a > 0$.

Reassuringly, we find that the wealth distributions of each of the four quick-fixing types as well as rational agents are essentially identical (Figure 7). Most cross-sectional variation in wealth is driven by large and persistent shocks to income. Any short-run differences in savings responses to these shocks wash out in the long-run, when households eventually reoptimize. As one concrete example: while savings fixers are as-if "hand to mouth" in response to small shocks, they are not actually "hand to mouth" in the long run. This represents an important difference from models in which some agents consume their income (*e.g.*, Campbell and Mankiw, 1989). These findings also contrast with those obtained in the class of models of agents with heterogenous discount factors and/or present bias, which naturally lead to very different long-run rates of saving.

We next explore how much quick-fixing contributes to heterogeneity in the marginal propensity to consume. To be consistent with our survey results, we measure a population distribution of the average MPC in response to the fourteen experiments from our survey. Table 4 reports the percent of variance in this object that can be explained by assets and income in the quick-fixing model and the nested rational model. This is a stronger notion of "predictability" than what we can reasonably accomplish by regressing MPCs on observables in survey data because, in the model, we can calculate exact conditional expectation functions and have no measurement error; thus, this calculation gives an *upper bound* for what assets and income might explain and a *lower bound* for what remains to be explained by other sources of heterogeneity. In the rational model, assets and income explain all variation by construction. This is strongly at odds with our findings as well as those from other studies in the literature (*e.g.*, Lewis et al., 2024). In our model, 27% of total MPC variance and 68% of variance conditional on $a > 0$ is unexplained by assets and income, and therefore introduced by quick-fixing behavior. Thus, quick-fixing helps break the tight connection in incomplete markets models between financial observables and MPCs.

Table 4: Variance in MPCs unexplained by assets and income

Model	**Overall**	**Conditional on** $a = 0$	**Conditional on** $a > 0$
Quick-fixing	27%	42%	68%
Rational	0%	0%	0%

Notes: In each model, we calculate $\text{Var}[MPC_i|a_i, y_i]$, where i indexes households, a_i is the household's wealth, and y_i is the household's income. We report $100 \cdot \text{Var}[MPC_i|a_i, y_i]/\text{Var}[MPC_i]$, or the fraction of variance unexpected by financial characteristics. Since (a, y) is the state variable in the rational problem, this is mechanically 0 in that model.

5.4 Responses to Transfer Shocks Vary Across Size and Horizon

We finally use the model to study the efficacy of government transfer shocks to stimulate aggregate consumption. To do this, we use the quantitative model to calculate a sequence of *intertemporal marginal propensities to consume* ("iMPCs"), or average consumption responses at various future horizons in response to contemporaneous transfer shocks. Intuitively, iMPCs measure how quickly a given stimulus is spent by households. Previous research shows that iMPCs are sufficient statistics for calculating the first-order effects of transfer shocks on aggregate output in Keynesian models (Auclert et al., 2024).

Concretely, for individual i with current idiosyncratic state z_i, we can define their iMPC at horizon h out of an income change x occuring at time t:

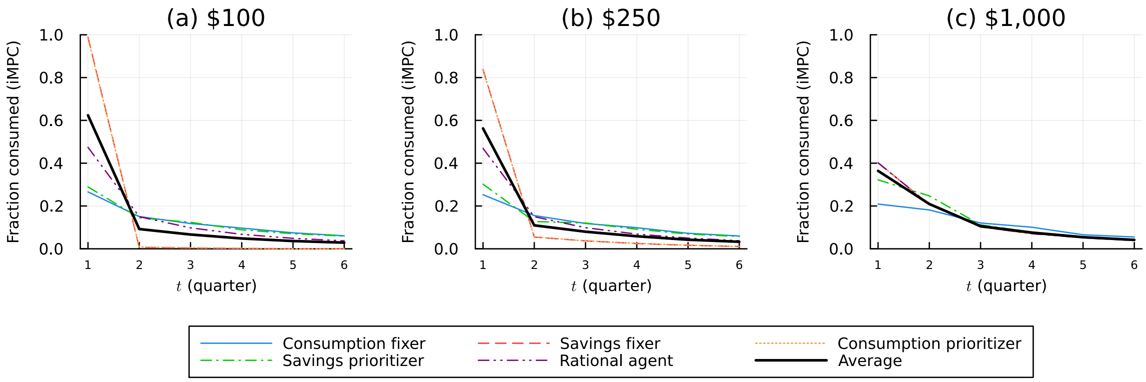
$$\text{MPC}_{h,x}(z_i) = \frac{\mathbb{E}[c_{i,t+h}|z_i, x] - \mathbb{E}[c_{i,t+h}|z_i, 0]}{x} \tag{21}$$

That is, averaged over realizations of income and expressed as a fraction of the shock, how much more does that household consume at $t + h$ because of an unanticipated shock of size x at t? Due to the budget constraint, intertemporal MPCs must add up to unity in present value: $\sum_{h=0}^{\infty} \frac{1}{(1+r)^h} \text{MPC}_{h,x}(z_i) = 1$ for all z_i. We define analogous measures averaged over our distribution of endogenous and exogenous states. While our survey directly disciplines the contemporaneous MPC (*i.e.*, MPC_0), the quantitative model helps us to understand how quick-fixing households spend their savings over subsequent quarters.

iMPC profiles vary considerably across types, shock sizes, and horizons (Figure 8(i)). For a $100 shock, average iMPCs belie significant heterogeneity. Savings fixers and consumption prioritizers consume almost everything in one quarter, consumption fixers and savings prioritizers keep about 40% saved after one year, and rational consumers behave somewhere in between. For a $1,000 shock, by contrast, iMPC profiles are more uniform across groups due to most types' reoptimizing — except for a significant fraction of consumption fixers who, consistent with our survey evidence, fully save even these large amounts.

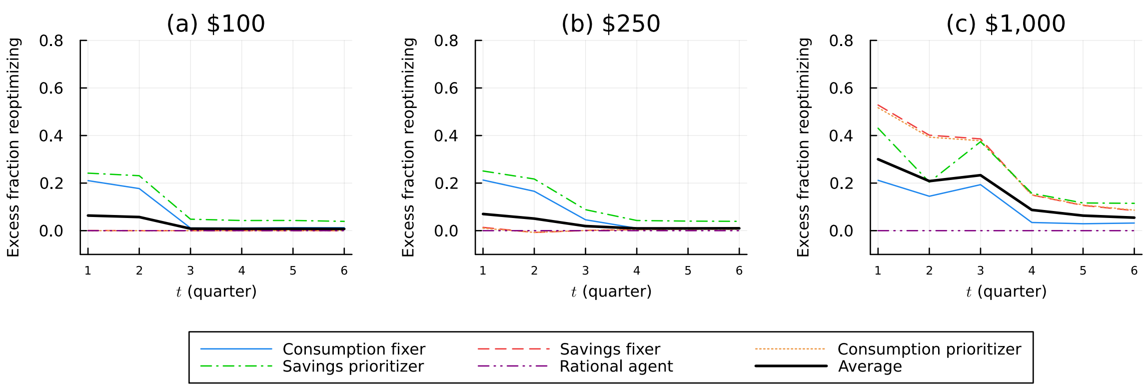
Figure 8: Dynamic consumption responses to transfer shocks

