Credit Card Borrowing in Heterogeneous-Agent Models: Reconciling Theory and Data*

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Abstract

Constrained, "hand-to-mouth," households with zero liquid wealth are a central building block of modern heterogeneous-agent consumption models. We document empirically that many of these seemingly borrowing-constrained households actually revolve intermediate levels of high-interest credit card debt, meaning that they are not constrained at either the zero-liquid-wealth kink nor at their credit card borrowing limit. This finding presents a challenge: how can heterogeneous-agent models generate empirically realistic marginal propensities to consume without relying on borrowing-constrained households? We show that present bias induces households to revolve modest levels of credit card debt, but their *indebted saving behavior* still generates elevated MPCs. We then apply this insight to highlight key channels through which credit card borrowing reshapes households' responses to fiscal and monetary policy.

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1 Introduction

Modern heterogenous-agent macroeconomics builds models from the ground up. This approach is based on the idea that matching household-level consumption and financial behavior is important for understanding the subsequent transmission of macroeconomic policy.

This literature often starts from the following two stylized facts. First, many households – especially those with little liquid wealth – have marginal propensities to consume (MPCs) that are larger than predicted by classical consumption models. Second, many households hold minimal liquid wealth, despite oftentimes holding sizable stocks of illiquid wealth simultaneously. From these two stylized facts, constrained "hand-to-mouth" households have become an essential ingredient in the rapidly growing heterogeneous-agent literature. Such households are typically modeled as holding little-to-no liquid assets — but also avoid borrowing at penalized interest rates. And because these households are constrained at a kink in their budget set, they display large MPCs. High-MPC households have since been shown to be central vectors for the transmission of fiscal policy, monetary policy, and more.[1] We will refer to this general modeling paradigm as "ZHtM" henceforth, as a shorthand for the centrality of "hand-to-mouth households with zero liquid wealth."[2]

In this paper, we document that the recently dominant ZHtM paradigm is inconsistent with the data on credit card borrowing. While the macroeconomic literature has often justified the ZHtM paradigm with the second stylized fact above, the timing mismatch between income and spending means that households' true liquid wealth positions are difficult to measure. Moreover, a sharper test of the extent to which households are truly borrowing-constrained requires an analysis of their gross borrowing positions, not just their net liquid wealth positions. We adopt such a portfolio-choice-based approach in this paper by investigating households' propensity to revolve high-interest credit card debt. We document that this propensity is at odds with the conventional ZHtM paradigm, discuss how to realign heterogeneous-agent models with the borrowing data, and evaluate the implications of credit

[1] See Kaplan and Violante (2022) for an illuminating review of this expansive literature.

[2] We refer to constrained households with zero liquid wealth as ZHtM for clarity. While ZHtM households are the hand-to-mouth households most often emphasized in consumption-saving models, they are a subset of the broader class of hand-to-mouth households (which could also include, e.g., households constrained at their borrowing limit after maxing out their credit cards).

card borrowing for household-level responses to macroeconomic policy.

As a first step, we examine the extensive margin of credit card borrowing in the data. Borrowing decisions reveal households' marginal intertemporal price of consumption and hence shed light on the intertemporal consumption choices at the core of macroeconomics and finance (Zinman, 2015). Using the Survey of Consumer Finances (SCF), we document that 52% of households with a credit card revolve high-interest credit card debt. That is, the majority of households with a credit card carry an interest-bearing balance from one billing cycle to the next. In addition, households with measured net liquid wealth of roughly zero – who the literature has previously classified as ZHtM – exhibit similarly large borrowing propensities. From the perspective of portfolio choice, such active "participation" in credit card borrowing reveals the extent to which households willingly incur the high marginal price of consumption that borrowing entails (the median credit card rate is 16% in our sample). This empirical borrowing behavior is at odds with the ZHtM modeling paradigm, however, which is instead built on the premise that many households have high MPCs because they are constrained due to their *avoidance* of high-cost debt.[3]

Despite the large extensive margin of credit card borrowing, we find on the intensive margin that borrowers are generally far from hitting their credit limit and instead revolve only intermediate amounts. That is, rather than the data exhibiting a large mass of constrained ZHtM households, the data instead points to the existence of a large mass of households with modest levels of credit card debt that are not constrained at either the zero-liquid-wealth kink nor at their credit limit. Our empirical analysis thus provides a third stylized fact about household finances for heterogeneous-agent models to target: households exhibit high extensive margin, but modest intensive margin, usage of credit card debt. In short, this third stylized fact suggests that a more accurate model is one of "aspirationally hand-to-mouth" households rather than ZHtM households — households would like to be ZHtM, but they have some credit card debt that needs to be paid off first.

We highlight two additional stylized facts that are useful for models aiming to match the

[3]Many heterogeneous-agent models generate ZHtM households by imposing a hard no-borrowing constraint that (counterfactually) prohibits borrowing completely. Of models that allow for unsecured borrowing, a seminal example is Kaplan et al. (2018), which predicts that 29% of households are constrained at exactly the zero-liquid-wealth kink, and 47% of households have between $0 and $2,000 of liquid wealth (inclusive), while only 15% of households borrow (at a borrowing wedge of 6%).

micro data on credit card borrowing. Our fourth stylized fact is that credit card debt is persistent. Our fifth stylized fact is that credit card borrowers simultaneously hold sizable levels of illiquid wealth. For example, the unconditional average net-worth level in our SCF sample is $300,000 (in 2019 dollars), and households with credit card debt still hold over $200,000 of wealth on average (almost all illiquid). This fifth fact is key for quantitative model-building, as it suggests that the prevalence of credit card borrowing cannot be attributed simply to households having high (exponential) discount rates (Laibson et al., 2024).

The empirical evidence above presents a theoretical challenge. MPCs are a core concept in modern macroeconomics (Kaplan and Violante, 2022). But economists' canonical modeling tool for generating realistic MPCs – borrowing-constrained, hand-to-mouth, households – is inconsistent with the credit card borrowing data. A modified theory is needed.

We turn to a theoretical analysis to illustrate that present bias can improve consumption-saving models' joint fit of credit card borrowing and MPCs. In contrast to standard exponential time preferences, present-biased preferences are time inconsistent: present-biased households are patient in the long run, but impatient in the short run (Strotz, 1956; Laibson, 1997). Present bias has received empirical support in the lab (e.g., Frederick et al., 2002; Cohen et al., 2020) and in a multitude of field settings, including applications to high-cost borrowing (e.g., Meier and Sprenger, 2010; Kuchler and Pagel, 2021; Allcott et al., 2022). From a technical standpoint, present bias is also a portable modeling technology. We build on recent continuous-time advances to show that present bias can be tractably incorporated into modern consumption-saving models (Harris and Laibson, 2013; Maxted, 2024b).

To make progress on the challenge outlined above, our model with present bias must: (i) generate a large share of households that revolve intermediate levels of high-cost debt, while (ii) leaving MPCs elevated despite households no longer being borrowing-constrained. We provide two propositions to illustrate that present bias can hit these two targets. Our first proposition shows that, in contrast to exponential discounting, present bias provides a natural motivation for households to persistently revolve modest levels of high-cost debt, consistent with what we find in the data. Our second proposition characterizes the MPCs of such households. Building on a result by Achdou et al. (2022), we show that households with modest amounts of credit card debt have a consumption function that is locally convex, and

hence display elevated MPCs despite not being constrained at the zero-liquid-wealth kink. Intuitively, households sharply cut back on consumption when they begin revolving high-cost debt – a pattern we refer to as *indebted saving behavior* – so wealth shocks that alleviate that debt can then generate large consumption responses. Combining our two propositions, the role of present bias is to get households to persistently revolve intermediate levels of high-cost debt, and households in this indebted state display large MPCs. In addition, because present-biased households are impatient in the short run but patient in the long run, we find that present bias can generate realistic levels of credit card borrowing alongside realistic levels of illiquid wealth holdings, again consistent with the data.

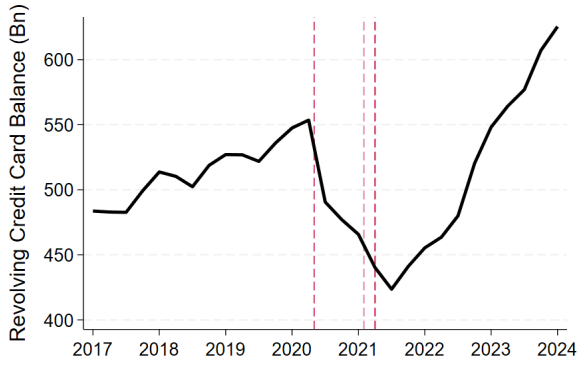
We also use our model to evaluate how credit card borrowing alters households' responses to macroeconomic policy, a key focus of the heterogeneous-agent literature. For fiscal policy, the local convexity of the consumption function implies that households with revolving credit card debt display MPCs that remain elevated even for larger wealth shocks. This prediction is consistent with the empirical evidence that spending responses remain elevated out of large liquidity injections (e.g., Fagereng et al., 2021; Sokolova, 2023). In contrast, the typical ZHtM framework generates MPCs that quickly decline as the size of a liquidity injection increases. This difference in predictions is critical for the conduct of fiscal policy: the indebted saving behavior induced by present bias increases the potential scope of fiscal policy, as it implies that even large stimulus checks can yield sizable spending responses.

Our model with present bias also yields novel predictions about households' dynamic response to fiscal stimulus. Our model predicts that households with credit card debt will pay down their debt upon receiving a stimulus check, but will then rebuild that debt soon after. This prediction implies that policymakers should expect any debt-relief benefits of liquidity injections to only be transient. It also helps to make sense of the data on revolving credit card debt around the COVID-19 recession, as shown by the black line in the lefthand panel of Figure 1 below. Consistent with the survey evidence collected at the time, many households paid down their credit card debt when stimulus checks were received (as marked by the vertical dashed lines). But that is not the end of the story. What is perhaps less recognized is that this paydown was fleeting, and revolving debt rebounded sharply thereafter. While this rapid rebound is at odds with the prediction of conventional models that households

eschew high-cost credit card debt, such a rebound follows naturally from present bias.

For monetary policy, present bias makes households modestly indebted rather than exactly constrained at the zero-liquid-wealth kink. Since credit cards are short-term variable-rate products that move with monetary policy,[4] this difference reshapes the channels through which monetary policy operates. Whereas constrained ZHtM households do not respond directly to monetary policy (e.g., Kaplan et al., 2018), unconstrained households with credit card debt will adjust their consumption following a change to credit card rates. This is particularly relevant at the time of writing, as the righthand panel of Figure 1 shows how rapidly credit card rates have risen alongside the federal funds rate over the past few years.

(a) Revolving Credit Card Balances



(b) Credit Card and Federal Funds Rates

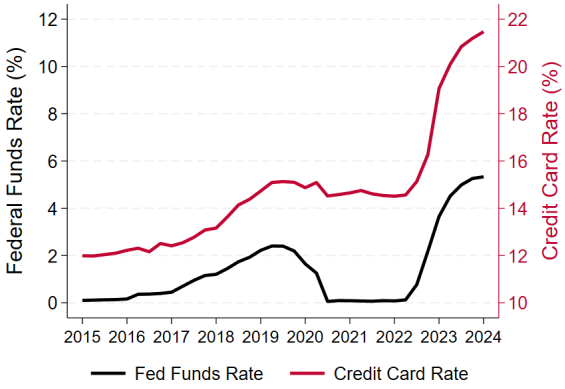


Figure 1: **Revolving Credit Card Balances and Interest Rates.** The lefthand panel plots aggregate revolving credit card balances (black curve; data from the Y-14M report for large banks only), using vertical dashed lines to mark the timing of the three rounds of stimulus payments. The righthand panel plots the credit card interest rate (red curve; data from the G.19 release) alongside the federal funds rate (black curve).

Section 2 reviews the heterogeneous-agent literature to provide a basis for our empirical tests. Section 3 presents our empirical analysis on the pervasiveness of high-cost borrowing. Our theoretical analysis begins in Section 4, where we use a stripped-down model to illustrate how present bias can induce high-cost borrowing while leaving MPCs elevated. Section 4 also studies the relevance of such borrowing for fiscal and monetary policy. Section 5 extends these insights to a richer model with stochastic income and illiquid assets. Section 6 concludes.

[4]While fixed-rate credit cards used to be more common, most credit cards in the modern sample period we focus on are variable-APR products with an interest rate based on the prime rate (Grodzicki, 2023).

2 ZHtM: A Brief Review of the Literature

To ground our empirical analysis, we start by briefly reviewing the canonical ZHtM paradigm.[5] This paradigm is often motivated with the following two stylized facts:

Stylized Fact 1. *The spending response to liquidity shocks is much higher than predicted by classical consumption models, particularly for low-liquidity households.*[6]

Stylized Fact 2. *A large proportion of households are measured to have roughly zero net liquid wealth (though such households often still have significant levels of illiquid wealth).*[7]

To fit these two stylized facts, the conventional modeling approach relies on borrowing constraints that bind at zero liquid wealth. Specifically, such constraints are used to generate a buildup of hand-to-mouth households with zero liquid wealth – i.e., ZHtM households – who will also exhibit elevated MPCs out of subsequent liquidity injections because these households want to consume more, but are prevented from doing so ex ante by the constraint.

In more detail, consider the discrete-time Euler equation of a standard time-consistent agent (without present bias) that is constrained at the zero-liquid-wealth kink.[8] This ZHtM agent will choose consumption c_t such that:

$$u'(c_t) > \delta(1+r)\mathbb{E}_t\left[u'(c_{t+1})\right] \quad \text{and} \quad u'(c_t) < \delta(1+r^{cc})\mathbb{E}_t\left[u'(c_{t+1})\right], \tag{1}$$

where δ is the exponential discount factor, r is the interest rate on liquid savings, and $r^{cc} > r$ is the costly borrowing interest rate (e.g., the credit card interest rate). The first inequality in (1) implies that the agent would like to consume more at time t if they could borrow at risk-free rate r, but the second inequality implies that they will not actually borrow at the true borrowing rate r^{cc}. The situation in (1) is sometimes referred to as being "off the Euler equation" — the agent chooses not to save because the return r is too low, but they also

[5] Foundational work includes Zeldes (1989), Deaton (1991), Carroll (1997), and Kaplan and Violante (2014). Some recent papers that provide a rich exploration of the theoretical mechanisms at play include Carroll et al. (2021), Achdou et al. (2022), Auclert et al. (2024), and Aguiar et al. (2024).

[6] E.g., Parker et al. (2013), Agarwal and Qian (2014), Cloyne and Surico (2017), Havranek and Sokolova (2020), Ganong et al. (2020), Fagereng et al. (2021), Boehm et al. (2024), and Borusyak et al. (2024).

[7] For empirical evidence, see for example Campbell (2006) and Kaplan et al. (2014).

[8] We use discrete time here for simplicity, though our later theoretical analysis will use continuous time.

choose not to borrow because the cost r^{cc} is too high. Importantly, this constrained ZHtM agent will then have an MPC of 1, because if they are given ϵ more liquidity at time t then the first inequality in (1) implies that they will optimally consume that liquidity now.