(i) Profiles of intertemporal marginal propensities to consume



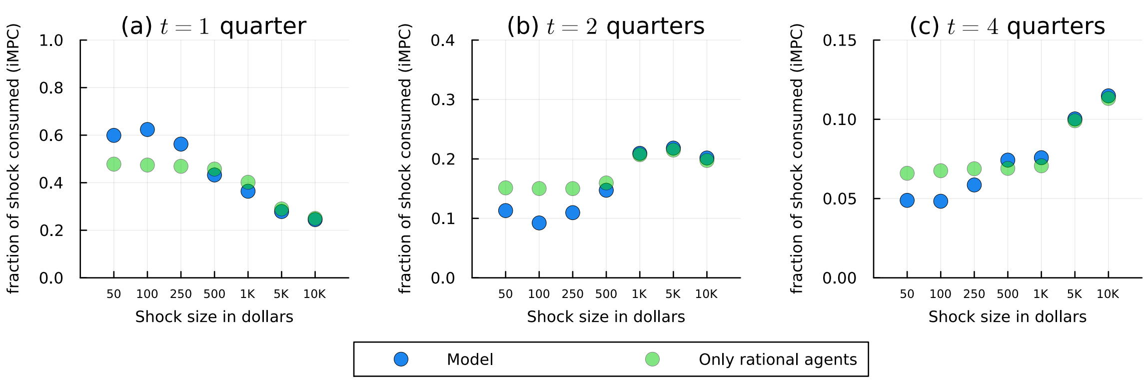
Notes: Each panel shows the intertemporal marginal propensity to consume (iMPC) in response to a different stimulus experiment. The black solid line is the population average, and the remaining colored lines decompose the responses of each household type.

(ii) Profiles of delayed reoptimization



Notes: Each panel shows the fraction of additional households that reoptimize compared to the steady state in response to a different stimulus experiment. The fraction at $t = 1$ is calculated based on whether households reoptimize in response to an income shock *or* the unanticipated stimulus.

(iii) Comparing iMPC profiles with the rational model



Notes: Each panel shows the intertemporal marginal propensity to consume (iMPC) averaged over households of all types in response to the specified shocks (x-axis) at the specified horizon. Blue dots correspond to the model prediction. Green dots correspond to the subset of rational agents.

Table 5: MPCs depend significantly on size

Amount	**Context**	MPC in **Full Model**	MPC in **Rational Model**
$100	Survey	0.62	0.47
$600	2001 Tax Rebate	0.41	0.44
$1200	2020-21, Round 2	0.35	0.39
$2400	2020-21, Round 1	0.31	0.34
$2800	2020-21, Round 3	0.30	0.33

Notes: This table reports contemporaneous (one-quarter) MPCs in the full model and the nested rational model for positive transfers of different amounts. Rows 2-5 correspond to baseline transfer amounts for two-taxpayer households in the indicated historical US stimulus policies.

To better illustrate how quick-fixing and reoptimization drive these patterns, Figure 8(ii) shows the "impulse response" of the fraction of agents who reoptimize. In response to small shocks (Panel A), very few households reoptimize on impact, and essentially no one does after three quarters. As shocks get larger (Panels B and C), households reoptimize both on impact and after many quarters.

Comparing the Near-Rational and Rational Models. Using the model, we can formally evaluate how the presence of quick-fixing affects aggregate consumption by comparing it to a world with only rational households. To isolate this, Figure 8(iii) plots iMPCs at specific horizons (1, 2, 4, and 6 horizons) for each gain scenario under the calibrated quick-fixing model and a restriction to only rational agents. For large shock sizes ($1,000 and above), the models are much closer to one another at all horizons. This is natural because, as uncovered in the survey, most households do not quick-fix when confronted with large shocks. For small shocks (less than $500), the rational model under-states contemporaneous responses and over-states long-run iMPCs. This quantitatively arises because behavioral types with high quick-fix MPCs are more influential than behavioral types with low quick-fix MPCs.

Size-Dependence in Transfer Responses. We also can revisit the size-dependent response to transfers uncovered by the survey and formally relate this to the presence of near-rationality. Table 5 calculates average MPCs for four benchmark amounts that have been used in US stimulus design as well as the $100 experiment in our survey. For each historical example, the exact size of transfer payments depends on other features (*e.g.*, the number of taxpayers and children in each household), so we benchmark to the payment for a two-taxpayer household. Transfer amounts have varied significantly over time. Our near-rational model suggests that if these amounts were transferred to a population that approximates current US households, their stimulus effects would widely differ. Much smaller stimulus checks, for instance of $100, could potentially have a significantly larger per-dollar effect on aggregate consumption. This prediction of sharp size-dependence is *not* shared with the rational model. Concretely, the difference in MPCs between a \$100 check and a \$1,200 check is 0.27 in the quick-fixing model versus 0.08 in the rational model, a more than three-fold difference between models.

A second takeaway is that measurements of MPCs based on transfers of a particular amount may not be informative about MPCs out of different amounts. In particular, those based on large income shocks may under-state the MPC in counterfactuals with small income shocks, and *vice versa*. This is a particular articulation of the Lucas (1976) critique of consumption functions, which we show is quantitatively relevant for measuring (i)MPCs.

6 Conclusion

In this paper, we use novel survey evidence to explore the near-rationality hypothesis for consumption and savings behavior. By asking respondents about their consumption response to a large number of hypothetical scenarios, we can recover the consumption policy functions required to test the theory. We find that many households *quick-fix* by following simple rules of fully spending or fully saving in response to small shocks, while pursuing a more moderate strategy for large shocks. Quick-fixing opens up the "black box" of latent heterogeneity in the marginal propensity to consume: quick-fixing types are essentially unpredictable by demographic and financial variables while accounting for a significant fraction of MPC variation. To interpret the aggregate consequences of these findings, we embed quick-fixing in a quantitative model of consumption and savings choice with incomplete markets. The quantitative model generates much more size-dependence in the aggregate response to transfer shocks compared to the nested rational model. The optimization costs that rationalize this finding are economically very small, in absolute terms and relative to quarterly income. Taken together, our analysis suggests that the near-rational model fits the household responses to income shocks and generates significantly different macroeconomic consequences than benchmark models based on perfect optimization.

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Appendices

A Proof of Proposition 1

Proof. We apply a state-dependent second-order approximation to $\mathcal{L}^{d_i}(z_i)$. Define:

$$U(c, z_i) = u(c) + \beta u(R(a_i + y_{i,1} - c) + y_{i,2}) \tag{22}$$

and observe that $U^{d_i}(z_i) = U(c^{d_i}(z_i), z_i)$. Toward approximating, we can define the loss function on an enriched domain as $\mathcal{L}^U(c, z_i) = U^*(z_i) - U(c, z_i)$, and we can again observe that

$$\mathcal{L}^{d_i}(z_i) = \mathcal{L}^U(c^{d_i}(z_i), z_i) \tag{23}$$

To approximate $\mathcal{L}^{d_i}$, we therefore approximate $\mathcal{L}^U(\cdot, z_i)$ to second order around the point $c^*(z_i)$ for every state z_i. This yields the following:

$$\begin{aligned} \mathcal{L}^{d_i}(z_i) = {} & \mathcal{L}^U(c^*(z_i), z_i) + \mathcal{L}_c^U(c^*(z_i), z_i)(c^{d_i}(z_i) - c^*(z_i)) \\ & + \frac{1}{2}\mathcal{L}_{cc}^U(c^*(z_i), z_i)(c^{d_i}(z_i) - c^*(z_i))^2 + O(|c^*(z_i) - c^d(z_i)|^3) \end{aligned} \tag{24}$$

We observe however that $\mathcal{L}^U(c^*(z_i), z_i) = 0$ by definition and that $\mathcal{L}_c^U(c^*(z_i), z_i) = 0$ by the optimality of c^*. Thus, we have obtained that:

$$\mathcal{L}^{d_i}(z_i) = \frac{1}{2}\mathcal{L}_{cc}^U(c^*(z_i), z_i)(c^{d_i}(z_i) - c^*(z_i))^2 + O(|c^*(z_i) - c^d(z_i)|^3) \tag{25}$$

We can moreover compute $\frac{1}{2}\mathcal{L}_{cc}^U(c^*(z_i), z_i)$ as:

$$\mathcal{L}_{cc}^U(c, z_i) = -\beta R^2 u''(R(a_i + y_{i,1} - c) + y_{i,2}) - u''(c) \tag{26}$$

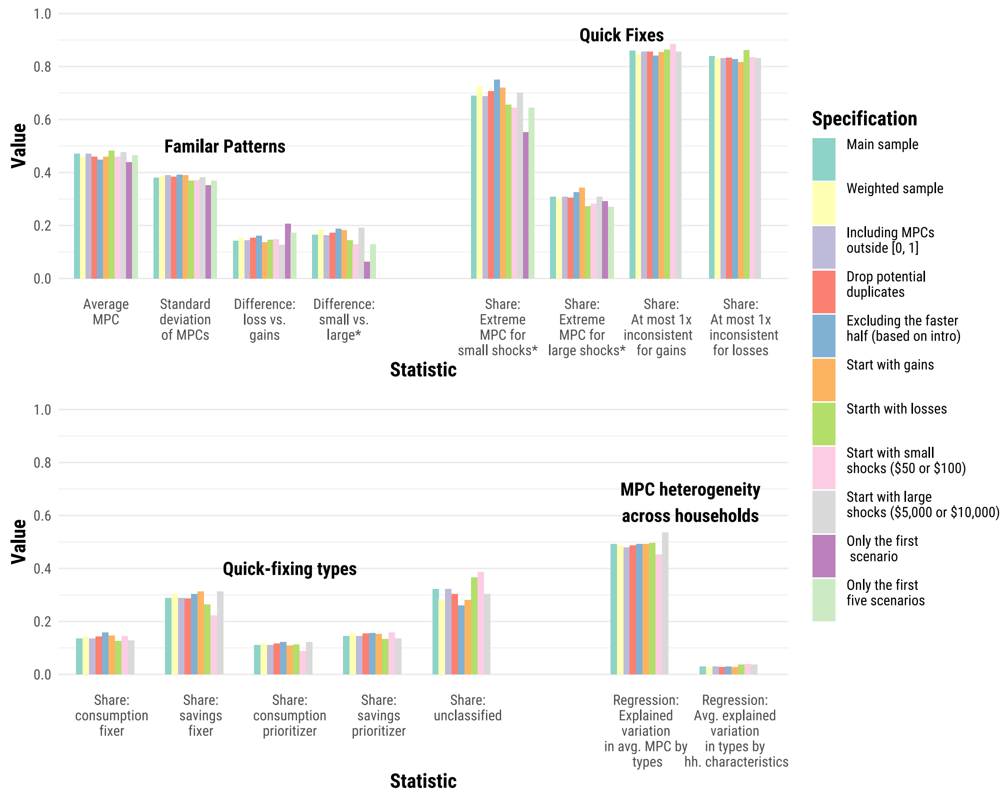
which yields:

$$\mathcal{L}_{cc}^U(c^*(z_i), z_i) = -(1 + \beta R^2) u''(c^*(z_i)) \tag{27}$$

Completing the proof. □

B Additional Figures and Tables

Figure B.1: Results are robust in a variety of sensitivity tests



Notes: We recalculate key statistics from Section 3 for a variety of robustness specifications:

- *Main sample*: We reproduce the statistics from the main text.
- *Weighted sample*: We use post-stratification weights that correct for possible imbalances across the variables reported in Table C.1.
- *Including MPCs outside [0, 1]*: We add 51 additional respondents whom we drop from the main analysis because they report MPCs outside [0, 1] (see Appendix C.1).
- *Drop potential duplicates*: We drop potential duplicate respondents who submitted similar data on the same day (see Appendix C.1).
- *Excluding the faster half (based on intro)*: We exclude the 50% fastest respondents who "speed through" the introductory instructions of the survey.
- *Start with gains*: We restrict the sample to respondents who first respond to gains.
- *Start with losses*: We restrict the sample to respondents who first respond to losses.
- *Start with small shocks ($50 or $100)*: We restrict the sample to respondents who first respond to a small income shock of $50, $100, −$50, or −$100.
- *Start with large shocks ($5,000 or $10,000)*: We restrict the sample to respondents who first respond to a large income shock of $5,000, $10,000, −$5,000, or −$10,000.
- *Only the first scenario*: We restrict the sample to the first MPC that respondents report.
- *Only the first five scenarios*: We restrict the sample to the first five MPCs that respondents report.

*Small shocks: $50 and $100. Large shocks: $5,000 and $10,000.

Table B.1: Additional significance tests

Statement	t-test	Randomization test	
	p-value	Statistic under H_0	p-value
Familiar Observations			
MPCs decline for larger shocks; e.g., for gains, 0.56 for $50 gain versus 0.30 for $10,0000 gain. Difference: 0.26.	< 0.001	0.000	< 0.001
The average MPC is larger for losses (0.54) than for gains (0.40). Difference: 0.14.	< 0.001	0.000	< 0.001
Quick Fixes			
From one shock to the next larger shock, a net share of 7% of households transition from an extreme MPC to a more moderate interior MPC.	–	0.000	< 0.001
Most households — namely 68% for gains and 67% for losses — switch to an interior MPC at most once and stick to interior MPCs thereafter. Average: 68%.	–	0.413	< 0.001
86% (for gains) and 84% (for losses) of households deviate from this pattern at most once. Average: 85%.	–	0.602	< 0.001
Extreme MPCs more common for small than large shocks, e.g. 74% for $50 gain versus 0.26% for $10,000 gain. Difference: 0.48.	< 0.001	0.000	< 0.001
Once households adopt their first interior MPC, their MPCs are relatively stable. While they continue to vary, the average absolute difference is only 0.14.	–	0.236	< 0.001