A "Portfolio Choice" Based Reexamination. To justify this ZHtM paradigm, much of the literature has pointed to Stylized Fact 2 that many households have measured net liquid wealth of roughly zero. But, both committed consumption and the timing mismatch between income and expenses imply that liquid-wealth snapshots provide a fuzzy (and in particular, upward-biased) picture of households' true liquidity (discussed e.g. in Kaplan et al., 2014).[9] So, in this paper we instead start from the observation that the ZHtM framework is premised not only on the fact that households hold zero net liquid wealth, but *also* that they bunch at the zero-liquid-wealth kink precisely to avoid revolving high-cost debt. This second clause is, in practice, a portfolio-choice prediction that is testable in the data. Specifically, if we observe that an agent is actively revolving a credit card balance, then that means they are not constrained at the zero-liquid-wealth kink as in (1). Rather, their usage of a high-cost borrowing margin implies that they are "on the Euler equation" for that asset (unless at their credit limit) and willingly incur a marginal price of consumption of r^{cc}.[10]

Summary and Empirical Test. To summarize, the key premise of models with ZHtM households is that these households bunch at the zero-liquid-wealth kink, and subsequently have high MPCs, because they are choosing not to utilize high-interest borrowing. So, if we instead observe a household revolving credit card debt, then that reveals a fortiori that the household is not at the zero-liquid-wealth kink and hence is not a ZHtM household.

Credit card borrowing data thus provides a simple but sharp test of the conventional ZHtM paradigm. In particular, we ask: (i) overall, what is the propensity for households to revolve high-cost credit card debt, and more specifically (ii) are households with measured net liquid wealth of roughly zero actually eschewing high-cost credit card debt?

[9] For example, a household with measured liquidity of $2,000 may effectively have -$1,000 of liquidity if they are surveyed right after their monthly paycheck has arrived, and their monthly spending is $3,000.

[10] More plainly, the fact that a household is revolving credit card debt (which compounds daily) means that it is funding marginal consumption at the cost of r^{cc}, since the household could have instead opted to cut back on consumption by $1 and used that dollar to repay some of its high-interest credit card debt.

Two Remarks. We focus on the "soft borrowing constraint" in this paper, which is the kink that arises at zero liquid wealth whenever households face a wedge between the interest rate on borrowing versus saving (as in (1)). Although it is also common for models to take that wedge to infinity to impose a "hard borrowing constraint" that prohibits any borrowing, this is not meant to be realistic for the majority of U.S. households that have quick access to bank credit (e.g., using a credit card). For these households, a hard no-borrowing constraint is typically interpreted as a simplification that approximates a soft constraint that is rarely breached. However, we will show in the data that borrowing is common.

Second, before continuing it is interesting to juxtapose the conventional ZHtM paradigm of the heterogeneous-agent macroeconomic literature – which relies on households avoiding credit card debt – with the empirical literature in household finance that documents the pervasiveness of high-cost borrowing.[11] While these literatures have largely developed separately from one another, a contribution of our paper is to bring them more closely together.

3 The Prevalence of Revolving Credit Card Debt

3.1 Data Overview

SCF Variable Definitions. Our main goal in this section is to use the Survey of Consumer Finances (SCF) to test for the prevalence of credit card borrowing. Our SCF analysis pools the 2013, 2016, and 2019 waves.[12] We adjust all nominal figures to 2019 dollars.

Our measure of pre-tax household income comes directly from the SCF summary extract file. For after-tax income, we calculate federal tax liabilities using the NBER TAXSIM program and then subtract an additional 5% for state taxes. Liquid wealth is defined as a household's liquid transactions account balances, plus government and corporate bonds, minus revolving credit card debt (as in Kaplan et al., 2018). Illiquid wealth is defined as the remaining SCF wealth categories that are not included in liquid wealth.[13]

Our definition of credit card debt again simply follows the SCF summary extract file.

[11] See e.g. Ausubel (1991), Agarwal et al. (2015), Zinman (2015), Keys and Wang (2019), Kuchler and Pagel (2021), Fulford and Schuh (2023), and relatedly the overconsumption results in Indarte et al. (2024).

[12] Appendix A.2 shows that our choice of waves does not drive our findings.

[13] Examples include CDs, retirement savings, and accumulated equity in real estate and vehicles.

The SCF first asks if a household holds a credit card, a store card, or a charge card. For each card type, the household is asked about the total balance still owed after the last payment was made (excluding new charges made since the statement close date). Total credit card debt is defined as the sum of the amount owed on each card type. This measure is designed to capture revolving credit card debt (i.e., the debt that accrues interest). The SCF also asks a question about the interest rate paid on the credit card with the largest balance. To ensure that our analysis excludes promotional low-APR products like balance-transfer cards, we focus on *high-interest credit card debt*, which we define as credit card debt on which the household reports paying an interest rate of greater than 5%. Finally, note that credit card debt is significantly underreported in the SCF (Zinman, 2009). This will downwardly bias our estimates of the share of households that revolve credit card debt.[14]

SCF Sample Criteria. We follow Kaplan and Violante (2014) and drop the top 5% of households by net worth.[15] We also drop retired households, as retirees face additional economic considerations that will not be well captured by our stationary consumption model with a calibrated labor-income process.[16] These restrictions will matter in Section 5 when we calibrate our model to match SCF wealth, though they have little effect on the credit card borrowing estimates below. We refer to the remaining sample as our *Overall SCF Sample*.

Where our approach differs more consequentially from many earlier empirical analyses is that we impose two additional restrictions on our overall SCF sample: we drop unbanked and underbanked households. We define unbanked households as those that do not have a checking, savings, or money market account, and underbanked households as those that report not having a credit card (nor a store or charge card).

Unbanked and underbanked households have much lower income and wealth than fully banked households (details in Appendix A.1). While there are obvious benefits to having both a bank account and a credit card,[17] supply-side restrictions often inhibit lower-

[14]We follow Beshears et al. (2018) and rescale households' credit card debt to partially account for underreporting. This adjustment only corrects the intensive margin, however. See Appendix A.2 for details.

[15]The calibrated heterogeneous-agent model that we build in Section 5 will not feature the sorts of richer income and return processes that are needed to describe such high net worth households.

[16]More precisely, we drop households where the head is 68 or older, neither the head nor spouse is in the labor force, or the head is 22 or younger.

[17]Note of course that using a credit card need not imply that the household revolves a balance. Benefits of

income/wealth households from accessing these financial products.[18] Since the typical ZHtM framework assumes that households have easy access to both a liquid checking/savings account and a higher-cost unsecured borrowing product like a credit card, our filtering of unbanked and underbanked households ensures that the remaining SCF sample does indeed have access to these two products. In doing so, we avoid the risk of spuriously drawing empirical conclusions based on households whose access to credit and/or savings products is inconsistent with the ZHtM framework we are evaluating.

One other reason to drop these households is that the SCF lacks coverage of many of the borrowing margins used by households without credit cards (e.g., pawn shop loans; Zinman, 2015). This mechanically generates an underestimation of such households' borrowing.

We are left with a final sample that captures 74% of the households in our overall SCF sample. We refer to this as our *Preferred SCF Sample*. Appendix A.1 further examines unbanked and underbanked households, and highlights the selection issues that would have arisen had we not removed these households from the analysis sample.

To be clear, we are by no means claiming that unbanked and underbanked households are unimportant for macroeconomic dynamics. In fact, we later model unbanked and underbanked households explicitly as separate household-blocks in Section 5.2. But, as our findings therein suggest, to the extent that such households may be important for the economic question at hand, they should be studied via differentiated models that account for their limited access to traditional consumer financial products.[19]

credit card usage include convenience, fraud protection, and discounts such as cash-back. Credit cards also help build credit history. Households typically need a recent tradeline to have a credit score, so households without credit cards may struggle to get bank credit in the future if the need arises (FDIC, 2017).

[18]For bank accounts, households with difficulties meeting minimum balance/deposit requirements often face access-reducing banking fees (e.g., FDIC, 2017). For credit cards, credit card lenders often restrict access to low-income borrowers (e.g., Bornstein and Indarte, 2023).

[19]Earlier drafts of this paper included a supplemental analysis using individual-level administrative credit bureau data. Although that analysis is now removed in order to focus on the household-level SCF data, that previous analysis suggested that credit card borrowing tended to be even more pervasive and persistent in the credit bureau data than in the SCF (potentially driven by the SCF underreporting already mentioned; Zinman, 2009).

3.2 Empirical Results: Credit Card Borrowing Decisions

Summary of Household Balance Sheets. Table 1 presents summary statistics for our preferred SCF sample. Households have mean after-tax income of $78,419. Households are measured to hold an average of $19,021 of liquid wealth alongside $287,285 of illiquid wealth for a total of $306,307, though there is also clear heterogeneity in all wealth categories. Our preferred SCF sample is skewed towards higher-income and higher-wealth households than the overall SCF sample, since we drop unbanked and underbanked households.

Despite this relative affluence, 52% of households in our preferred SCF sample report holding a high-interest credit card balance that they did not repay in full at the end of the last billing cycle. In short, credit card borrowing is common in the SCF, and occurs at much higher levels than predicted by many heterogeneous-agent models (see footnote 3).[20]

	Mean	SD	10th	25th	50th	75th	90th
Before-tax income	101,817	89,113	31,254	49,044	80,434	127,172	195,063
After-tax income	78,419	60,382	27,521	41,679	64,043	97,742	143,917
Liquid wealth	19,021	63,005	-12,449	-1,950	3,500	20,000	60,060
Illiquid wealth	287,285	481,175	-1,600	24,047	127,730	366,300	845,000
Total wealth	306,307	505,633	-5,300	25,145	136,115	388,299	901,404
Has high-interest CC debt	.525	-	0	0	1	1	1

Table 1: **Preferred SCF Sample Summary Statistics.** This table provides summary statistics for our preferred SCF sample (mean, standard deviation, and 10th, 25th, 50th, 75th, and 90th percentile levels). See text for definitions of the variables summarized here.

Credit Card Borrowing and Near-Zero Measured Liquid Wealth. The ZHtM paradigm is premised on the existence of a large set of households that are constrained at the zero-liquid-wealth kink by their avoidance of credit card debt. We now ask whether the households with near-zero measured liquid wealth that have previously been identified as ZHtM are, in fact, not borrowing on credit cards. To do so, Table 2 considers households whose measured net liquid wealth to income ratio is within one month's pay of zero (0 to $\frac{1}{12}$), two weeks' pay of zero (0 to $\frac{1}{26}$), and one week's pay of zero (0 to $\frac{1}{52}$). The first (last) row of Table 2 lists the share of households in our preferred (overall) SCF sample that fall into each liquidity bucket. These low-measured-liquidity households are commonly viewed as representing ZHtM households. But as discussed above, a sharper test of the ZHtM paradigm

[20] Our 52% estimate is in line with other survey and administrative data sources – see Appendix A.2.

looks not only at (fuzzily measured) net liquid wealth, but also at credit card debt.[21] So, we estimate the proportion of households within each liquidity bucket that revolve a high-interest balance, as reported in the second row with standard errors in parentheses below.

	Within One Month	Within Two Weeks	Within One Week
Share of Preferred SCF Sample	0.218	0.122	0.073
Proportion (within) with high-interest CC debt	0.495	0.523	0.532
	(0.011)	(0.016)	(0.023)
Share of Overall SCF Sample	0.354	0.245	0.171

Table 2: **Credit Card Borrowing by Low-Measured-Liquidity Households.** This table considers households with measured net liquid wealth that is within one month's, two weeks', or one week's pay of zero. The first (last) row gives the share of households in our preferred (overall) SCF sample in each liquidity bucket. The second row reports the proportion of households within each liquidity bucket that revolve high-interest credit card debt. Standard errors for this estimate are reported in parentheses.

The main takeaway from Table 2 is that measured net liquid wealth alone does not provide sufficient justification for the prevailing ZHtM paradigm. Using a portfolio-choice-based analysis of households' borrowing decisions, we find that roughly 50% of households with near-zero measured liquid wealth also report that they are borrowing on a high-interest credit card. That is, despite these households holding measured net liquid wealth levels that would have previously classified them as ZHtM, they are not constrained at the zero-liquid-wealth kink because they are actively revolving high-interest credit card debt.

Comparing the first and last rows of Table 2, a second takeaway is that there are fewer low-liquidity households in the preferred SCF sample than in the overall SCF sample. This gap underscores the risks of ZHtM identification being confounded by unbanked/underbanked households, who are not well captured by the SCF nor well described by models with bank account and credit card margins (see Appendix A.1 for more).

[21] For seminal examples of ZHtM identification, see e.g. Kaplan and Violante (2014) and Kaplan et al. (2018). Highlighting the difference in identification approaches, Kaplan and Violante (2014) write that:

> "To measure HtM households at the zero kink for liquid wealth, we start from the observation that, since these households do not borrow and do not save through liquid assets, they do not carry any liquid wealth across pay-periods. [Given the timing mismatch of income and spending], a strict criterion to identify these HtM agents in the data is to count those households in the SCF whose average balance of liquid wealth is equal to or less than half their earnings per pay-period."

Here, we instead start from the observation that "since these households do not borrow," another test of the ZHtM paradigm is to look directly at whether households are borrowing on credit cards or not.

Intensive Margin of Credit Card Borrowing. Having thus far focused on the extensive margin of credit card borrowing, we now analyze the intensive margin. Conditioning on households that revolve credit card debt, the left- and righthand panels of Figure 2 plot, respectively, the distribution of credit card debt relative to credit limits and relative to income.[22] The key takeaway from Figure 2 is that even though households are active users of credit card debt on the extensive margin, they typically remain away from their credit limits and accumulate only modest debt levels.

(a) Credit Card Debt to Credit Limit



(b) Credit Card Debt to Income

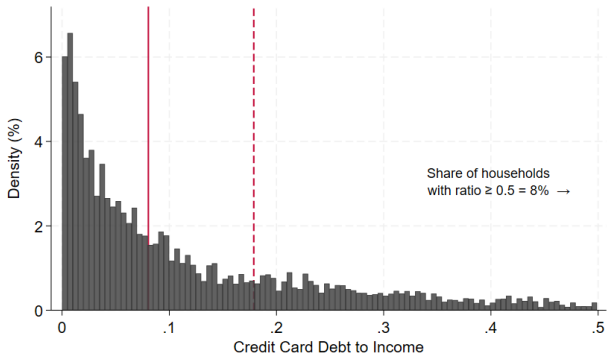


Figure 2: **Intensive Margin of Credit Card Borrowing.** For households revolving credit card debt, the lefthand (righthand) panel shows how much debt they revolve scaled relative to their credit limit (income). The median (mean) ratio of credit card debt to the credit limit is 0.33 (0.39). The median (mean) ratio of credit card debt to income is 0.08 (0.18).

We summarize our analysis thus far with a third stylized fact about household balance sheets that heterogeneous-agent models should aim to fit:

Stylized Fact 3. *Households exhibit high extensive margin, but modest intensive margin, usage of credit card debt.*

We will return to this key stylized fact in Section 4, where we argue that present bias is a natural candidate for generating precisely this sort of borrowing behavior.