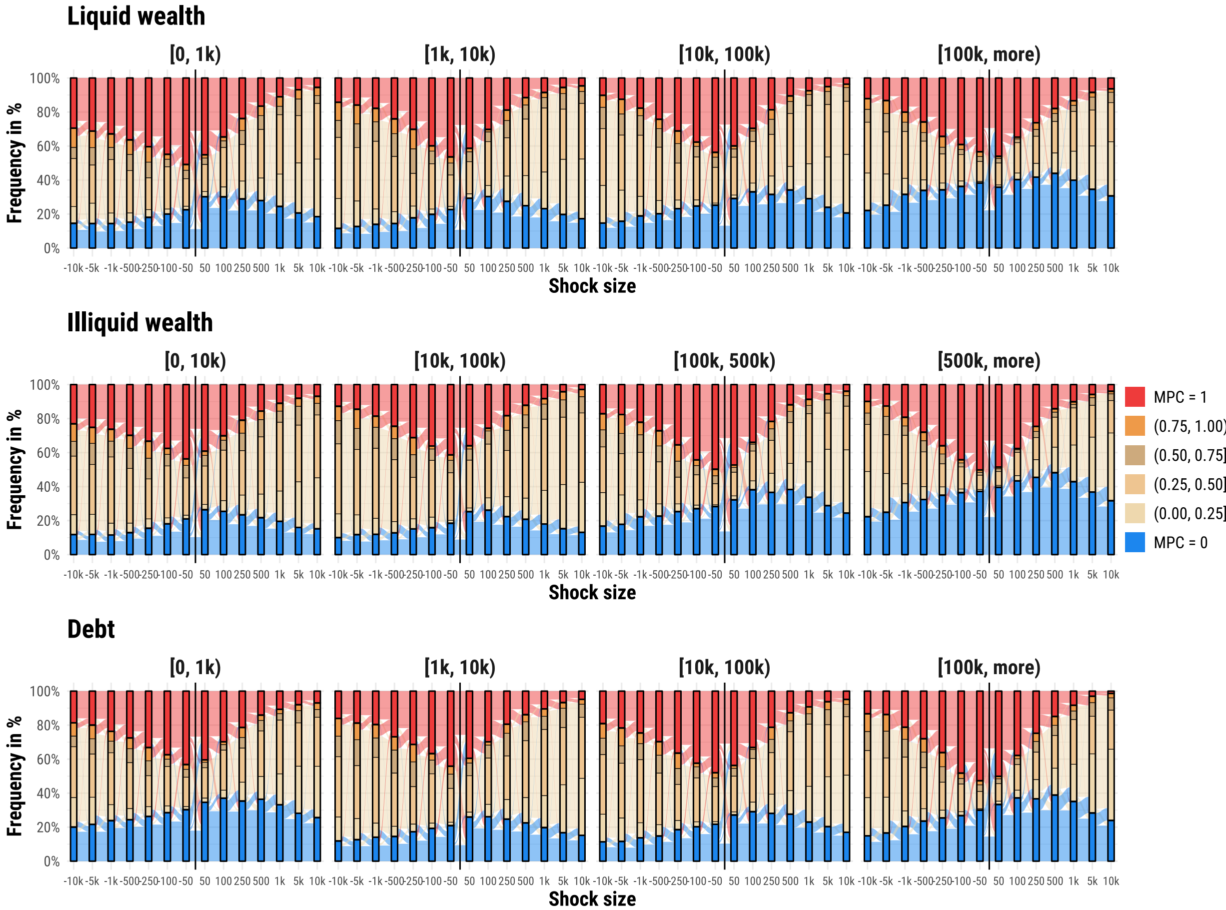
Notes: This table reports whether the statistics reported in the statements are significantly different from the patterns we would expect to result from pure chance. The t-test column reports p-values from two-sided t-tests that test for differences in MPCs between shocks. We also use a more flexible randomization test that derives the distribution of the statistics under the null hypothesis that there is no link between MPCs, shock sizes, and valence. To achieve this, we permute the data within each household by (i) reshuffling MPCs within gains, and (ii) reshuffling MPCs within losses, and (iii) randomly replacing all gain MPCs with loss MPCs and vice versa. We draw 10,000 permuted data sets. The column "Statistic under H_0" reports the average value of the statistic in the permuted data sets. The last column reports the p-values of the randomization tests.

Table B.2: Exploring the variation in MPCs across households

	MPCs		Type membership					Switching point	
	Average MPC		Consump. fixer	Savings fixer	Consump. priori.	Savings priori.	Unclass-ified	Average log(shock size)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Consumption and income									
Mthly spending (log.)		0.012***	−0.012***	0.011**	0.005	0.000	−0.005		−0.091***
		(0.003)	(0.004)	(0.005)	(0.003)	(0.004)	(0.005)		(0.023)
Annual income (log.)		0.007	0.005	0.000	−0.009	−0.018**	0.022**		0.126***
		(0.005)	(0.007)	(0.010)	(0.007)	(0.008)	(0.010)		(0.044)
Income risk (std.)		0.020***	−0.022***	−0.021***	−0.020***	−0.022***	0.084***		0.057*
		(0.004)	(0.005)	(0.007)	(0.004)	(0.005)	(0.007)		(0.031)
Liquid wealth: dummies with reference group: [0k, 1k)									
[1k, 10k)		−0.052***	0.012	−0.051***	0.003	−0.010	0.046**		−0.438***
		(0.009)	(0.013)	(0.019)	(0.013)	(0.015)	(0.018)		(0.082)
[10k, 100k)		−0.069***	0.020	−0.086***	0.005	−0.026	0.088***		−0.205**
		(0.010)	(0.015)	(0.020)	(0.015)	(0.017)	(0.019)		(0.087)
[100k, more)		−0.072***	0.070***	−0.088***	0.037**	−0.045**	0.026		0.052
		(0.013)	(0.020)	(0.026)	(0.019)	(0.020)	(0.023)		(0.104)
Illiquid wealth: dummies with reference group: [0k, 10k)									
[10k, 100k)		−0.018*	−0.002	−0.000	−0.003	0.015	−0.009		−0.053
		(0.010)	(0.015)	(0.022)	(0.014)	(0.017)	(0.021)		(0.100)
[100k, 500k)		−0.025***	0.001	0.050**	0.016	0.020	−0.086***		0.111
		(0.010)	(0.014)	(0.020)	(0.014)	(0.016)	(0.019)		(0.084)
[500k, more)		−0.067***	0.061***	0.082***	0.003	0.043**	−0.189***		0.141
		(0.012)	(0.019)	(0.024)	(0.017)	(0.019)	(0.021)		(0.098)
Debt: dummies with reference group: [0k, 1k)									
[1k, 10k)		0.030***	−0.057***	−0.002	0.008	0.009	0.042**		−0.364***
		(0.009)	(0.013)	(0.018)	(0.012)	(0.014)	(0.018)		(0.083)
[10k, 100k)		0.039***	−0.051***	0.046**	−0.000	0.017	−0.012		−0.269***
		(0.009)	(0.013)	(0.018)	(0.012)	(0.014)	(0.017)		(0.076)
[100k, more)		0.018*	−0.039**	0.045**	0.034**	0.038**	−0.077***		−0.363***
		(0.010)	(0.016)	(0.020)	(0.015)	(0.016)	(0.018)		(0.080)
Other characteristics									
College		0.004	−0.011	−0.021	0.007	−0.019*	0.045***		−0.005
		(0.007)	(0.011)	(0.015)	(0.010)	(0.011)	(0.013)		(0.061)
Age (in 10y)		−0.015***	0.016***	0.010**	0.011***	0.007**	−0.045***		0.100***
		(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)		(0.018)
Female respondent		0.009	−0.009	0.015	−0.017*	−0.003	0.014		−0.011
		(0.006)	(0.010)	(0.013)	(0.009)	(0.010)	(0.012)		(0.056)
Household size		0.010***	−0.013***	0.005	0.003	−0.007	0.012**		−0.029
		(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)		(0.025)
Quick-fixing types									
Consump. fixer	−0.346***							0.236***	
	(0.007)							(0.085)	
Savings fixer	0.165***							−0.218***	
	(0.006)							(0.073)	
Consump. prioritizer	−0.094***							−0.555***	
	(0.008)							(0.093)	
Savings prioritizer	−0.073***								
	(0.006)								
Constant	0.492***	0.396***	0.138*	0.134	0.089	0.324***	0.315***	7.960***	6.987***
	(0.003)	(0.050)	(0.077)	(0.099)	(0.067)	(0.082)	(0.103)	(0.059)	(0.459)
Obs.	4,981	4,981	4,981	4,981	4,981	4,981	4,981	3,381	3,381
R^2	0.492	0.109	0.057	0.017	0.020	0.020	0.174	0.024	0.058

Notes: This table reports regressions that explore the heterogeneity of households' MPCs. Columns 1–2 analyze households' mean MPC (averaged across all 14 shocks), Columns 3–7 analyze households' type (binary indicators), and Columns 8–9 analyze households' mean log switching threshold (the smallest shock for which they switch from an extreme to an interior MPC, averaged across gains and losses). Columns 8–9 restrict the sample to the four quick-fixing types. Appendix C.3 describes how we measure the economic background variables. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure B.2: MPC profiles across the wealth distribution



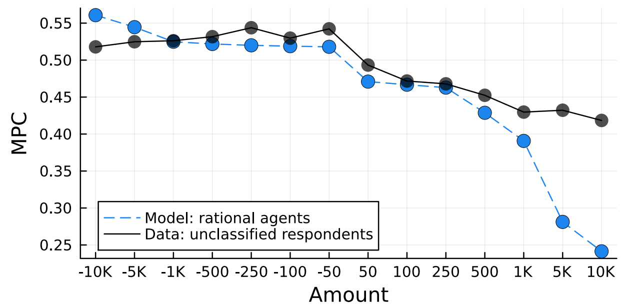
Notes: The alluvial graphs summarize the MPC profiles of households with varying liquid wealth, illiquid wealth, and debt (see Appendix C.3 for variable definitions). In each panel, each of the 14 columns displays the distribution of MPCs for one particular shock size, and the streams between bars indicate how households' MPCs transition between two neighboring shocks.