Persistence of Credit Card Debt. The SCF is not a panel, which makes persistence difficult to measure. However, the SCF does survey households about their repayment tendencies. Among households with a high-interest balance, 41% answered that they "hardly

[22] In the lefthand panel, we exclude store- and charge-card balances from the numerator because the SCF question on credit limits relates to credit cards specifically.

ever" repay in full, 32% answered that they "sometimes" repay in full, and only 26% answered that they "almost always" repay in full. This suggests that revolving tends to be persistent, though with some heterogeneity across households.[23] We summarize with a fourth stylized fact, which we will again return to in our theoretical analysis in Section 4:

Stylized Fact 4. *Revolving credit card debt tends to be persistent.*

Credit Card Debt and Total Wealth. Finally, Table 3 summarizes the income and wealth of households that do, and do not, revolve credit card debt. One takeaway from Table 3 is that borrowers and non-borrowers are, perhaps, more similar than one might expect. Borrowers are not especially low-income on average (as many low-income households cannot access credit cards in the first place). And, despite carrying persistent credit card debt, many borrowers still hold sizable stocks of (essentially all illiquid) wealth at the same time.[24]

	Mean	SD	10th	25th	50th	75th	90th
Panel A: Has High-Interest CC Debt							
After-tax income	71,425	50,456	27,084	40,019	60,051	89,244	127,585
Total wealth	210,093	344,870	-16,704	12,502	88,600	263,306	597,318
Panel B: No High-Interest CC Debt							
After-tax income	86,159	68,915	28,214	43,182	69,623	108,196	158,428
Total wealth	412,773	620,794	4,470	54,045	212,028	578,600	1,189,636

Table 3: **Income and Wealth of Credit Card Borrowers.** This table summarizes the income and total wealth of households with and without high-interest credit card debt.

Building on Laibson et al. (2024), the results in Table 3 are important for quantitative model-building. In particular, while one potential way to generate the *aggregate* wealth and credit card borrowing shown in Table 1 is with two types of agents – one patient (who does the saving) and one impatient (who does the borrowing) – such a model will struggle to replicate the total wealth of households *with* credit card debt. Table 3 thus provides a fifth stylized fact about household finances for heterogeneous-agent models to target:

Stylized Fact 5. *Households with high-interest credit card debt also hold sizable levels of illiquid wealth on average.*

[23] See also Keys and Wang (2019), Grodzicki and Koulayev (2021), Fulford and Schuh (2023), and Dempsey and Ionescu (2024) for analyses of persistence.

[24] Appendix Table 9 provides a breakdown of total wealth into its liquid and illiquid components.

Stylized Fact 5 illustrates that many households simultaneously appear to act both impatiently (borrowing on credit cards) and patiently (saving for the long run in illiquid assets like homes and retirement accounts). We will show in our two-asset model in Section 5 that present bias – which makes households impatient in the short run but patient in the long run – can help to reproduce this stylized fact (see also Laibson et al., 2024).

3.3 A New Empirical Tension for Heterogeneous-Agent Models

As discussed in Section 2, the conventional logic underlying high MPCs in many heterogeneous-agent models is that ZHtM households are constrained at the zero-liquid-wealth kink – and hence have high MPCs – because they are avoiding high-cost debt. We tested this key premise above and found that it fails empirically.[25]

This empirical failure presents a theoretical challenge. While models with high MPCs are needed to match Stylized Fact 1, the prevailing ZHtM paradigm for doing so is not supported by the available data. Instead, our empirical analysis suggests that heterogeneous-agent models must (i) generate a large share of households that revolve intermediate levels of high-interest debt, while still (ii) leaving MPCs elevated despite the fact that households are generally not constrained at a kink in their budget set. In our theoretical analysis to follow, we will show that present bias provides a parsimonious path forward.

Why Present Bias? There are three empirical properties that jointly lead us to present bias. First, we document a high extensive margin usage of credit card debt. Second, despite this high extensive margin, the intensive margin usage of debt is more modest. These two points are summarized in Stylized Fact 3 above. Third, we find that households also tend to hold sizable stocks of illiquid wealth (Table 1 and Stylized Fact 5).

To fit the first empirical property that more than 50% of households revolve high-interest debt, a standard Euler equation like (1) would imply that these households' intertemporal consumption behavior satisfies: $u'(c_t) = \delta(1 + r^{cc})\mathbb{E}_t\left[u'(c_{t+1})\right]$, where the median credit card interest rate r^{cc} reported in the SCF is 16%. In a conventional model, this is a difficult con-

[25] Our findings are also inconsistent with models that rely on hard no-borrowing constraints, as household borrowing behavior will be poorly captured by models that assume away the possibility of borrowing.

dition to satisfy for the majority of households. While one ostensible way to get households to borrow at a 16% interest rate is simply to calibrate a low discount factor δ, this conflicts with the other two facts that borrowers often revolve only small amounts, and that even borrowers have considerable illiquid wealth.[26,27,28] Instead, the strategy that we pursue in this paper is to generalize the Euler equation with present bias (Harris and Laibson, 2001).

The world is complex, and there are undoubtedly a variety of modeling enrichments besides present bias that, when included together, can help to explain the constellation of facts presented above. Nonetheless, there is a key theoretical benefit to present bias: it is tractable. Present bias can be introduced in a way that adds almost no additional computational complexity relative to a model without present bias (details below). This makes present bias a parsimonious and portable solution that can be used broadly in the heterogeneous-agent literature to more accurately fit the micro data on credit card borrowing. Our goal is not to rule out other modeling enrichments, but rather to rule in present bias as a realistic and tractable resolution to the theoretical challenge presented above.[29]

[26]There are a few other recent, complementary, papers studying high-interest borrowing and MPCs (see e.g. Koşar et al., 2023; Boutros and Mijakovic, 2024). However, models studying unsecured borrowing often generate realistic borrowing levels by calibrating a large exponential discount rate, and hence these models do not typically focus on jointly matching households' overall net worth. As will be shown in the two-asset model in Section 5, a benefit of the present-bias approach in this paper is that we will be able to replicate the micro data on households' overall wealth accumulation in addition to their credit card borrowing.

[27]We note quickly that another way to generate such prevalent borrowing could be for many households to expect rapid consumption growth so that $u'(c_t) \gg \mathbb{E}_t\left[u'(c_{t+1})\right]$. However, we show in Appendix Figure 10 (righthand panel) that even households near retirement age exhibit similar borrowing propensities. Still, the results in Pfäuti et al. (2024) suggest that overconfidence is likely to be part of the story.

[28]This simple Euler equation ignores default, though default considerations are unlikely to be a key driver of borrowing for the large set of households that borrow only modest amounts. Although there is a literature in macroeconomics that bases households' unsecured borrowing rates on their default probabilities (e.g., Chatterjee et al., 2007), this sort of pricing schedule often implies that the first dollar of credit card debt will cost roughly the risk-free rate. That is, this type of model removes the kink that realistically arises at zero liquid wealth, and hence is ill-suited for the question we explore in this paper of why so many households breach that kink in the first place. However, there is also recent work in that literature studying consumption and default behavior in quantitatively rich models with realistic credit card contract terms (e.g., Dempsey and Ionescu, 2024; Chatterjee and Eyigungor, 2024). For simplicity, we abstract from much of this richness.

[29]We also emphasize here that our later results on fiscal and monetary policy (Section 4.3) do not rely specifically on present bias per se. These sections study how households' responses to policy change once households are modeled as revolving some credit card debt instead of being constrained at the zero-liquid-wealth kink; present bias is the tool we use to generate realistic borrowing behavior.

4 Using Present Bias to Reconcile Theory and Data

We now provide a theoretical analysis to show that present bias can resolve the tension summarized in Section 3.3. We do so in two steps. First, in this section we use a simplified model to introduce our main theoretical insights on how present bias can lead to modest levels of high-cost borrowing alongside elevated MPCs. We also discuss several implications of credit card borrowing for fiscal and monetary policy. Second, in Section 5 we extend the analysis to a richer heterogeneous-agent model with stochastic income and liquid and illiquid assets. This two-asset model will also allow us to evaluate whether present bias can help to generate realistic levels of illiquid wealth alongside credit card borrowing.

4.1 Present Bias in Continuous Time: Instantaneous Gratification

We model present bias in continuous time following the Instantaneous Gratification (IG) specification of Harris and Laibson (2013).[30] The IG discount function is the limiting discount function that results from shrinking the length of time that each self lives down to a single instant. In the continuous-time limit, the IG discount function is:

$$D(t) = \begin{cases} 1 & \text{if } t = 0 \\ \beta e^{-\rho t} & \text{if } t > 0 \end{cases}. \tag{2}$$

Parameter ρ is the exponential discount rate. $\beta < 1$ introduces present bias by creating a disproportionate focus on utils experienced "now" instead of "later," thus making agents more impatient in the short run than in the long run. Standard exponential discounting is recovered by setting $\beta = 1$.

We assume that agents are sophisticated about their present bias, meaning that agents are fully aware of their future self-control problems. This is without loss of generality, however, because there is an observational equivalence between sophistication and naivete in the models studied below (Maxted, 2024b).

Since the limiting IG discount function has an arbitrarily short "now," IG preferences

[30] Foundational work on present bias in continuous time includes Barro (1999), Luttmer and Mariotti (2003), and Cao and Werning (2016). More recently, see also Acharya et al. (2020) and Maxted et al. (2024).

should be thought of as a mathematical construction. However, Laibson and Maxted (2022) show that IG preferences provide a close approximation to models in which "now" lasts for a psychologically appropriate length of time, typically found to be roughly one week or less (see e.g. McClure et al., 2007; Augenblick and Rabin, 2019). The benefit of the IG specification is its tractability. Specifically, Maxted (2024b) shows that with IG preferences, a present-biased agent's behavior can be characterized with a simple two-step algorithm: (i) solve the model without present bias; and (ii) use closed-form transformations to characterize the corresponding policy and value functions of an agent with present bias.[31]

4.2 Present Bias in a Simplified Model: Key Insights

We now spell out our main theoretical insights on how present bias can generate agents with elevated MPCs *and* intermediate levels of high-cost debt. For expositional clarity, we start by presenting these insights in a stripped-down environment.[32]

Cake-Eating Model with a Credit Card. We begin with a deterministic cake-eating problem, but enrich this basic setup slightly by adding high-cost credit card borrowing.

The model is as follows. The household earns a constant income flow of $\bar{y}$ and chooses consumption c. The household has access to a liquid asset b. When $b \geq 0$, the household earns a constant return of r. When $b < 0$ and the household is borrowing (e.g., on a credit card), we assume that the household must pay a borrowing wedge of $\omega^{cc} > 0$ over the interest rate r. This wedge between the interest rate on saving versus borrowing creates a "soft borrowing constraint" (a kink) at $b = 0$. The dynamic budget constraint is:

$$\dot{b}_t = \bar{y} + rb_t + \omega^{cc} b_t^- - c_t, \tag{3}$$

where $b_t^- = \min\{b_t, 0\}$. Borrowing is allowed up to the natural borrowing limit of $\frac{-\bar{y}}{r+\omega^{cc}}$.

[31] These transformations rely on two main assumptions: CRRA utility and hard borrowing constraints that do not bind in equilibrium. We discuss the latter assumption further in Section 5.

[32] Much of this section's modeling and analysis builds on the benchmark insights of Achdou et al. (2022, especially Appendix G.3), who present an elegant theoretical analysis of continuous-time consumption models for the standard case of exponential discounting (i.e., without present bias).

Equilibrium. We assume that the household has CRRA utility:

$$u(c) = \frac{c^{1-\gamma} - 1}{1-\gamma}. \tag{4}$$

We also impose the parameter restriction throughout that $\gamma > 1 - \beta$.[33]

Under sophisticated present bias, dynamic disagreement between the current and future selves means that consumption-saving decisions are the equilibrium outcome of a dynamic intrapersonal game (Strotz, 1956; Laibson, 1997). Throughout this paper, we restrict our focus to the Markov-perfect equilibrium construction presented in Maxted (2024b).

The Effect of Present Bias on Consumption. We first introduce the following terminology in order to characterize the behavior of a present-biased agent relative to the behavior of an agent that does not have present bias ($\beta = 1$) but is otherwise-identical.

Definition (Debiased Exponential Agent)**.** *For any present-biased agent with $\beta < 1$, we define the "debiased exponential agent" as the agent that has no present bias ($\beta = 1$) but is otherwise identical to the present-biased agent (i.e., the debiased exponential agent is what the present-biased agent would be if their present bias was turned off). We denote the policy functions of the debiased exponential agent with an upside-down hat (e.g., $\check{c}(b)$).*

With this definition in hand, we can apply a result from Maxted (2024b) here:[34]

Lemma 1. *Let $\psi = \frac{\gamma-(1-\beta)}{\gamma}$. Let $\check{c}(b)$ denote the consumption function of the debiased exponential agent. Relative to the debiased exponential agent, the consumption of the present-biased agent is given by:*

$$c(b) = \frac{1}{\psi}\check{c}(b). \tag{5}$$

Lemma 1 implies that present bias increases consumption by a multiplicative factor of $\frac{1}{\psi} > 1$.[35] Lemma 1 thus provides the intuitive result that present-biased agents overconsume

[33] We will always set $\gamma \geq 1$, so this restriction never comes into play in this paper. See Harris and Laibson (2013) for a discussion of this restriction, which heuristically implies that the household's desire to smooth consumption (γ) is greater than their time inconsistency ($1 - \beta$).

[34] See also Harris and Laibson (2013) for a similar result, though in a different model than we study here.

[35] Our earlier parameter restriction that $\gamma > 1 - \beta$ ensures that the numerator of ψ is positive.

relative to how they would behave if they instead had $\beta = 1$.

A key implication of Lemma 1 is that present bias will increase agents' propensity to persistently revolve small amounts of credit card debt, consistent with the borrowing behavior documented in Stylized Facts 3 and 4. We will return to this effect in detail shortly with the aid of a numerical illustration.

Illustrative Calibration. We now calibrate and solve this simple model to highlight the key mechanisms at play. We normalize income $\bar{y} = 1$. We set the interest rate r to 1%, and the borrowing wedge ω^{cc} to 15%. We set the exponential discount rate $\rho = 3\%$. To introduce present bias, we set the short-run discount factor $\beta = 0.9$. We set the coefficient of relative risk aversion $\gamma = 1.5$. These parameters are all broadly consistent with our calibration of the richer heterogeneous-agent model in Section 5 (additional details therein).[36]

Model Solution. The lefthand panel of Figure 3 shows the consumption function for both the present-biased agent ($c(b)$) and the debiased exponential agent ($\check{c}(b)$). As detailed in Lemma 1, the relationship between the two is: $c(b) = \frac{1}{\psi}\check{c}(b)$. The righthand panel of Figure 3 shows the corresponding saving function (i.e., the drift of b), $s(b) = \bar{y} + rb + \omega^{cc}b^{-} - c(b)$. In both panels, the dotted vertical lines highlight where each agent sets $s(b) = 0$ and hence $\dot{b} = 0$. In this deterministic model the dotted lines therefore mark each agent's steady state (absorbing point), where once they hit that level of wealth they remain there forever. Agents save to the left of their absorbing point, and dissave to the right of it.

Next, Figure 4 presents quarterly MPCs as a function of liquid wealth b. Similar to Achdou et al. (2022), we define the τ-year MPC out of a liquidity injection of size χ as:

$$MPC_{\tau}^{\chi}(b) = \frac{C_{\tau}(b+\chi) - C_{\tau}(b)}{\chi}, \tag{6}$$

where $C_{\tau}(b) = \mathbb{E}\left[\int_0^{\tau} c(b_t)dt | b_0 = b\right]$ is cumulative consumption over τ years. The lefthand panel of Figure 4 shows MPCs out of a small shock of $\chi \approx 0$, while the righthand panel shows MPCs out of a larger shock of $\chi = 0.05$ (i.e., 5% of annual income).

[36] We make the household slightly more patient here relative to the model in Section 5, since there is no precautionary motive in this deterministic model.

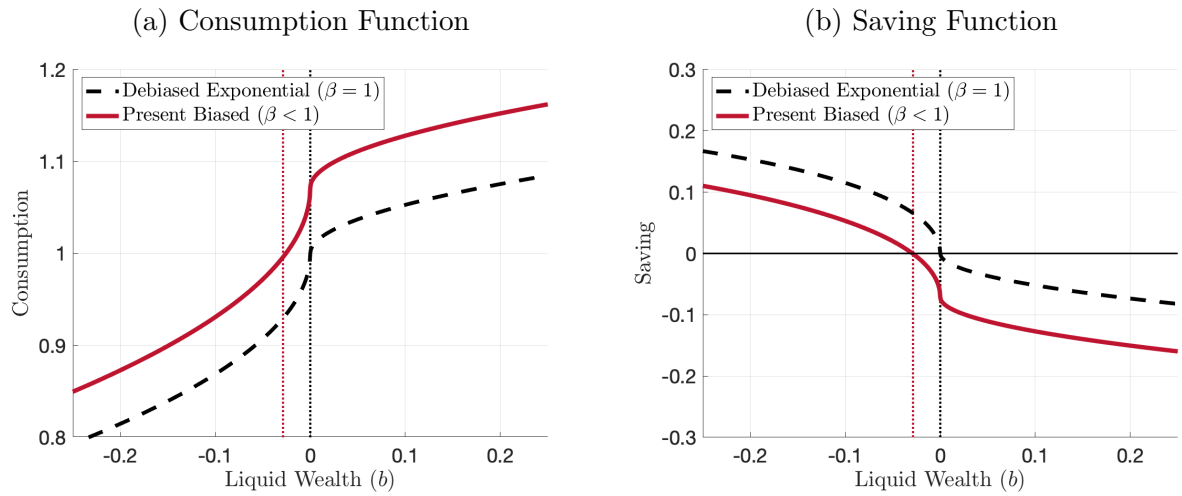


Figure 3: **Consumption and Saving Functions.** The lefthand panel plots the consumption function for the debiased exponential agent (dashed black curve) and the present-biased agent (red curve). The righthand panel plots the corresponding saving functions for the two agents. The dotted vertical lines mark the absorbing states for the two agents.

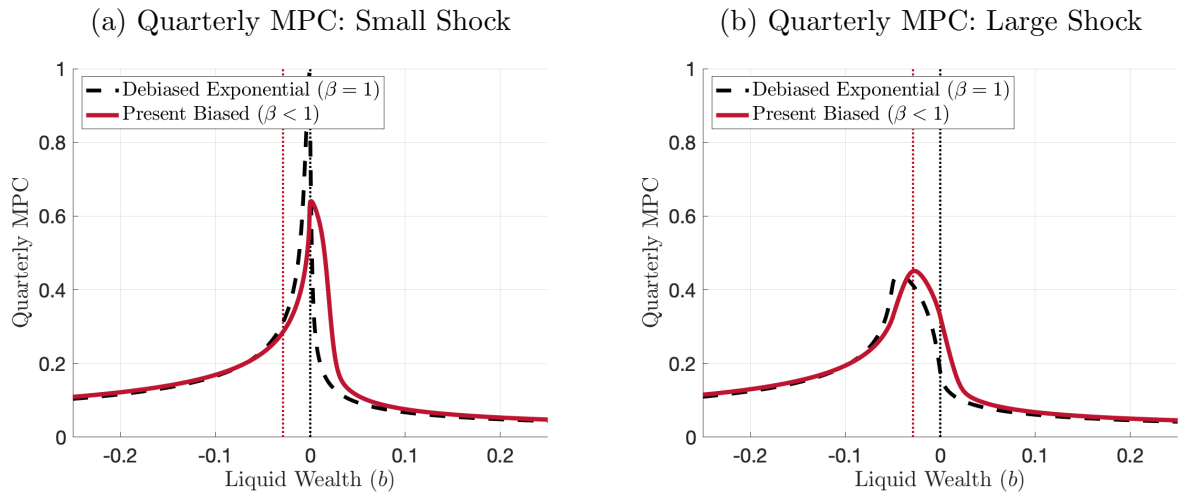


Figure 4: **MPCs out of Small and Large Shocks.** The lefthand panel plots the quarterly MPC out of a small wealth shock for the debiased exponential agent (dashed black curve) and the present-biased agent (red curve). The righthand panel plots the quarterly MPC out of a larger wealth shock that is 5% of annual income. The dotted vertical lines mark the absorbing states for the two agents.

Discussion: Debiased Exponential Agent and ZHtM Behavior. We start by describing the behavior of the debiased exponential agent, as illustrated by the dashed black curves in Figures 3 and 4. The debiased exponential agent is the agent without present bias that economists typically study, and their behavior here is relatively standard.

Starting with Figure 3, the first point to highlight is that the debiased exponential agent

dissaves whenever $b > 0$ since the return on saving is too low (i.e., $\rho > r$), but saves whenever $b < 0$ since the cost of credit card borrowing is too high (i.e., $\rho < r + \omega^{cc}$). At the zero-liquid-wealth kink of $b = 0$, the debiased exponential agent optimally chooses to simply stay put and consume their flow income forever thereafter, $\check{c}(0) = \bar{y}$. This means that the zero-liquid-wealth kink is an absorbing point for the debiased exponential agent, as marked by the dotted black vertical line at $b = 0$.

The second point to highlight is that the debiased exponential agent's consumption function is concave to the right of $b = 0$. This implies that the debiased exponential agent will have an elevated MPC out of small wealth shocks. But, it also implies that their MPC declines as wealth shocks get larger. This explains the difference between the debiased exponential agent's MPC at $b = 0$ in the left- and righthand panels of Figure 4.

Overall, the debiased exponential agent's behavior follows the standard ZHtM paradigm reviewed in Section 2. The debiased exponential agent dissaves to the right of $b = 0$, but stops dissaving exactly at $b = 0$ in order to avoid revolving high-cost debt. In doing so, they will be constrained at $b = 0$ and will have a high MPC out of subsequent (small) liquidity injections. However, we showed in Section 3 that this ZHtM paradigm is inconsistent with the data, which instead suggests that the zero-liquid-wealth kink is frequently breached.

Discussion: Present Bias and High-Cost Borrowing. Next, we use Lemma 1 to examine how present bias reshapes behavior. We ask two questions. First, how does present bias affect agents' propensity to breach the soft constraint and take on high-cost credit card debt? Second, how are MPCs affected if agents are no longer constrained at the zero-liquid-wealth kink? We provide two propositions to answer these two questions.

Starting with the effect of present bias on borrowing, Lemma 1 implies right away that present-biased agents will choose to revolve some amount of credit card debt in this simple model. This key implication of Lemma 1 is summarized below in our first proposition:

Proposition 1 (Maxted, 2024b)**.** *Assume that $r < \frac{\rho}{\beta}$, as in the calibration here, so that the present-biased agent dissaves for $b > 0$. Regardless of ω^{cc}, the present-biased agent chooses to accumulate debt at $b = 0$ by setting $s(0) < 0$.*

Proof. The intuition for Proposition 1 is straightforward: if the debiased exponential agent

sets $\check{c}(0) = \bar{y}$ and hence $\check{s}(0) = 0$, the present-biased agent overconsumes by setting $c(0) = \frac{1}{\psi}\bar{y}$ and hence $s(0) = \left(1 - \frac{1}{\psi}\right)\bar{y} < 0$. Full details are provided in Maxted (2024b). □

Proposition 1 implies that once $\beta < 1$, the zero-liquid-wealth kink no longer prevents borrowing completely. Whereas the debiased exponential agent sets $\check{c} = \bar{y}$ at $b = 0$ and hence stays at the kink forever, the present-biased agent instead dissaves at $b = 0$ and hence takes on some credit card debt (i.e., the present-biased agent's saving function is negative at $b = 0$, as illustrated in Figure 3).

However, just because the present-biased agent accumulates some credit card debt, this is not to say that they will max out their credit card. Figure 3 also shows that consumption drops off quickly once $b < 0$ because consumption is now being funded through high-cost borrowing. That is, once in the borrowing domain the present-biased agent's saving quickly turns from negative to positive. So, while the present-biased agent will persistently revolve some high-cost debt, their steady-state debt level can still be modest overall (as shown by the dotted red vertical line shifting only slightly to the left of $b = 0$ in Figure 3). In particular, as $\beta \uparrow 1$ the red curve of the present-biased agent converges to the dashed black curve of the debiased exponential agent, and hence the extent to which the present-biased agent borrows converges to 0. Thus, present bias provides a natural mechanism for fitting the high extensive margin but modest intensive margin borrowing documented empirically in Stylized Fact 3.

It is important to emphasize that the borrowing behavior of the present-biased agent is fundamentally different from that of the exponential agent in this simple model. For an exponential agent with $\beta = 1$, there are generically only three possible outcomes for long-run wealth: (i) they will save forever if $\rho < r$; (ii: the case here) they will get to the kink at $b = 0$ and then stay there forever if $\rho \in (r, r + \omega^{cc})$; or (iii) they will dissave forever and steadily approach the natural borrowing limit if $\rho > r + \omega^{cc}$. In short, when $\beta = 1$ this cake-eating model can be calibrated either so that agents never borrow or so that they gradually borrow as much as possible, but it cannot be calibrated to produce the intermediate levels of borrowing that we see in the data. Though we are studying a highly simplified model here, the benefit of showing this result in such a stripped-down framework is that it underscores that Stylized Fact 3 poses a fundamental challenge to models without

present bias.[37] Alternatively, present bias very naturally generates the behavior in Stylized Fact 3: $\beta < 1$ implies that present-biased agents will borrow something on the extensive margin (Proposition 1), but their simultaneous long-run patience also means that they don't want to borrow too much at such a high interest rate. Returning to an observation in the introduction, this highlights how the phrase "aspirationally hand-to-mouth" captures the key intuitions at play in Figure 3. The present-biased agent wants be ZHtM in the long run, but their present bias means that they persistently carry some credit card debt instead.

The paragraph above hints that there is something specific about time-inconsistency in reshaping borrowing behavior. This can be fleshed out further using the generalized Euler equation. Let $\tilde{r}(b_t)$ denote the marginal interest rate, which here is r if $b > 0$ and $r + \omega^{cc}$ if $b < 0$. At all points except the kink at $b = 0$, consumption satisfies the following generalized Euler equation (Harris and Laibson, 2001; Cao and Werning, 2016; Maxted, 2024b):

$$\frac{\dot{c}_t}{c_t} = \frac{1}{\gamma}\left(\tilde{r}(b_t) - \Big[\rho + (1-\beta)c'(b_t)\Big]\right). \tag{7}$$

The lefthand side of (7) is the growth rate of consumption. For $\beta = 1$ we recover the standard continuous-time Euler equation of $\frac{\dot{c}_t}{c_t} = \frac{1}{\gamma}(\tilde{r}(b_t) - \rho)$, which highlights why the model with time-consistent $\beta = 1$ agents only allows for three possible long-run wealth outcomes (generically), depending on whether $\rho < r$, $\rho \in (r, r + \omega^{cc})$, or $\rho > r + \omega^{cc}$. Alternatively, the generalized Euler equation in (7) takes a more flexible form when $\beta < 1$ and agents are time-inconsistent. In particular, we can interpret the term in brackets as the present-biased agent's effective discount rate, which *varies* over the state space based on the slope of the consumption function, $c'(b_t)$.[38] Setting $\dot{c}_t = 0$ in (7), an absorbing point for the

[37] In particular, richer models with stochasticity can generate some high-cost borrowing as a transitory state. As already discussed in Sections 2 and 3, however, when $\beta = 1$ these models often struggle to generate debt that is as pervasive and persistent as we see in the data (Stylized Facts 3 and 4). Moreover, the zero-liquid-wealth kink generally implies a Dirac mass (i.e., bunching) at $b = 0$ for $\beta = 1$ households (Achdou et al., 2022), a prediction for which there is no clear support in Table 2. Finally, a $\beta = 1$ model should be able to fit the fact that borrowers also hold sizable stocks of illiquid wealth (Stylized Fact 5). We will show in Section 5 that present bias helps to reproduce this joint holding of credit card debt alongside illiquid wealth by making households impatient in the short run but patient in the long run (Laibson et al., 2024).

[38] Since the current self knows that future selves will overconsume, the current self's willingness to set aside a dollar of savings depends on future selves' propensity to (over)consume out of that dollar (Harris and Laibson, 2001). This propensity is determined by the slope of the consumption function. When $c'(b)$ is elevated, the current self will be less willing to save and hence will act as if they are relatively more impatient.

present-biased agent can arise whenever $\left[\rho+(1-\beta)c'(b_t)\right] = \tilde{r}(b_t)$. Since $c'(b)$ varies over the state space and particularly around $b = 0$ (discussed further below), intermediate amounts of credit card borrowing can be easily obtained once $\beta < 1$.

For more, Appendix Figure 11 plots the time path of wealth, consumption, and saving to further illustrate the dynamic behavior of exponential and present-biased agents near $b = 0$.

Discussion: Indebted Saving and MPCs. Now that we've shown how present bias can generate the high-cost borrowing that we see in the data (Stylized Facts 3 and 4), we next study how MPCs are affected once households are no longer constrained at the zero-liquid-wealth kink. We provide our second proposition to motivate this discussion, extending a result from Achdou et al. (2022) to the generalized case of present bias:

Proposition 2. *Assume that $r < \rho < r + \omega^{cc}$, as in the calibration here. The derivative of consumption function $c(b)$ is unbounded at $b = 0$, with $c'(b) \to \infty$ both as $b \downarrow 0$ and as $b \uparrow 0$.*

Proof. When $\beta = 1$, Achdou et al. (2022, Appendix G.3) prove that $c'(b) \to \infty$ both as $b \downarrow 0$ and as $b \uparrow 0$. Since Lemma 1 implies that the present-biased agent's consumption is $\frac{1}{\psi}$ times the debiased exponential agent's consumption, this result continues to hold when $\beta < 1$. □

Proposition 2 provides the key result that explains why MPCs can still be elevated even though households are unconstrained once $\beta < 1$.[39] The MPC will be large whenever the slope of the consumption function $c'(b)$ is steep, and Proposition 2 implies that the consumption function will be steep both to the right *and also to the left of* $b = 0$ (see Figure 3). That the consumption function is concave with a steep slope to the right of the kink at $b = 0$ is well known, and is precisely the mechanism that has been used to generate large MPCs for ZHtM agents constrained at $b = 0$. However, the fact that the consumption function is *convex* with a steep slope to the left of $b = 0$ is the key mechanism needed in this paper, because it implies that agents with small amounts of high-cost debt will still have elevated MPCs even though they are unconstrained. As Figure 3 illustrates, the steepness of the consumption function to the left of $b = 0$ follows from households sharply cutting their consumption (and increasing their saving) upon breaching the soft constraint and starting to

[39] Proposition 2 focuses on the $\rho > r$ case, but similar results arise when $\rho \in (\beta r, r)$. See Appendix B.2.

take on high-cost debt. We refer to the sharp cut in consumption that arises once households start funding their spending with high-cost debt as *indebted saving behavior*.