Table B.3: Deliberation negatively predicts extreme MPCs

	Extreme MPC of 0 or 1 (binary indicator)					
	(1)	(2)	(3)	(4)	(5)	(6)
Deliberation (std.)	−0.263***	−0.274***	−0.248***	−0.254***	−0.257***	−0.276***
	(0.011)	(0.020)	(0.011)	(0.020)	(0.013)	(0.020)
Respondent FE	✓	✓	✓	✓	✓	✓
Weights	–	✓	–	✓	–	✓
Measure	**Carefully consider how to change spending**		**Assess overall financial situation**		**Discuss with household members**	
Observations	3,619	3,619	3,619	3,619	3,080	3,080
R^2	0.740	0.761	0.723	0.744	0.711	0.719

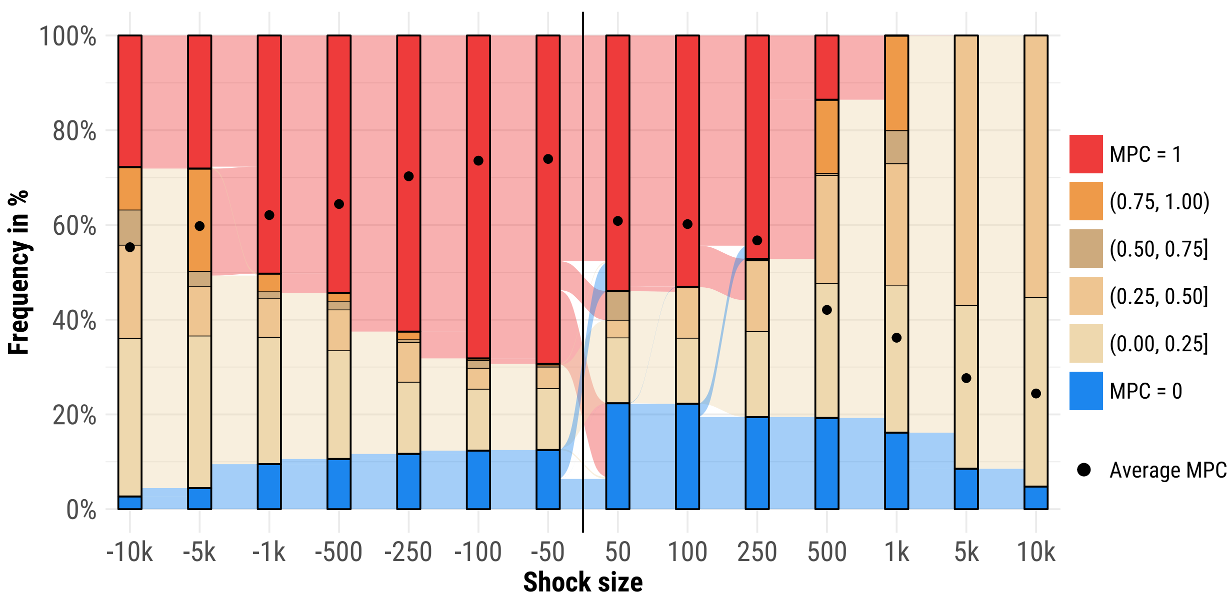
Notes: This table reports regression results and uses data from the deliberation ratings study. We regress a binary indicator for whether a household adopts an extreme MPC of 0 or 1 on different standardized deliberation measures (see row "Measure"). Columns 1, 3, and 5 display unweighted results. Columns 2, 4, and 6 use post-stratification weights that correct for imbalances in the distribution of demographic characteristics (see Table C.2). All regressions use household-level fixed effects, and the robust standard errors are clustered on the household level.

Figure B.3: Quantitative model fit for marginal propensities to consume (MPCs)



Notes: The line graphs compare empirical measurements and model predictions for the average marginal propensity to consume out of shocks of different amounts, among Unclassified respondents in the survey (black line and dots) and rational agents in the model (blue line and dots). We calibrate the discount factor β to minimize the sum of squared differences between these model predictions and measurements.

Figure B.4: Quantitative model fit for the MPC distribution



Notes: The alluvial graph summarizes the MPC predictions generated by the quantitative model, following the format of Figure 1. Each of the 14 columns displays the distribution of MPCs for one particular shock size, with colors indicating the size of the MPC. The streams between bars indicate how households' MPCs transition between two neighboring shocks. Black dots depict the average MPCs for each shock. We exclude a few respondents with MPCs outside [0, 1] to facilitate the visual presentation.

C Additional Material for the Empirical Studies

C.1 Sample

Sampling. We recruited respondents in October and November 2023 collaborating with the survey company Bilendi. We recruited respondents from different parts of the Bilendi respondent pool in order to approximate the general US population in terms of gender, age, income, education, and region.

Final Sample Characteristics. Table C.1 presents demographic summary statistics for our final sample and compares them to the demographic characteristics of the US adult population.

Exclusion Criteria. Three exclusion criteria are preregistered. The sample does not contain the following responses: (i) incomplete responses, (ii) responses at both extreme 1% tails in the response duration, and (iii) responses with duplicate IDs (very rare cases).

In addition, we exclude 51 respondents who have at least one MPCs outside the interval [0, 1]. Many of these respondents report just one or a few MPCs outside [0, 1], which could simply reflect response error. Excluding them simplifies the visual presentation of the results and ensures that outliers do not distort our analyses of averages. Unsurprisingly, the robustness check in Appendix Figure B.1 confirms that we obtain virtually the same results with the full sample.

Attention Screener. Only participants who pass an attention screener at the beginning of the survey can proceed to the main part of the survey.

Survey Duration. The survey is relatively short to avoid response fatigue and ensure that respondents are willing to respond carefully to the open questions. The median response duration is approximately 14 minutes and most respondents complete the survey within 9 and 24 min (20%-80% quantile range).

Potential duplicate responses. Even though we included a captcha and an attention screener, we observe a couple of very similar respondents who start the survey at a similar time. About 75 respondents have identical answers to 23 different demographic questions and start the survey at a similar time. Fortunately, our results are robust to excluding them. Figure B.1 takes an even more conservative approach and drops roughly 7% of responses with the most similar demographic data within each day. Again, the results are virtually identical.