Before using Proposition 2 to interpret the MPCs in Figure 4, one caveat is needed. Proposition 2 characterizes the slope of the consumption function $c'(b)$ (i.e., the instantaneous MPC), which is not exactly the cumulative MPC defined in equation (6) and presented in Figure 4. Nonetheless, Proposition 2 provides the key intuitions at play. In particular, setting $\beta < 1$ shifts households from the concave part of their consumption function (at $b = 0$) to the convex part of their consumption function (to the left of $b = 0$), which, as we discuss below, will have implications for MPC *size effects* and MPC *sign asymmetries*.

Using Proposition 2 as a guide, we now examine how present bias affects the MPCs shown by the red curves in Figure 4. Looking first at the small wealth shock in the lefthand panel, we see that MPCs remain elevated to the left of $b = 0$ because the consumption function is still steep in this region. As we move further to the left of $b = 0$ we do see that the MPC drops off to some extent, however. Accordingly, present bias leads to a somewhat smaller (though still elevated) MPC at the respective absorbing states.[40]

Alternatively, for the larger wealth shock (righthand panel) we now see that present bias amplifies the MPC at the respective absorbing states. This MPC size effect illustrates some of the nuances of indebted saving behavior. Because the present-biased agent's consumption function is locally convex, their MPC can actually grow as the size of the shock gets larger. More intuitively, a small wealth shock that leaves the agent with a high-cost debt burden will generate a somewhat muted consumption response, whereas a bigger wealth shock that alleviates that debt more fully will leave the agent freer to consume at a more rapid rate. Note that this prediction differs from the $\beta = 1$ agent at the zero-liquid-wealth kink, whose MPC declines as the size of the shock gets larger (discussed above).

Indebted saving behavior also has implications for MPC sign asymmetries (i.e., the MPC out of positive versus negative shocks). When $\beta = 1$ and households are stuck at $b = 0$, the local concavity of the consumption function implies that the MPC out of positive shocks is smaller than the MPC out of negative shocks. But when $\beta < 1$ and households shift to the

[40] It is worth emphasizing this (counterintuitive) result. Whereas one may be inclined to conjecture that adding present bias will always increase MPCs, this is not the case here. The lefthand panel of Figure 4 shows that present bias leads to somewhat smaller MPCs out of small wealth shocks.

left of $b = 0$, now the local convexity of consumption instead implies that the MPC out of positive shocks is larger than the MPC out of negative shocks (Appendix Figure 12 provides an illustration). This indebted saving effect is consistent with the evidence in Baugh et al. (2021), who find in account-level data that taxpayers tend to increase consumption following a tax refund, but do not decrease consumption following a tax bill.[41]

Summary. Our two propositions above suggest that present bias is a promising avenue for overcoming the empirical tension summarized in Section 3.3. Present bias prevents soft constraints from binding, and induces agents to revolve some (often small) amount of credit card debt (Proposition 1). Such agents then become subject to indebted saving behavior, with MPCs that remain elevated even though they are "on the Euler equation" (Proposition 2). Together, these propositions show that the behavior of present-biased agents is consistent with Stylized Facts 1, 2, 3, and 4. Although the model in this section is intentionally simplified for pedagogy, we will later introduce a two-asset model in Section 5 to show that present bias can reproduce Stylized Facts 1–4 on MPCs and high-cost borrowing while also helping to generate realistic wealth levels for credit card borrowers (Stylized Fact 5).

4.3 Applications to Fiscal and Monetary Policy

We now discuss the implications of credit card borrowing for household responses to fiscal and monetary policy.

Credit Card Debt and Fiscal Policy. A key implication of the MPC size effect discussed above is that present bias increases the scope for fiscal policy to remain potent, because it allows for larger stimulus checks to still produce meaningful consumption responses. Figure 5 shows how the quarterly MPC varies with the size of a liquidity injection (with agents starting from their respective steady-state wealth level). Whereas the MPC declines quickly when $\beta = 1$ and agents are located at the zero-liquid-wealth kink, the MPC remains elevated over much larger transfers when $\beta < 1$ and agents begin with some credit card debt. Empirically,

[41] Sokolova (2023) also finds in a meta-analysis that the MPC is larger out of income gains than losses. However, Fuster et al. (2021) find the opposite effect using hypothetical survey questions: households report that they will cut spending more following losses than they will increase spending following gains.

it is commonly found that households' spending responses remain elevated for large liquidity injections (e.g., Kueng, 2018; Fagereng et al., 2021; Hamilton et al., 2023; Sokolova, 2023). Present bias helps to reconcile consumption-saving models with this feature of the data.[42]

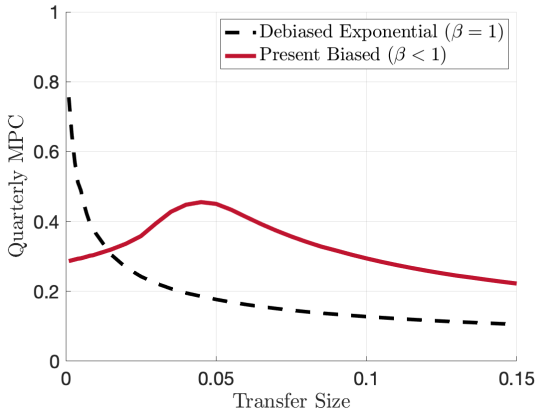


Figure 5: **Quarterly MPCs for Different Transfer Amounts.** This figure plots the quarterly MPC for the debiased exponential agent (dashed black curve) and the present-biased agent (red curve). Prior to receiving the liquidity injection, each agent starts from their respective steady-state (absorbing) wealth level.

Our model with present bias also yields novel predictions about how a typical household will utilize a stimulus check. Credit card debt is a recurrent state in our model with present bias. So, even when households use a liquidity injection to pay down their debt, the high consumption rate that they subsequently adopt means that their credit card debt will rebound quickly thereafter (see also Appendix Figure 11). This prediction is consistent with the lefthand panel of Figure 1, and we discuss this prediction further in Section 5 below.

Finally, we find that present bias affects the "intertemporal MPCs" that discipline the general equilibrium propagation of fiscal stimulus (Auclert et al., 2024). For example, Appendix Figure 13 plots the consumption response following news at time $t = 0$ of a wealth shock that arrives at $t = 2$. The key difference between the present-biased agent and the debiased exponential agent is that the present-biased agent's consumption response begins earlier and is more spread out over time. This is because the present-biased agent is unconstrained at $t = 0$, and hence exhibits an anticipatory consumption response to the news shock.[43]

[42]The notable hump-shape in Figure 5 gets smoothed out in the richer two-asset model with stochasticity (see Appendix Figure 15). Present bias is complementary to other mechanisms that can increase households' spending response to large transfers, such as durable adjustment frictions (Beraja and Zorzi, 2023).

[43]This is consistent with the empirical evidence in Agarwal and Qian (2014), who find in transaction-level data that consumers exhibit a strong anticipatory consumption response to a fiscal policy announcement.

Nonetheless, the present-biased agent's behavior is still far from the classical consumption-smoothing benchmark, as anticipatory consumption must be traded off against the cost of bearing additional high-interest debt until the wealth injection arrives.

Credit Card Debt and Monetary Policy. The monetary policy experiment that we consider in this stylized partial-equilibrium framework is an unexpected, transitory, shock to interest rate r. Following Kaplan et al. (2018), we feed in a -1% shock at time 0, which then reverts at rate $\eta = 2$ (such that the quarterly autocorrelation is $e^{-\frac{\eta}{4}} = 0.61$).

Figure 6 below plots the on-impact consumption elasticity to this rate cut. For any liquid wealth level b, the present-biased agent and the debiased exponential agent have exactly the same consumption elasticity, which follows from equation (5). But, monetary policy can still operate differentially across the two calibrations based on where agents locate themselves in the liquid-wealth state space.

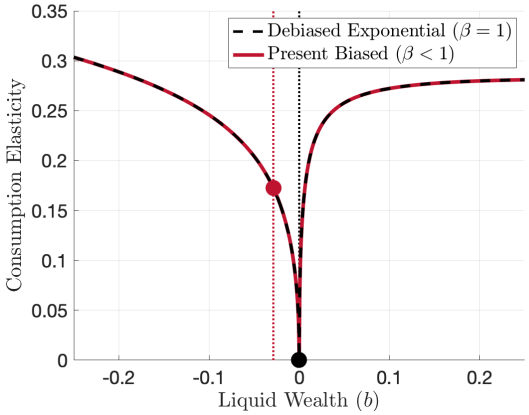


Figure 6: **Consumption Response to Rate Cut.** For each level of liquid wealth b, this figure plots the consumption response to an interest rate cut for the debiased exponential agent (dashed black curve) and the present-biased agent (red curve). The dotted vertical lines mark the absorbing states for the two agents.

For the exponential agent (black dot), in the long run they sit constrained at exactly $b = 0$ and therefore they will have *zero* direct response to the rate cut (for more, see e.g. Kaplan et al., 2018). Alternatively, the present-biased agent (red dot) has a sizable consumption response to the same rate cut because they are no longer constrained. Figure 6 therefore shows that the direct response to monetary policy depends critically on whether or not households are exactly constrained at $b = 0$. Once households have even small amounts

of credit card debt – as in our present-bias calibration and consistent with the empirical evidence in Section 3 – the model generates a larger direct response to rate cuts.

Importantly, present bias does not necessarily imply that indirect (general equilibrium) effects become an insignificant part of monetary policy. To the extent that indirect effects depend on agents' MPCs,[44] indebted saving behavior means that MPCs remain elevated when agents have some credit card debt (Proposition 2). Rather, the takeaway from this analysis is that a model in which households typically carry some credit card debt (Stylized Fact 3) and have elevated MPCs (Stylized Fact 1) can feature an important role for both direct and indirect responses to monetary policy. While a full general equilibrium analysis is an important future research step, the goal of Figure 6 is to highlight that credit card borrowing can have key implications for the channels through which monetary policy operates.

The simple exercise in Figure 6 assumes a complete pass-through from monetary policy to credit card interest rates. This assumption broadly fits the post-CARD-Act period that we study (Nelson, 2022; Grodzicki, 2023), though credit card rates may have been less sensitive to monetary policy in the past (Ausubel, 1991). This also suggests that regulatory changes to the credit card market can affect the transmission of monetary policy, again underscoring why it is important for policymakers to have models that are consistent with the credit card debt observed empirically. Relatedly, the exercise in Figure 6 assumes that households are fully attentive to their credit card interest rate. We maintain this assumption so that present bias is the only behavioral deviation that we consider, though it is potentially an unrealistic assumption (e.g., Han and Yin, 2024). Nonetheless, many revolvers make only the minimum payment (Keys and Wang, 2019) – and changes to interest rates often affect the minimum payment – such that even passive households will mechanically be affected by rate changes.

5 Extension to Two-Asset Heterogeneous-Agent Model

We now study a richer heterogeneous-agent model that features illiquid assets and stochastic income. This will allow us to look at Stylized Facts 1–4 in a more realistic model, and will also allow us to address Stylized Fact 5. Our analysis remains in partial equilibrium.

[44] For more, see e.g. Werning (2015), Kaplan et al. (2018), and Auclert (2019).

5.1 Present Bias in a Two-Asset Heterogeneous-Agent Model

The Household Balance Sheet. Households face idiosyncratic income risk, which follows a calibrated finite-state Poisson process. We denote a household's time-t income flow by y_t. The average income flow is normalized to 1.

As above, households have access to a liquid asset b. When liquid wealth is positive, households earn a constant return of r. When liquid wealth is negative, households must pay a marginal borrowing wedge of $\omega(b) > 0$ on each additional dollar of borrowing that they incur (as in Maxted, 2024b). Note that this generalizes the setup relative to the stylized model above, as borrowing wedge $\omega(b)$ can now depend on b.[45] We denote the *average* borrowing wedge by $\mathcal{W}(b)$, which is given by $\mathcal{W}(b) = \frac{\int_b^0 w(q)dq}{-b}$ for $b < 0$. We allow households to borrow up to the natural borrowing limit, which is defined implicitly by $\underline{b} = \frac{-\min\{y\}}{r+\mathcal{W}(\underline{b})}$.[46]

We also now give households access to an illiquid asset a, since, in the data, many households hold a large share of their wealth in assets that are relatively risky and illiquid. The illiquid asset a offers an expected return of r^a and has a volatility of σ^a. The asset is illiquid for two reasons. First, we follow Kaplan and Violante (2022) and assume that households can only make intermittent adjustments to the illiquid asset, with adjustment opportunities arriving stochastically at Poisson rate λ^a.[47] Second, any adjustments that the household decides to make are subject to a transaction cost of $\chi(\cdot)$ (details below). Households cannot take short positions in the illiquid asset ($a_t \geq 0$).

More formally, in-between adjustments the household's balance sheet evolves as follows:

$$db_t = \left(y_t + rb_t + \mathcal{W}(b_t)b_t^- - c_t\right) dt \tag{8}$$

$$\frac{da_t}{a_t} = r^a dt + \sigma^a dZ_t, \tag{9}$$

with the constraints that $b_t \geq \underline{b}$ and $a_t \geq 0$. Z_t is a standard Brownian motion.

[45] $\omega(b)$ need not be continuous, and can have a finite number of discontinuities to capture situations such as a household switching to payday loans after hitting its credit card limit.

[46] As mentioned in footnote 31, borrowing constraint $\underline{b}$ cannot bind in equilibrium for the results of Maxted (2024b) to hold. However, note that we have placed no restriction on how onerous borrowing wedge $\omega(b)$ can become as households borrow more. See Maxted (2024b) for further discussion of this assumption.

[47] As discussed in Maxted (2024b), this restriction is not necessary but it is technically convenient because it simplifies the structure of the HJB equation characterizing equilibrium. λ^a can be made large if desired (e.g., $\lambda^a = 365$) and, in practice, extracting home equity or retirement funds does often take some time.

When the household receives an adjustment opportunity, it can choose a new liquid-wealth value b' and a new illiquid-wealth value a', subject to the budget constraint of:

$$a' + b' = a_t + b_t - \chi(a' - a_t), \tag{10}$$

and the constraints that $b' \geq \underline{b}$ and $a' \geq 0$. Our calibration of $\chi(\cdot)$ will be detailed shortly.

To roughly capture lifecycle dynamics, households retire at rate λ^R. We follow the "perpetual youth" framework of Blanchard (1985) to avoid needing an additional state variable capturing age. Retired households are replaced by households with zero wealth and an income state drawn randomly from the ergodic income distribution.

Equilibrium. As in Section 4.2, households have CRRA utility (see equation (4)), and we continue to follow the Markov-perfect equilibrium construction of Maxted (2024b).

The Effect of Present Bias on Policy Functions. The model here has three state variables: liquid wealth b, illiquid wealth a, and income state y. To reduce notation, let $x = (b, a, y)$ denote the vector of state variables.

Households make two decisions in this model. They choose consumption c, and they choose an asset allocation of (b', a') conditional on receiving a rebalancing opportunity. For the consumption decision, Lemma 1 above continues to hold here, meaning that present bias causes households to consume $\frac{1}{\psi}$-times more than they would if they were not present biased: $c(x) = \frac{1}{\psi}\check{c}(x)$. For the illiquid asset allocation decision, a result from Maxted (2024b) again applies with the key property being that the asset allocation decision is independent of β:

Lemma 2. *Let $\check{b}'(x)$ and $\check{a}'(x)$ denote the asset allocation policy function of the debiased exponential agent. Conditional on receiving an adjustment opportunity at point x in the state space, the present-biased agent and the debiased exponential agent have the same asset allocation policy function: $b'(x) = \check{b}'(x)$ and $a'(x) = \check{a}'(x)$.*

There are two key takeaways from these results. First, from a technical standpoint Lemmas 1 and 2 imply that present bias is tractable even in a richer two-asset framework: we can again recover the behavior of a present-biased agent directly from that of the debiased

exponential agent. Second, the juxtaposition of Lemmas 1 and 2 shows how present bias can help to generate Stylized Fact 5 that households with credit card debt also hold sizable levels of illiquid wealth. Specifically, Lemma 1 implies that setting $\beta < 1$ causes overconsumption and hence credit card debt, but Lemma 2 implies that setting $\beta < 1$ does not affect households' desire to accumulate illiquid wealth. This is again in contrast to a model with exponential preferences ($\beta = 1$), where any increase in discounting ($\rho \uparrow$) to fit credit card borrowing will simultaneously lower households' willingness to build illiquid wealth.

External Calibration. Our calibration is relatively standard, and full calibration details are given in Appendix B.3. Summarizing the main parameters here, we set the return on positive liquid wealth to $r = 1\%$. When households borrow, the credit card borrowing wedge is 15.18%, consistent with households' self-reported borrowing rate in the SCF. Households can borrow up to one-quarter of average annual income on a credit card ($b^{cc-limit} = -0.25$; Kaplan et al., 2018). The interest rate beyond that point is set to 362%, which equates to a typical payday loan rate of 15% per two-week borrowing period.

The illiquid asset is modeled as a diversified stock index, with a risk premium of 4% and a volatility of 18% (Gomes and Michaelides, 2005). We assume that deposits into the illiquid asset are costless but withdrawals are subject to a 10% penalty, which loosely replicates defined-contribution (DC) retirement plans. We set the arrival rate of adjustment opportunities to $\lambda^a = 12$, as in Kaplan and Violante (2022), meaning that households can rebalance once per month on average. We continue to set the coefficient of relative risk aversion $\gamma = 1.5$. We calibrate the income process following Guerrieri and Lorenzoni (2017), and normalize the average income flow to 1.

Because we treat the illiquid asset a as a diversified stock index, Brownian shock dZ is common across all households. For simplicity, when we numerically characterize the model's "steady state" (using the Kolmogorov forward equation) we will assume that $dZ_t \equiv 0$. That is, households consider asset risk when determining their policy functions, but we then study one specific sequence in which asset-return shocks never materialize.[48]

[48]Since we calibrate our model to SCF-reported wealth from 2013–2019, another reasonable approach would be to feed in a sequence of shocks that replicates U.S. equity performance leading up to that period.

Internal Calibration and Model Fit. To calibrate long-run discount rate ρ and short-run discount factor β we use two calibration targets. First we target a mean wealth level of 3.9, which is the average wealth to average income ratio reported in Table 1 for our preferred SCF sample ($\frac{306,307}{78,419}$). Second, we target that 52% of households revolve credit card debt, again consistent with the high-interest credit card borrowing reported in Table 1.

Our calibration of β and ρ is reported in Table 4 below (in the column labeled "Model"). We set $\beta = 0.84$ to generate 52% of households with credit card debt, and $\rho = 3.17\%$ to generate average total wealth of 3.9. For comparison, in the two rightmost columns of Table 4 we restrict $\beta = 1$ (no present bias) and calibrate either $\rho = 4.08\%$ to match the wealth moment, or $\rho = 14.20\%$ to match the credit card borrowing moment. Neither calibration of the $\beta = 1$ model provides an accurate description of the data. We can match the total wealth moment with $\beta = 1$ and $\rho = 4.08\%$, but this calibration underpredicts borrowing by a factor of almost 3. Alternatively, we can match the 52% borrowing moment with $\beta = 1$ and $\rho = 14.2\%$, but then households' total average wealth is only 0.1. In short, the $\beta = 1$ model can be calibrated so that households act patiently or impatiently, but not both, and hence it does not provide as good of a fit to the empirical moments.[49]

	Data	Model	$\beta = 1$ (Wealth)	$\beta = 1$ (CC Debt)
Discount Function				
β	-	0.84	1	1
ρ	-	3.17%	4.08%	14.20%
Calibration Targets				
Has high-interest CC debt	52%	52%	19%	52%
Total wealth	3.9	3.9	3.9	0.1

Table 4: **Discount Function Calibration.** This table gives the discount function calibration for our model with and without present bias.

Reconciling Theory and Data: Borrowing and MPCs. For the present-bias model, Figure 7 below plots the liquid wealth distribution (bars) alongside average quarterly MPCs (lines). Starting with the liquid wealth distribution, on the one hand Figure 7 illustrates that a large proportion of households have close to zero liquid wealth. But, these households are often not exactly constrained at the zero-liquid-wealth kink. Instead, their present bias

[49] Further description of the $\beta = 1$ calibrations is provided in Appendix B.4.

means that they commonly revolve some credit card debt, consistent with Stylized Fact 3.[50]

Looking next at MPCs, Figure 7 plots the average quarterly MPC conditional on liquid wealth for a \$1,000 shock (bold red line) and, for reference, for a small shock of \$100 (transparent red line) and a larger shock of \$3,000 (transparent gray line). We continue to see that households with modest levels of credit card debt engage in indebted saving behavior that leads to elevated MPCs. There is also a spike in the MPC for households at the precipice of maxing out their credit card and turning to payday loans (near $b = -0.25$), though few households are in this part of the state space.

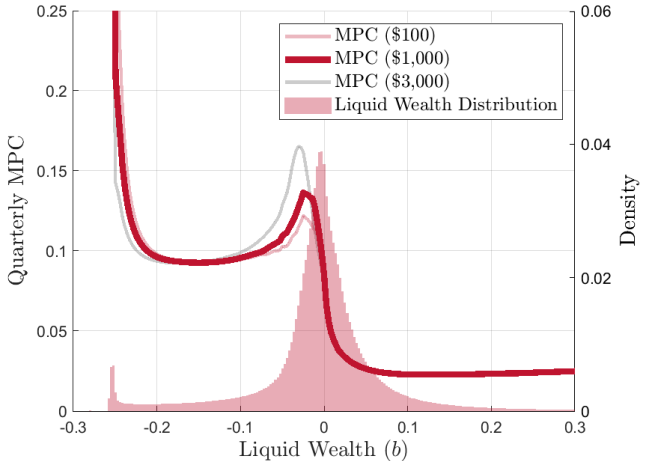


Figure 7: **MPCs and Liquid Wealth.** The lines plot average quarterly MPCs conditional on liquid wealth. The bars show the liquid wealth distribution.

Across all households, the average quarterly MPC out of \$1,000 is 8.8%. While the MPC is a measure of the notional consumption response to a liquidity shock, an alternative measure – the marginal propensity for expenditure (MPX) – instead captures the response of total expenditure (Laibson et al., 2022).[51] The average quarterly MPX in our model is 23.6%. In addition, Appendix Figure 15 shows that the average MPC and MPX remain elevated even for relatively large transfers. Overall, the model generates sizable and empirically realistic responses to liquidity injections, consistent with Stylized Fact 1.[52] Thus, even in

[50]Figure 7 also shows a small grouping of households near $b = -0.25$, which is the point where households max out their credit card and switch to payday loans (1.6% of households are borrowing with payday loans).

[51]We follow the mapping from model-based notional MPCs to MPXs in Laibson et al. (2022) (further detailed in Appendix B.4). The key difference between the two measures comes from spending on durable goods, which results in up-front expenditure that translates only slowly into notional consumption.

[52]Estimated quarterly MPCs are often in the range of 15-25% (Kaplan et al., 2018), though recent research using novel econometric techniques finds somewhat smaller responses (see e.g. Boehm et al., 2024; Borusyak

this enriched heterogeneous-agent framework, present bias continues to provide a tractable and parsimonious resolution to the empirical tension summarized in Section 3.3.

	Data	Model
Consumption and Expenditure		
Quarterly MPC ($1,000)	-	8.8%
Quarterly MPX ($1,000)	-	23.6%
Persistence of CC Debt		
One-quarter repayment probability	-	39.7%
One-year repayment probability	-	57.9%
Conditional Wealth		
Total wealth | high-interest CC debt	2.7	2.1
Total wealth | no high-interest CC debt	5.3	5.8

Table 5: **Summary Statistics for Two-Asset Model.** This table provides summary statistics for our calibrated heterogeneous-agent model with present-biased households.

Digging further into the stylized facts from Section 3, we next examine the persistence of credit card debt. Table 5 reports the probability that a household with credit card debt will repay that debt within one quarter or one year.[53] Our model is broadly consistent with Stylized Fact 4 that credit card debt is persistent, though our read of the available data is that credit card debt is somewhat less persistent in the model than in the data.[54]

Returning finally to Stylized Fact 5, the bottom panel of Table 5 reports the average total wealth of households with and without credit card debt. Our present-bias model performs reasonably well at matching the wealth-holdings of households with credit card debt, particularly in comparison to the $\beta = 1$ and $\rho = 14.2\%$ calibration in Table 4 that generates essentially no wealth accumulation at all.[55] For more, Appendix Table 12 compares the full wealth distribution to the data, both unconditionally and conditional on revolving.

et al., 2024; Orchard et al., 2024). Estimated quarterly MPXs are typically two to three times larger than MPCs (Laibson et al., 2022). Our model's aggregate MPC/MPX will also increase in Section 5.2, once we additionally include unbanked and underbanked households.

[53]This is computed using a Kolmogorov backward equation. See Maxted (2024a, Appendix D.2) for details.

[54]For example, Fulford and Schuh (2023) estimate from credit bureau data that 72.4% of revolvers will remain revolvers from one quarter to the next. In the model, it is relatively easy for households to cash-out illiquid wealth to pay off credit card debt. Larger costs to accessing illiquid wealth, or optimization frictions that lessen households' ability to manage their liquidity, are likely to make credit card debt more persistent.

[55]In the data, we report the average conditional wealth to average unconditional income ratio of $\frac{210{,}093}{78{,}419} = 2.7$ and $\frac{412{,}773}{78{,}419} = 5.3$, respectively, for households with and without credit credit card debt. Even our present-bias model underpredicts the wealth of households with credit card debt to some extent, which we view as an interesting result. Present bias introduces a time-inconsistency precisely so that households are simultaneously willing to borrow on credit cards and hold illiquid wealth (Lemmas 1 and 2), but even our model with present bias is unable to produce as much illiquid wealth for revolvers as we see in the data.

In summary, present bias continues to help reconcile heterogeneous-agent models with the data on credit card borrowing. Our model with present bias generates elevated MPCs, while also inducing borrowing patterns consistent with Stylized Facts 3 and 4. Moreover, our model with present bias can fit these empirical patterns of high borrowing propensities and high MPCs – which taken alone could suggest that households are simply impatient – while still producing realistic levels of total wealth at the same time. Thus, by allowing households to act both impatiently and patiently, present bias can improve heterogeneous-agent models' fit of key empirical properties of household finances (Laibson et al., 2024).[56]

Stimulus Checks and the Paydown-Rebound of Credit Card Debt. As one further test of the model, we return to the lefthand panel of Figure 1 and use our model to simulate how credit card debt responds to the stimulus checks (EIPs) that were received in the COVID-19 recession. This simulation is presented in Figure 8 below. Starting from the steady state, we feed in three liquidity shocks of the same magnitude as each average EIP payment (vertical dashed lines) and trace the subsequent evolution of credit card debt.[57]

This is only a back-of-the-envelope exercise, but there is a clear takeaway: our present-bias model predicts that credit card borrowing is a recurrent state. Hence, policymakers should expect for the debt-relief benefits of liquidity injections to only be transient. This also relates to the MPC size-effect finding above: although households receive a large cumulative transfer of over $6,000 in the simulation, they spend that extra liquidity relatively quickly.

While our simulation broadly fits the COVID-19 period, there are two main inconsistencies relative to the data. First, the simulation predicts a rebound in credit card debt over the third and fourth quarters of 2020 (after EIP 1 but before EIPs 2 and 3) that did not materialize in reality. Second, the simulation predicts a rebound in credit card debt that starts quickly but ends slowly, whereas in the data the rebound starts more slowly but then ends faster. Of course, this back-of-the-envelope exercise ignores many of the unique

[56] See also Indarte et al. (2024) for a wedge-based empirical analysis documenting that models of household consumption should feature frictions causing both underconsumption (like financial constraints such as an elevated borrowing rate) *and* overconsumption (like $\beta < 1$).

[57] Simulation details are provided in Appendix B.4. This is only a stylized exercise, and for simplicity we are intentionally ignoring many important economic considerations of the period such as the unemployment spike in 2020, the added difficulty of purchasing certain goods during lockdowns, extended UI, and so on.

economic considerations of the period (e.g., lockdowns), so an imperfect fit is not surprising.

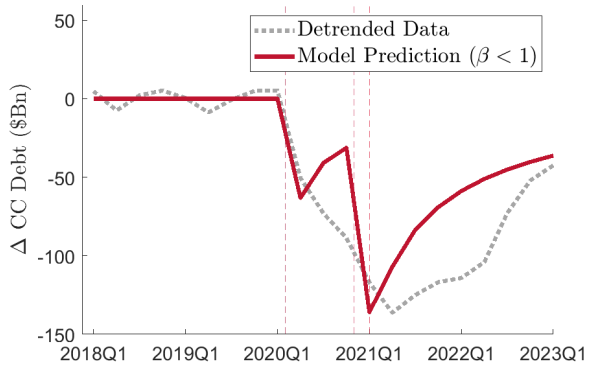


Figure 8: **Paydown-Rebound of Credit Card Debt.** This figure plots the detrended path of revolving credit card debt around the COVID-19 recession (dotted gray curve; see Figure 1), and the corresponding path of credit card debt predicted by the model (red curve). Simulation details are provided in Appendix B.4.

Figure 8 also suggests a critical, though often overlooked, methodological point relating to how economists measure the spending response to stimulus payments. A common approach is to survey households about whether they intend to use a stimulus check to "mostly spend," "mostly save," or "mostly pay off debt."[58] However, given that credit card borrowing is often a recurrent state, our model suggests that this survey question is difficult to interpret. Consider, for example, households with $2,000 of credit card debt. In the model, these households will immediately use a stimulus check to repay debt (which is natural given that credit card debt compounds daily and has a high interest rate). But, many of these households also have an MPX of more than 50% over the next quarter. Whether these households should report using a stimulus check to repay debt or to spend is ambiguous. Thus, one lesson from our model (or the data in Figure 1) is that survey designs should incorporate the fact that debt-repayment and spending are not mutually exclusive, even over relatively short horizons like a quarter or year. In addition, and as highlighted by Figures 1 and 8, just because households report using a stimulus check to pay down debt, policymakers should not necessarily expect for that additional buffer to remain for long.

[58]For foundational work, see e.g. Shapiro and Slemrod (2009). These surveys have become particularly impactful following the COVID-19 crisis as a way to quickly evaluate the spending response to Economic Impact Payments (e.g., the New York Fed Survey of Consumer Expectations; Armantier et al., 2020)

Discussion: Model Limitations. A goal of this paper is to highlight the need for further research on the causes and consequences of credit card borrowing in heterogeneous-agent models. The model presented in this section – although enriched with two assets and stochastic income – is still stylized in many ways. To this end, Appendix B.5 discusses some of the main ways in which the model here remains incomplete, with the hope that this discussion can guide future research on the types of refinements that can improve both the model's fit and the richness of its policy predictions.