Table C.1: Demographic characteristics of the sample

Variable	ACS (2022)	Sample
Gender		
Female	50%	50%
Age		
18-34	29%	27%
35-54	32%	33%
55+	38%	40%
Household income		
Below 50k	34%	34%
50k-100k	29%	28%
Above 100k	37%	37%
Education		
Bachelor's degree or more	33%	40%
Region		
Northeast	17%	17%
Midwest	21%	21%
South	39%	39%
West	24%	23%
Sample size	1,980,550	4,981

Variable	SCF (2022)	Sample
Liquid assets		
Below 1k	20%	29%
1k-10k	31%	25%
10k-100k	31%	28%
Above 100k	19%	18%
Illiquid assets		
Below 10k	26%	38%
10k-100k	11%	14%
100k-500k	34%	26%
Above 500k	29%	22%
Debt		
Below 1k	27%	35%
1k-10k	10%	21%
10k-100k	27%	25%
Above 100k	36%	19%
Sample size	4,602	4,981

Notes: This table presents summary statistics for the sample of US households and compares them to benchmark characteristics for the US adult population based on data from the American Community Survey 2022 and the Survey of Consumer Finances 2022. Appendix C.3 describes how we measure the economic background variables.

Table C.2: Demographic characteristics in the additional studies

Variable	ACS (2022)	Deliberation ratings study	Qualitative study
Gender			
Female	50%	50%	49%
Age			
18-34	29%	43%	47%
35-54	32%	48%	46%
55+	38%	10%	7%
Household income			
Below 50k	34%	25%	32%
50k-100k	29%	40%	35%
Above 100k	37%	35%	33%
Education			
Bachelor's degree or more	33%	63%	64%
Region			
Northeast	17%	19%	18%
Midwest	21%	15%	17%
South	39%	49%	41%
West	24%	18%	25%
Sample size	1,980,550	517	502

Variable	SCF (2022)	Deliberation ratings study	Qualitative study
Liquid assets			
Below 1k	20%	26%	26%
1k-10k	31%	32%	27%
10k-100k	31%	32%	37%
Above 100k	19%	10%	10%
Illiquid assets			
Below 10k	26%	38%	38%
10k-100k	11%	21%	19%
100k-500k	34%	24%	25%
Above 500k	29%	18%	19%
Debt			
Below 1k	27%	20%	22%
1k-10k	10%	23%	18%
10k-100k	27%	26%	30%
Above 100k	36%	30%	30%
Sample size	4,602	517	502

Notes: This table presents summary statistics for the sample of US households in the additional studies and compares them to benchmark characteristics for the US adult population based on data from the American Community Survey 2022 and the Survey of Consumer Finances 2022. Appendix C.3 describes how we measure the economic background variables.

C.2 Instructions

The complete instructions are available online at https://osf.io/2s7cf. The survey begins with a participation information and informed consent form. Respondents who participate on a mobile device are screened out. Next, respondents have to pass an attention check. Subsequently, respondents fill out a block of demographic questions. Then, the main part of the survey begins (see below). The survey ends with additional questions on households' economic situation.

Introduction

In this survey, we are seeking to understand how your household reacts to unanticipated changes in income. By “household”, we mean everyone who usually lives with you in your primary residence including yourself (but excluding roommates and renters).

You will be presented with various hypothetical scenarios that involve shifts in your income, and we will ask you how such changes would impact your household's spending and saving. Below, we provide a short description of what we mean by “spending” and “saving”. Please read them carefully.

Spending: Spending includes all money spent on goods and services, including rent. Goods include durable goods (such as electronics, furniture, or car maintenance) and nondurable goods (such as groceries, vacations, or gasoline).

Saving: **Saving means that, instead of using money today, you reserve it for future use.** Examples of savings include cash reserves, money in bank accounts, retirement accounts, financial assets, or real estate. **Repaying debt is also an important form of saving.** By repaying debt today, you owe less money in the future, which means that more money is available for future use.

On the next pages, you will consider hypothetical situations where your household unexpectedly receives a

one-time payment today.

That is, your household's income will be higher for one month due to a one-time payment. The one-time payment comes unexpectedly.

Comment: We randomize whether income losses or gains are displayed first.

A one-time payment
Situation 1

Consider a hypothetical situation where your household unexpectedly receives a

one-time payment of $250 today.

How would this one-time extra income cause your household to change its spending and saving over the next three months?

Note: Your responses need to add up to $250.
Enter $0 if your household's spending/saving would not change.
Enter negative numbers for *de*creases in your household's spending/saving.

Increase in spending (By how much) would your household increase its monthly spending over the next three months?	$ 0
Increase in saving (By how much) would your household increase its monthly saving (which includes increases in debt repayment or decreases in debt-taking) over the next three months?	$ 0
Total	$ 0

Comment: Situation 2–7 are analogous. We randomize the order of shock sizes. Each respondents faces seven shocks: $50, $100, $250, $500, $1,000, $5,000, and $10,000.

On the next pages, you will consider hypothetical situations where your household unexpectedly incurs a

one-time income loss today.

That is, your household's income will be lower for one month due to a one-time income loss. The one-time income loss comes unexpectedly.

A one-time income loss
Situation 1

Consider a hypothetical situation where your household unexpectedly incurs a

one-time income loss of $100 today.

How would this one-time income loss cause your household to change its spending and saving over the next three months?

Note: Your responses need to add up to $100.
Enter $0 if your household's spending/saving would not change.
Enter negative numbers for *in*creases in your household's spending/saving.

Decrease in spending (By how much) would your household decrease its monthly spending over the next three months?	$ 0
Decrease in saving (By how much) would your household decrease its monthly saving (which includes decreases in debt repayment or increases in debt-taking) over the next three months?	$ 0
Total	$ 0

Comment: Situation 2–7 are analogous. We randomize the order of shock sizes. Each respondents faces seven shocks: $50, $100, $250, $500, $1,000, $5,000, and $10,000.

Deliberation study

The complete instructions are available online at https://osf.io/2s7cf. Below, we show the example screen for a $50 income gain.

A one-time payment
Situation 1

Consider a hypothetical situation where your household unexpectedly receives a

one-time payment of $50 today.

How would this one-time extra income cause your household to change its spending and saving over the next three months?

Note: Your responses need to add up to $50.
Enter $0 if your household's spending/saving would not change.
Enter negative numbers for *decreases* in your household's spending/saving.

Increase in spending (By how much) would your household increase its monthly spending over the next three months?	$ 0
Increase in saving (By how much) would your household increase its monthly saving (which includes increases in debt repayment or decreases in debt-taking) over the next three months?	$ 0
Total	$ 0

In response to the unexpected one-time payment of $50 ...
On a scale from 1 (not at all) to 6 (very carefully), how carefully would your household consider how to change its spending and saving?

Would not consider it at all. 1	2	3	4	5	**Would consider it very carefully.** 6

In response to the unexpected one-time payment of $50 ...
What is the percent chance that you would discuss with other household members (like your partner) how your household should change its spending and saving?

0%	1-20%	21-40%	41-60%	61-80%	81-99%	100%

In response to the unexpected one-time payment of $50 ...
What is the percent chance that you would assess and consider your household's overall financial situation prior to deciding how to change your household's spending and saving?

0%	1-20%	21-40%	41-60%	61-80%	81-99%	100%

C.3 Definition of Additional Variables

Age Age of the respondent.

Education Highest education level of the respondent.

Gender Gender of the respondent.

Household size Size of the respondent's household, capped at 10 to account for outliers.

Income, annual Household income in 2022 before taxes and transfers.

Income risk Households indicate whether their monthly household income varies by less than 5% (1), between 5% and 10% (2), between 10% and 25% (3), or by more than 25% (4). We derive a standardized index based on ordinal response (1–4).

Monthly spending Household spending (in contrast to saving and debt repayment) in a typical month, capped at the 95% quantile to account for outliers.

Region Census region.

Wealth: Liquid The total value of a household's financial savings and investments, such as cash holdings, checking and savings accounts, money market funds, government/municipal bonds or treasury bills, stocks and bonds in publicly held corporations, stock and bond mutual funds.

Wealth: Illiquid The sum of (i) the total value of the land and real estate a household owns, including primary residence, second homes and other real estate, and (ii) the total value of a household's currently non-withdrawable financial savings and investments, such as the value of your retirement accounts (401(k)s, IRAs, thrift accounts, and future pensions), the cash value of life insurance policies, certificates of deposit, and saving bonds.

Wealth: Debt Total household debt including credit card debt, mortgages, and other debt, such as student loans, auto loans, and personal loans.

C.4 Comparison of Cross-Sectional Results to Previous Work

In the cross-section of MPCs, our data replicate many patterns that are familiar to the literature. This appendix section compares our cross-sectional results in Section 3.2 to related work. It is important to keep in mind that we estimate households' marginal propensity to consume over a three-month horizon in response to unexpected one-time income shocks and that our survey-based consumption measure includes both nondurable and durable consumption. This means we do not measure *notational consumption* as defined by Laibson, Maxted and Moll (2022) but *consumption expenditures*, which is common in the literature.

High average MPCs. The average MPC in on our data is 0.47, but the comparison to other estimates becomes easier if we focus on the MPC to a larger income gain, *e.g.*, the \$1,000 shock, for which we estimate an MPC of 0.35 (Figure 1).

This estimate is within the range of typical estimates in the literature. Using a survey-based approach, Jappelli and Pistaferri (2014) estimate an MPC of 0.48 in Italy, Christelis et al. (2019) estimate an MPC of 0.39 in the Netherlands, Drescher, Fessler and Lindner (2020) find MPCs ranging from 33% to 57% in 17 European countries over the first twelve months, and Colarieti et al. (2024) estimate an MPC of 0.16 over the first quarter, which continues to increase over subsequent months. An exception is Fuster et al. (2021) who observe an MPC of 0.07 for \$500, mainly because 74% of respondents report an MPC of 0. Studying consumption responses to the 2008 US tax rebate, Borusyak, Jaravel and Spiess (2024) and Orchard, Ramey and Wieland (2024) estimate an MPC of 30%, correcting earlier higher estimates by Parker, Souleles, Johnson and McClelland (2013) and Broda and Parker (2014). Estimates for the consumption response to the 2020 Economic Stimulus Payment in the US range from 8–28% (Parker, Schild, Erhard and Johnson, 2022), to 25%-30% (R. Baker, Farrokhnia, Meyer, Pagel and Yannelis, 2023), or 40% (Coibion, Gorodnichenko and Weber, 2020). In a randomized experiment, Boehm, Fize and Jaravel (2024) observe a one-month MPC of 0.23 in response to an unanticipated 300 Euro transfer. Ganong, Jones, Noel, Farrell, Greig and Wheat (2023) study responses to typical income shocks and find an MPC of 0.21 for nondurable consumption on a monthly basis and 0.29 on a quarterly basis. Fagereng, Holm and Natvik (2021) estimate a within-year MPC of around 0.50 out of lottery winnings.

MPCs decline for larger shocks. MPCs decline with larger shock size. This has been observed, *e.g.*, by Kueng (2018), Fagereng et al. (2021), and Colarieti et al. (2024). An exception are Fuster et al. (2021) who find that MPCs increase with shock size, though they also find a negative relationship on the intensive margin.

MPCs are larger for losses. An asymmetry between equally-sized gains and losses has been observed, *e.g.*, by Bunn, Le Roux, Reinold and Surico (2018), Christelis et al. (2019), Fuster et al. (2021), and Colarieti et al. (2024).

Heterogeneity in MPCs. MPCs vary widely in the cross-section of households (see, *e.g.*, Jappelli and Pistaferri, 2014; Lewis et al., 2024; Misra and Surico, 2014; Boehm et al., 2024; Fuster et al., 2021).

Extreme MPCs of 0 or 1 are common. Identifying extreme MPCs requires identifying MPCs on the household level. Due to the inherent noise in households' consumption processes, most studies only estimate and report average MPCs or average MPCs in a subgroup of the population. Here, survey-based methods are at an advantage because they can directly elicit household-level MPCs from each respondent. These studies typically find many households who report an MPC of either 0 or 1, *e.g.*, Drescher et al. (2020) who use HFCS data from 17 European countries, Andreou, Demetriadou and Tryphonides (2024) who work with the NielsenIQ Consumer Panel 2008 tax rebate survey in the US, Coibion et al. (2020) who study consumer responses to the 2020 Economic Stimulus Payment in the US, or Jappelli and Pistaferri (2020) who use survey data from Italy. An exception is Fuster et al. (2021) who observe an extremely large share of MPCs of 0 (74% for a $500 gain) but few MPCs close to 1.[11]

Recent research has started to attempt inferring the distribution of MPCs in field settings. Misra and Surico (2014) estimate quantile consumption effects of the 2001 and 2008 US tax rebates and find that many households have an MPC close to 0, while a smaller group of households has MPCs close to 1. Karger and Rajan (2020) estimate consumption responses to the Covid stimulus payments. Their estimated individual-level distribution is noisy but exhibits spikes at 0 and 1 (Figure A11 and A12 in their paper). Lewis et al. (2024) estimate the latent distribution of MPCs in response to the 2008 US tax rebate, taking a parametric approach and assuming that there are three latent MPC types, which they estimate to have MPCs of 0.04, 0.23, and 1.33, respectively. However, their clustering approach is not designed to detect spikes in the distribution. Boehm et al. (2024) use a non-parametric approach to recover the distribution of MPC profiles from receiving an additional 300 Euro debit card in a randomized field. Although they do not detect exact mass points of zero and one, some smoothing of the density is inevitable due to measurement error and the kernel density deconvolution method that the authors employ to non-parametrically recover the CDF.

C.5 Additional Qualitative Evidence

Sample and Design. How do households explain their extreme MPCs for small shocks and their transition to interior MPCs for large shocks? We survey 502 additional US households and ask them for their consumption-savings responses to $100 and $1,000 income shocks. We recruit households with the survey company Prolific. The demographic characteristics of the sample are summarized in Table C.2.

57% of households adopt an extreme MPC for the $100 shocks, but only 23% do so for the $1,000 shocks. We ask respondents who switch from an extreme MPC to an interior MPC to explain why they do so. This *qualitative* approach complements our main quantitative

[11] If we had to speculate, we would attribute this difference to their two-stage response format. Respondents are first asked whether they would increase, not change, or decrease their spending, debt repayment, or savings. Only then can households specify their precise responses. This means response noise overproportionally favors MPCs of 0 and below 0 (8% of respondents select an MPC below 0 for a $500 gain), while it is hard to indicate an MPC of 1.

evidence and helps us shed light on why households prefer extreme MPCs for small shocks.

For example, households who report an MPC of 1 for a small income gain of $100 but an MPC below 1 for an income gain of $1,000 are asked:

> [Q1] You responded that your household would not increase its saving in response to a $100 one-time payment. You would spend everything.
>
> Please explain why your household would spend everything and would not increase its saving.
>
> [Open-ended text box]

> [Q2] However, you responded that your household would increase its saving in response to a $1,000 one-time payment.
>
> Please explain why your household would respond differently in these two situations.
>
> [Open-ended text box]

We ask analogous questions for households who report an MPC of 0 for the small income gain but an MPC above 0 for a large income gain, and we ask analogous questions for losses.

Results. We manually identify common themes in households' responses, develop a coding scheme, and assign each response to the themes it contains. Table C.3 provides an overview of the resulting coding scheme. We discuss the results and provide example responses below.

We focus on gains first. For gains, the coded text data reveal that almost all households — namely 86% — explicitly refer to the contrast in shock size ($100 versus $1,000) when explaining their extreme MPC for the small shock or their transition from extreme MPCs to an interior MPC.