5.2 Underbanked and Unbanked Households

While this paper focuses primarily on fully banked households, we end by extending our analysis to underbanked and unbanked households. Banked households compose 74% of our overall SCF sample, while underbanked households compose 20% and unbanked households compose 6%. We summarize our procedure and findings here, with details in Appendix B.6.

To account for underbanked and unbanked households' lack of access to various financial products, we differentially calibrate the household balance sheet model above for these households. Our recalibration changes three externally calibrated parameters: average household income, the interest rate on liquid savings, and the interest rate on borrowing. For income, we maintain the normalization that average income equals 1, but we redefine average income based on our SCF estimates for underbanked and unbanked households. For the liquid return, we continue to set $r = 1\%$ for underbanked households, but for unbanked households we set $r = -2\%$ since cash typically loses real value over time. Finally, since underbanked and unbanked households do not have credit cards, we assume that they turn to payday loans for credit.[59] We therefore set the borrowing rate to 362%.

We also internally recalibrate parameters ρ and β, as summarized in Table 6. Following our procedure above, we calibrate ρ to match average wealth of 1.8 for underbanked households and 0.9 for unbanked households. To calibrate β we can no longer use credit card debt (since these households do not have credit cards), so we instead match the propensity to use nonbank credit of 12% for underbanked households and 16% for unbanked households. Since the SCF's coverage of nonbank credit (e.g., payday and pawn shop loans) is limited,

[59] Some unbanked households have credit cards in the SCF, but this is rare — see Appendix A.1 for details.

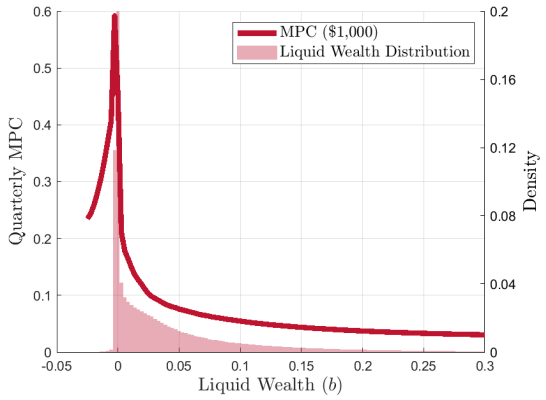
we calculate these targets using the FDIC National Survey of Unbanked and Underbanked Households (details in Appendix B.6).[60] For underbanked households we calibrate $\rho = 4.70\%$ and $\beta = 0.91$. For unbanked households we calibrate $\rho = 6.40\%$ and $\beta = 0.93$. Given the very high interest rates that typify nonbank credit, our calibration suggests that both types again require $\beta < 1$ to match the observed borrowing propensities.

	Underbanked		*Unbanked*	
	Data	Model	Data	Model
Discount Function				
β	-	0.91	-	0.93
ρ	-	4.70%	-	6.40%
Calibration Targets				
Has nonbank debt	12%	12%	16%	16%
Total wealth	1.8	1.8	0.9	0.9

Table 6: **Discount Function Calibration for Underbanked/Unbanked Households.** This table gives the discount function calibration for underbanked and unbanked households.

Next, Figure 9 replicates the analysis in Figure 7 for underbanked and unbanked households. Despite still having $\beta < 1$, we now see much less borrowing due to the very high cost of payday loans. This highlights the importance of explicitly modeling households' lack of access to credit, because their present bias suggests that these households would borrow more if given a (lower-cost) credit card to do so. Said differently, the equilibrium liquid wealth distribution relies critically on the financial products available to households.

(a) Underbanked



(b) Unbanked

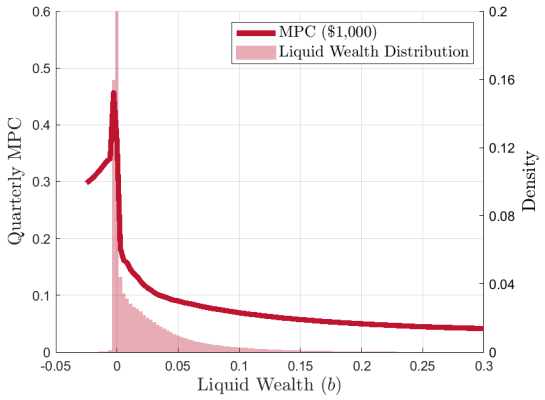


Figure 9: **MPCs and Liquid Wealth.** This figure replicates the analysis in Figure 7 for underbanked and unbanked households.

[60] These borrowing moments are likely to be lower bounds, since even this FDIC Survey does not capture all forms of credit that households may use (e.g., checking overdrafts; Stango and Zinman, 2014).

Putting It All Together: Aggregate MPCs. To end, we aggregate the three household types to evaluate the overall MPC and MPX. We consider liquidity injections of \$1,000, \$3,000, and \$5,000. Table 7 reports the aggregate quarterly MPC (MPX), and the relative contribution of banked, underbanked, and unbanked households to that MPC.

	Aggregate		*MPC Share*		
	MPC	(MPX)	Banked	Underbanked	Unbanked
\$1,000 Transfer	12.6%	(34%)	52%	36%	12%
\$3,000 Transfer	10.0%	(28%)	64%	27%	9%
\$5,000 Transfer	8.9%	(26%)	68%	24%	8%

Table 7: **Quarterly MPCs for Different Transfer Amounts.** This table reports the model's aggregate MPC (MPX), and the contribution of each household-block to that MPC.

For a \$1,000 transfer, the aggregate quarterly MPC (MPX) is 12.6% (34%), from which the relative contribution of banked, underbanked, and unbanked households is 52%, 36%, and 12%. For a \$5,000 transfer, the aggregate quarterly MPC (MPX) is 8.9% (26%), from which the relative contribution of banked, underbanked, and unbanked households is 68%, 24%, and 8%. In all cases, the banked households that compose 74% of the population are also the largest contributor to the overall MPC. Moreover, banked households' relative contribution increases as the transfer gets larger. This goes back to MPC size effects: unbanked and underbanked households generally have positive liquidity and hence are on the concave part of their consumption function, while banked households are much more likely to be borrowers and hence be on the convex part of their consumption function.

Finally, we emphasize again that present bias allows for fiscal policy to remain potent when enacted at large scales. Even for a stimulus of \$5,000, our present-bias model predicts a sizable quarterly MPC of 9% and MPX of 26%. This prediction contrasts with ZHtM-style models.[61] To contextualize the importance of this difference, recall the policy response to the recent COVID-19 recession, where a typical household received over \$5,000 of EIP payments. For a policymaker trading off the benefits of shrinking the output gap against the costs of inflationary pressure, correctly modeling the magnitude of the household consumption response is crucial for getting the size of stimulus checks correct.

[61] For example, in the canonical model of Kaplan and Violante (2014), the MPC drops from 20% for a \$500 transfer down to 3% for a \$5,000 transfer.

6 Conclusion

Modern consumption-saving models typically generate empirically realistic MPCs by having a large mass of ZHtM households that are constrained at the zero-liquid-wealth kink due to their avoidance of high-interest debt. However, this paradigm is inconsistent with the data, which instead suggests that households frequently revolve a credit card balance. We turn to present bias to fit the borrowing patterns that we document. Present bias generates a large share of households with modest amounts of credit card debt, whose *indebted saving behavior* still produces elevated MPCs. We also highlight key channels through which such borrowing alters households' responses to macroeconomic policy.

The prevalence of credit card borrowing that we observe in the data suggests several directions for future investigation. We highlight two. First, our extension to underbanked and unbanked households points to the importance of building models that account for households' differential access to consumer financial products. Second, while this paper identifies present bias as a tractable way of improving heterogeneous-agent models' fit of household borrowing patterns, our analysis here is only a first step. We encourage future research to continue exploring both the drivers and the policy implications of the credit card borrowing that has often been largely missing from macroeconomic models to date.

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ONLINE APPENDIX

A Additional Empirical Analysis and Robustness

A.1 SCF Best Practices: Controlling for Unbanked and Underbanked Households

This section examines the SCF households that are dropped by our two main filters in Section 3.1 in order to highlight the selection issues that would have arisen had we not dropped unbanked and underbanked households. For the broader literature, the contribution of this subsection is to provide a set of best practices by illustrating the importance of controlling for these households. Unbanked and underbanked households' balance sheets are often not well described by consumption models with a credit card borrowing margin – plus these households instead often borrow using credit products that are not well covered by the SCF – yet unbanked and underbanked households compose a non-trivial share of the low-measured-liquidity households in the raw SCF.

Table 8 below presents summary statistics for our overall SCF sample, and then for the two sets of households that we subsequently exclude: unbanked households without a bank account, and underbanked households without a credit card. Looking first at the overall SCF sample in Panel A, we emphasize two points. First, our preferred SCF sample is skewed toward higher-income and higher-wealth households (see Table 1). Second, the overall SCF sample features lower borrowing propensities than our preferred sample. For example, the share of households that report high-cost credit card borrowing drops from 52% in our preferred sample to 39% here. However, recall that the overall SCF sample includes unbanked and underbanked households, who generally do not have access to credit cards in the first place.

Panel B lists summary statistics for households that are unbanked. Unbanked households are not well described by typical consumption models, which assume agents have easy access to a (non-cash) liquid asset. Importantly, Panel B shows that almost all unbanked households have essentially zero measured liquid wealth (which is largely mechanical). This suggests

that had we not dropped unbanked households, we would have spuriously identified too large of a mass of ZHtM households relative to the households with bank accounts that are typically modeled.[62]

Panel C shows summary statistics for households that do not have a credit card. Households without a credit card have lower income and wealth than households with a credit card, which – given the benefits of having a credit card – suggests that it is a lack of credit supply that prevents many households from attaining one. Households that are excluded from traditional unsecured credit markets are unlikely to be accurately described by models that allow households to quickly utilize a credit card borrowing margin when desired. Panel C also shows that households without a credit card typically have minimal measured liquidity, and, unsurprisingly, do not have credit card debt. This again suggests that if we had not dropped households without a credit card, our results would have been biased toward estimating too large of a mass of low-liquidity households with too little credit card debt.

	Mean	SD	10th	25th	50th	75th	90th
Panel A: Overall SCF Sample							
Before-tax income	86,816	83,166	22,293	37,672	65,741	109,928	173,514
After-tax income	67,856	56,711	20,877	33,252	53,430	85,547	129,868
Liquid wealth	15,275	55,717	-8,937	-110	1,596	13,050	46,620
Illiquid wealth	227,859	433,424	-4,682	8,784	77,883	275,464	693,821
Has high-interest CC debt	.394	-	0	0	0	1	1
Panel B: Unbanked Households							
Before-tax income	27,269	18,620	9,029	15,088	23,710	34,554	48,498
After-tax income	25,622	15,460	9,015	15,077	23,526	33,552	42,883
Liquid wealth	-21	3,310	-234	0	0	180	692
Illiquid wealth	22,190	74,223	-8,125	0	4,100	15,263	81,900
Has high-interest CC debt	.0623	-	0	0	0	0	0
Panel C: Underbanked Households (No CC)							
Before-tax income	43,790	38,418	12,933	21,555	34,554	55,732	82,985
After-tax income	37,525	27,229	12,520	21,048	32,347	47,070	67,196
Liquid wealth	4,709	21,664	0	60	570	2,229	8,356
Illiquid wealth	56,458	150,747	-10,000	0	10,087	58,415	164,800
Has high-interest CC debt	0	-	0	0	0	0	0

Table 8: **Summary Statistics for Overall SCF Sample and Dropped Households.** This table replicates Table 1 for the overall SCF sample, and for the dropped households that are unbanked or underbanked.

[62]Though unbanked households are unlikely to borrow on a credit card, more than 85% of unbanked households report not having a credit card.

A.2 SCF Robustness

Underreporting of Credit Card Debt in the SCF. As mentioned in Section 3.1, Zinman (2009) observes that aggregate credit card debt in the SCF is significantly smaller than the amount of revolving debt in the Federal Reserve's G-19 Consumer Credit release. To partially correct for this underreporting, we adopt the method proposed by Beshears et al. (2018) and scale up each household's reported credit card debt by the scaling factors in Web Appendix C of Beshears et al. (2018).[63] These scaling factors are obtained by comparing aggregate credit card debt in the SCF with the equivalent statistics computed from various administrative sources, including the G.19 survey and Nilson Reports.

Other Data Sources: Extensive Margin of Credit Card Borrowing. We report in Section 3.2 that 52% of households in our preferred SCF sample revolve high-interest credit card debt, which is in line with other survey and administrative data sources. In account-level administrative data, the CFPB's biannual report finds that roughly 60% of accounts revolved a balance in 2019 (CFPB, 2021). Similarly, Bornstein and Indarte (2023) estimate in individual-level credit bureau data from 2010-2020 that 71% of individuals with a credit card revolved a balance at least once per quarter. In other surveys, the Federal Reserve's 2019 SHED survey reports that 52% of households with at least one credit card carried a balance in the past year (FRB, 2020). In the Atlanta Fed's 2019 SCPC survey, 47% of credit card adopters carried an unpaid balance over the past month (Foster et al., 2020).

Summary Statistics Conditional on Revolving. Adding further details to the analysis leading to Stylized Fact 5, below we present complete summary statistics for households in our preferred SCF sample that do, and do not, have high-interest credit card debt.

As already mentioned in Section 3.2, borrowers and non-borrowers are comparable in many respects: borrowers are not especially low-income on average, and many borrowers still hold sizable stocks of illiquid wealth. The largest difference (in relative terms) between borrowers and non-borrowers relates to liquid wealth, though this is somewhat mechanical.[64]

[63] In 2013 and 2016 these are 1.8 and 1.5, respectively. Beshears et al. (2018) do not report a scaling factor for the 2019 SCF wave, so we continue to use the 2016 value of 1.5.

[64] Although some households in Panel B have credit card debt, they are not counted as having *high-interest*

	Mean	SD	10th	25th	50th	75th	90th
Panel A: Has High-Interest CC Debt							
Before-tax income	91,473	75,266	31,210	46,835	73,567	115,317	171,655
After-tax income	71,425	50,456	27,084	40,019	60,051	89,244	127,585
Liquid wealth	3,446	38,422	-20,994	-6,983	-250	6,756	25,270
Illiquid wealth	206,647	333,021	-8,235	15,200	90,800	259,792	574,900
Total wealth	210,093	344,870	-16,704	12,502	88,600	263,306	597,318
Has high-interest CC debt	1	-	1	1	1	1	1
Panel B: No High-Interest CC Debt							
Before-tax income	113,263	101,046	32,325	51,731	88,057	142,541	217,701
After-tax income	86,159	68,915	28,214	43,182	69,623	108,196	158,428
Liquid wealth	36,257	78,505	-569	2,128	11,910	37,333	94,606
Illiquid wealth	376,516	591,484	2,100	44,250	190,397	522,659	1,079,035
Total wealth	412,773	620,794	4,470	54,045	212,028	578,600	1,189,636
Has high-interest CC debt	0	-	0	0	0	0	0

Table 9: **Summary Statistics Conditional on Credit Card Borrowing.** This table expands on Table 3 to provide full summary statistics for households with and without high-interest credit card debt.