Many households view small shocks as insignificant and conveniently addressed with an extreme MPC of 0 or 1. The following respondent expresses it directly:

> "One hundred bucks is not that much. It's great, don't get me wrong, but it's something you either spend on a dinner or put away. Where we're at right now, it's going right in the bank." *(MPC=0 for $100, MPC=0.2 for $1,000)*

By contrast, the large shock of $1,000 is often described as a significant change to their household finances, and households realize that this requires a more balanced approach.

> "Since the amount of $1000 is fairly significant, and we are increasing our savings by a good amount, I think taking $100 dollars out and saving the other $900 is fair and feels rewarding from both a long-term and short-term perspective." *(MPC=0 for $100, MPC=0.1 for $1,000)*

Why do households adopt extreme MPCs for small shocks? The reasons for this behavior can be multifaceted. For example, some households (16%) refer to **habits** or rules such as fixed spending budgets (leading to an MPC of 0) or saving targets (leading to an MPC of 1) that they do not want to overturn for small shocks.

> "I have a budget for a reason and generally stick to it unless there are major changes." *(MPC=0 for $100, MPC=0.2 for $1,000)*
>
> "$100 is not such a big amount that it will make me change my spending habits." *(MPC=0 for $100, MPC=0.1 for $1,000)*
>
> "My wife and I already contribute regularly to our savings." *(MPC=1 for $100, MPC=0.25 for $1,000)*

Many households recognize the unexpected income as a welcome opportunity to **treat themselves**. Some households are ready to immediately spend the $100 on a treat for themselves or their families, but they view it as "irresponsible" to not save a good part of the larger windfall.

> "$100 is not all that much when it comes down to it. It will cover one or maybe 2 utility bills. Why not just use the unexpected $100 to spend on something you can enjoy or something that can help you in the short-term?" *(MPC=1 for $100, MPC=0.75 for $1,000)*
>
> "The $1,000 is a larger amount so I would be overindulging if I did spend it all and increased my spending instead of saving. I could have done a percentage and saved the $100 but I felt like $100 was an appropriate gift for myself. When the dollar amounts get much larger, the impact is much bigger if I don't save anything." *(MPC=1 for $100, MPC=0.2 for $1,000)*

Other households instead choose to maintain their **household discipline**. They seek to avoid "frivolous consumption" for small shocks, but, in case of a larger payment, they "feel comfortable" to treat themselves and spend a part of the larger income shock.

> "$100 is not a lot of money and since it came unexpectedly, I would put it in savings. That way I could use it later. I think if I spent the money now, it would be spent frivolously." *(MPC=0 for $100, MPC=0.5 for $1,000)*
>
> "An extra $1000 feels like it is a lot more extra than an extra $100. While I would still want to save the majority of it, it feels more comfortable to be able to use some of the larger sum of money for extra spending right now versus saving it." *(MPC=0 for $100, MPC=0.2 for $1,000)*

In total, we code 41% of households as talking about the desire to treat themselves and 17% as referring to household discipline. As illustrated above, the two arguments often occur together.

Another prominent argument that 25% of households express is that the $100 would **not have any meaningful impact** if split between spending and saving. To avoid such a "drop in the bucket", they choose an extreme, one-sided response. For example, the following household cannot think of a meaningful way to spend a small amount of money and hence opts to save the entire amount (MPC = 0).

> "Our bills are mostly covered and we do not have significant debt. This amount of money is not really large enough to make an impact on our spending. It would be put into our savings as we typically save extra money." *(MPC=0 for $100, MPC=0.3 for $1,000)*

Interestingly, other households make the opposite case, arguing that it "would not make a dent" in their savings if they save part of the $100 (MPC = 1), hence preferring to spend everything.

> "It [$100] is not enough money to make a real dent in any debt payments. We would use this money like a "treat" to go out to dinner or the movies." *(MPC=1 for $100, MPC=0.4 for $1,000)*
>
> "The $100 is not really enough to move the needle in saving. It is a very small amount that spending it would actually provide more joy and benefit from it then it would to save." *(MPC=1 for $100, MPC=0.1 for $1,000)*

The results are similar for losses where households who absorb the small $100 loss with their savings do not view the loss as substantial enough to disrupt their regular spending habits. This strategy becomes infeasible or undesirable for the larger $1,000 loss. Households who absorb the $100 loss with their spending provide a mirror image. They do not want to disrupt their savings routines and find it easy to cut back on discretionary expenses like dining out, entertainment, or non-essential purchases. But for the $1,000 loss, households want or need to draw on their savings or even increase debt (through loans or credit) to manage this larger loss without cutting important expenditures.

It thus seems that multiple factors could make extreme MPCs convenient solutions for small income changes. First, households refer to habits and routines, *e.g.*, a fixed spending budget, a fixed monthly transfer to savings, or the goal to maximize savings, and deviating from such default rules could come at a cost. Second, for small shocks, extreme MPCs appear to be easier to imagine, evaluate, and appreciate. By contrast, interior MPCs lead to two small, seemingly imperceptible changes that are not perceived to “make a dent” in households’ savings or spending. Third, many households recognize an income gain as a welcome opportunity to treat themselves or their families. Most balance consumption and saving for the large shock, but they approach the smaller \$100 gain differently. Some conclude that they should “indulge” and spend everything, while others choose to maintain “discipline” and save everything. Of course, it seems plausible that further psychological forces are at work, which are harder for households to explicitly articulate. For example, finding a good compromise between consumption and saving could require more computational effort.

Our model of quick-fixing captures the convenience of extreme MPCs for small shocks and the transition pattern from extreme to interior MPCs, thus providing a plausible representation of households’ introspection.

Table C.3: Overview of the coding scheme

Theme (and detected freq.)	**Description**
Gains	
199 cases where respondents choose an extreme MPC for small shock but not for large shock.	
Shock size (86%)	Respondent mentions the difference in the shock sizes, e.g. contrasts the two shocks or says that \$100 is little or \$1000 a lot.
Habit (16%)	Respondent mentions that they generally try to save/spend in situations with small income gains.
Does not make a difference (25%)	Respondent mentions that spending/saving the money would not make a meaningful difference to their spending or savings.
Household discipline (17%)	• MPC of 0 for \$100: Only in case of a larger amount, respondent feels comfortable to spend part of the amount, but they avoid "frivolous" spending for the small amount. • MPC of 1 for \$100: Respondent is fine with spending the small amount, but they argue it would be "irresponsible" to fully spend the larger amount.
Treat oneself (41%)	• MPC of 0 for \$100: Only in case of a larger amount, respondent wants to use a part to treat themselves. • MPC of 1 for \$100: Respondent wants to use the \$100 to treat themselves.
Need (15%)	• MPC of 0 for \$100: Respondent argues that they do not need additional purchases. • MPC of 1 for \$100: Respondent immediately needs the money for essential purchases.
Lumpy consumption plans (6%)	Respondent has a specific spending plan or need, but \$100 is not yet enough to realize it.
Losses	
184 cases where respondents choose an extreme MPC for small shock but not for large shock.	
Shock size (84%)	Respondent mentions the difference in the shock sizes, e.g. contrasts the two shocks or says that \$100 is little or \$1000 a lot.
Habit (13%)	Respondent mentions that they generally try to cut saving/spending in situations with small income losses.
Buffer (49%)	• MPC of 0 for 100: Respondent can easily draw on a buffer of savings. • MPC of 1 for 100: Respondent can easily cut discretionary, non-essential consumption.
Balance required (34%)	Interior MPC for large loss because respondents do not want to or simply cannot afford to reduce their spending/savings by the full \$1000.
Budget already tight (8%)	Respondent reports having such a tight spending budget they they prefer to not reduce spending any further in response to a \$100 loss.

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