Discussion: Coholding. A close inspection of Panel A of Table 9 reveals some potential coholding of credit card debt and liquid wealth (Gross and Souleles, 2002; Telyukova, 2013). Some of the apparent coholding in Table 9 is simply due to the timing mismatch between income and expenses discussed in the main text. Still, it is well known that a subpopulation of households cohold credit card debt and liquid wealth, whereas our model precludes such coholding (and instead focuses on the coholding of credit card debt and *illiquid* wealth). However, at least to the extent that coholding is rational, this simplification is unlikely to significantly affect our conclusions. Specifically, to the extent that coholding is driven by a rational response to liquidity needs (see e.g. Telyukova, 2013), then the fact that a household with some positive liquid assets simultaneously revolves credit card debt reveals that the shadow value of that household's positive liquid holdings is effectively the credit card interest rate (if not, the household could pay down its credit card). From the lens of our model with a single liquid asset, this observation then implies that it is more accurate to label a coholding household as a borrower rather than a ZHtM household, since this household's marginal intertemporal price of consumption is still reflected by the high credit card interest rate (e.g., 16%) that they are willing to pay.[65]

credit card debt if they report an APR of 5% or less.

[65]Said differently, rational coholding doesn't disturb the key point from Section 2 that a household's usage of a high-cost borrowing margin implies that the household is "on the Euler equation" for that asset.

On the other hand, our conclusions could be more seriously affected if coholding is driven by an alternative behavioral bias such as mental accounting (see e.g. Batista et al., 2024; Gathergood and Olafsson, 2024). If this is the case, then it could also imply that credit card borrowing more broadly is driven by that alternative behavioral bias (rather than present bias). We leave the modeling of this potential alternative bias, and its consequences for macroeconomic policy, as an interesting topic for future research.

Further Robustness Checks. We provide three additional robustness checks on our empirical analysis in Section 3.2. First, Table 10 below replicates Table 2 from the main text, but bins households based on dollars of measured liquid wealth rather than the liquid wealth to income ratio. Results are comparable in both cases. Second, the lefthand panel of Figure 10 plots the credit card borrowing propensity in each SCF wave (otherwise using the same sample criteria as in our preferred sample). In the main text, we chose to study the 2013, 2016, and 2019 SCF waves with the following criteria in mind: (i) we want a large sample that spans multiple SCF waves; (ii) we want a more recent sample; and (iii) we do not want our results to be overly influenced by the Great Recession nor the COVID-19 recession. Nonetheless, Figure 10 shows that we see similar (or even higher) levels of high-cost borrowing across SCF waves. Third, the righthand panel of Figure 10 plots the credit card borrowing propensity by 5-year age buckets (grouping together households with heads aged 23-27, 28-32, 33-37, and so on). There is potentially a slight inverse-U shape, but credit card borrowing propensities are broadly comparable across all ages that we study.

	[0, $5,000]	[0, $3,000]	[0, $1,000]
Share of Preferred SCF Sample	0.217	0.157	0.073
Proportion (within) with high-interest CC debt	0.480	0.477	0.491
	(0.012)	(0.012)	(0.017)
Share of Overall SCF Sample	0.369	0.310	0.199

Table 10: **Credit Card Borrowing by Low-Measured-Liquidity Households.** This table is similar to Table 2, but bins households based on dollars of measured liquid wealth.

(a) Credit Card Borrowing by SCF Wave



(b) Credit Card Borrowing by Age

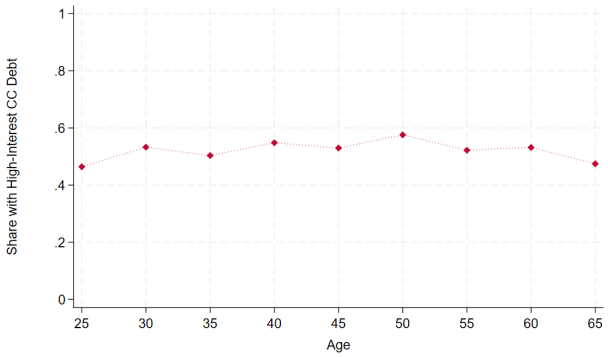


Figure 10: **Credit Card Borrowing by SCF Wave and Age.** The lefthand (righthand) panel plots the share of households that report revolving high-cost credit card debt in each SCF wave (by age group).

B Additional Modeling Details and Results

B.1 Additional Analysis of Cake-Eating Model with a Credit Card

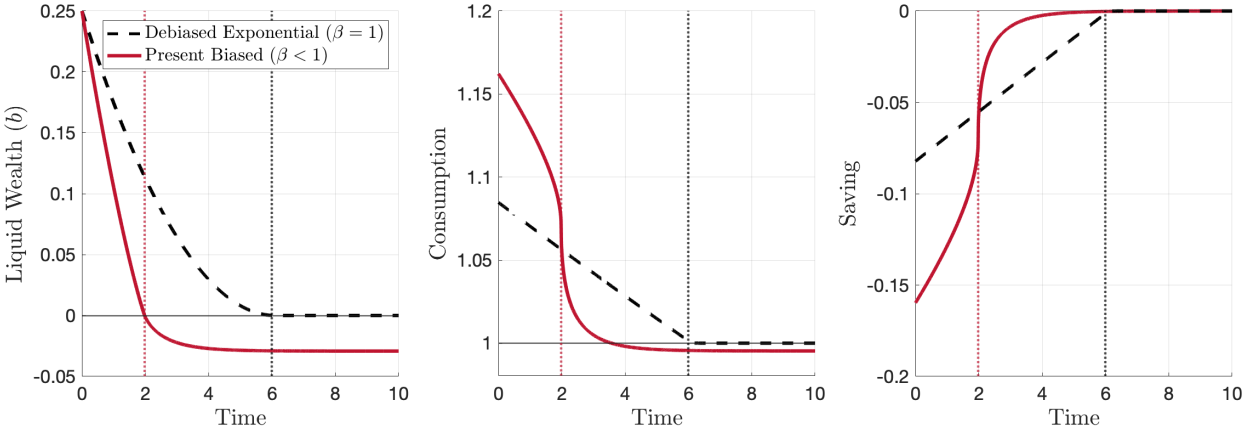


Figure 11: **Time Path of Wealth, Consumption, and Saving.** This figure plots the time path of liquid wealth (left), consumption (middle), and saving (right) for the debiased exponential agent (dashed black curve) and the present-biased agent (red curve). Wealth is initialized to $b_0 = 0.25$, and the vertical dotted lines mark where each agent hits $b = 0$. The present-biased agent revolves some credit card debt in the long run, whereas the debiased exponential agent never goes below the soft constraint of $b = 0$.

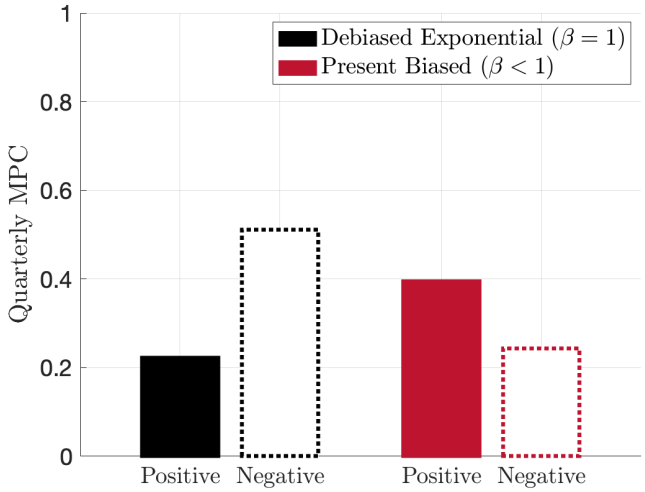


Figure 12: **MPC Sign Asymmetry.** This figure plots the quarterly MPC out of both a positive and a negative liquidity shock of $\chi = 0.03$ (i.e., 3% of annual income). The lefthand panel (black) plots the $\beta = 1$ case, and the righthand panel (red) plots the $\beta < 1$ case. Prior to receiving the liquidity injection, each agent starts from their respective steady-state (absorbing) wealth level. This figure shows that MPCs are generally larger out of negative shocks than positive shocks when $b \geq 0$, but MPCs are generally larger out of positive shocks than negative shocks when $b < 0$.

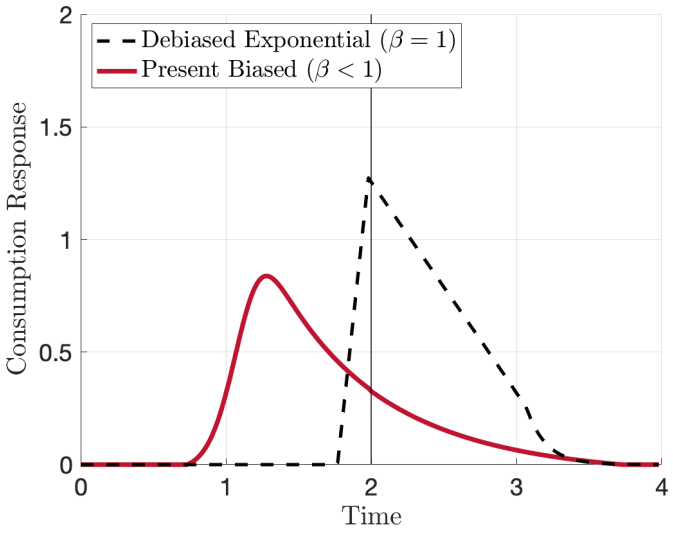


Figure 13: **Consumption Response to Future Wealth Shock.** This figure plots the consumption response to a wealth shock that occurs at time $t = 2$ for the debiased exponential agent (dashed black curve) and the present-biased agent (red curve). Prior to receiving news of the shock at time $t = 0$, each agent starts from their respective steady-state (absorbing) wealth level. The consumption response is scaled relative to the shock χ.

B.2 Footnote 39: Additional Details on $\beta r < \rho < r$ Case

Maxted (2024) shows that present bias will cause the agent to dissave for $b \geq 0$ so long as $\rho > \beta r$ (rather than $\rho > r$ in the $\beta = 1$ case). When $\beta r < \rho < r$, we now have that $c'(b) \to \frac{1}{\psi}\left(\frac{\rho-(1-\gamma)r}{\gamma}\right) \times \left(\frac{r+\omega^{cc}-\rho}{r-\rho}\right)$ as $b \uparrow 0$ and $c'(b) \to \frac{1}{\psi}\left(\frac{\rho-(1-\gamma)r}{\gamma}\right)$ as $b \downarrow 0$. Though the derivatives are no longer unbounded at $b = 0$, it is still the case that the left derivative is greater than the right derivative so long as $\omega^{cc} > 0$. That is, we again see that the soft borrowing constraint increases the slope of $c'(b)$ to the left of $b = 0$.

To prove this result, we start with the property that the debiased exponential agent consumes $\check{c}(b) = \frac{\rho-(1-\gamma)r}{\gamma}\left(b + \frac{\bar{y}}{r}\right)$ for $b \geq 0$ in this deterministic model (see e.g. Fagereng et al., 2019). Since Lemma 1 implies that the present-biased agent's consumption is $\frac{1}{\psi}$ times the consumption of the debiased exponential agent, we therefore have that $c'(b) \to \frac{1}{\psi}\left(\frac{\rho-(1-\gamma)r}{\gamma}\right)$ as $b \downarrow 0$.

For $b < 0$, we can differentiate the HJB equation of the debiased exponential agent to get (see equation (18) of Achdou et al. (2022) for details):

$$(\rho - (r + \omega^{cc}))u'(\check{c}(b)) = u''(\check{c}(b))\check{c}'(b)\left(\bar{y} + (r + \omega^{cc})b - \check{c}(b)\right).$$

Taking the limit as $b \uparrow 0$ and using the property that $\check{c}(0) = \frac{\rho-(1-\gamma)r}{\gamma}\left(\frac{\bar{y}}{r}\right)$ gives that $\check{c}'(b) \to \left(\frac{\rho-(1-\gamma)r}{\gamma}\right) \times \left(\frac{r+\omega^{cc}-\rho}{r-\rho}\right)$ as $b \uparrow 0$. Using Lemma 1 to scale up the consumption function by $\frac{1}{\psi}$ completes the proof.

B.3 Heterogeneous-Agent Model Calibration Details

Here we provide calibration details for the two-asset heterogeneous-agent model (for banked households) presented in Section 5. Our full calibration is summarized in Table 11 below.

Starting with household preference parameters, discount function parameters β and ρ are calibrated internally to fit average wealth and credit card borrowing moments estimated from the SCF. See Section 5 for details. Risk aversion parameter γ is set to 1.5, consistent with Lee et al. (2021) and in the range of typical values used in the heterogeneous-agent literature.[66]

[66]For example, Kaplan et al. (2018) calibrate a relative risk aversion of 1 while Auclert et al. (2024)

We follow Guerrieri and Lorenzoni (2017) in calibrating the income process based on Floden and Lindé (2001). Floden and Lindé (2001) estimate an AR(1) process for log income, which we convert to a continuous-time Ornstein-Uhlenbeck (OU) process following the method in the Appendix of Maxted et al. (2024). We set the max/min income state to ±2 unconditional standard deviations of the OU process, and discretize the OU process across 15 states using finite difference methods. Average income $\bar{y}$ is normalized to 1.

We set the risk-free return on the liquid asset r equal to 1%, as in Maxted et al. (2024). When households first start borrowing, we assume that they do so on a credit card. We set the credit card borrowing wedge ω^{cc} to 15.18%, because households in our preferred SCF sample report a median borrowing interest rate of 16% whereas the average federal funds rate over this period was 0.82%.[67] We set the credit card borrowing limit to $b^{cc-limit} = -0.25$ (i.e., one-quarter of average annual income) following Kaplan et al. (2018). Beyond that point, any subsequent borrowing must be done with payday loans. Since a typical payday loan rate is 15% per two-week borrowing period,[68] we set the payday loan rate to 362%.[69]

The risk premium on the illiquid asset is 4% with a volatility of 18%, following the calibration of Gomes and Michaelides (2005). We set the arrival rate of adjustment opportunities to $\lambda^a = 12$, as in Kaplan and Violante (2022). Relative to other papers in the literature, one difference with our setup for asset illiquidity is that we allow for differential costs on deposits versus withdrawals. Given that we treat the illiquid asset as a stock index – like wealth held in a defined-contribution (DC) retirement plan – this additional flexibility is natural. We assume that households can costlessly contribute to the illiquid asset when given an adjustment opportunity.[70] However, withdrawals are subject to a 10% penalty rate in order to capture the typical 10% penalty tax rate charged to early withdrawals in the United States. For numerical stability and to prevent households from making trivial fine-tuning

calibrate a risk aversion of 2.

[67] We use the median reported interest rate to account for potential outliers.

[68] For details on the cost of payday loans, see e.g. https://www.consumerfinance.gov/ask-cfpb/what-are-the-costs-and-fees-for-a-payday-loan-en-1589/

[69] A 15% two-week interest rate equates to a renormalized nominal payday loan rate given by $1.15 = \exp(r^{payday} \times \frac{14}{365})$, or roughly $r^{payday} = 364\%$. We subtract 2% to account for inflation.

[70] On the one hand, this ignores the employer match that households may receive when contributing to a DC retirement account. On the other hand, retirement accounts are subject to contribution limits that we do not model here.

adjustments, we also impose a very small fixed adjustment cost of \$10. Overall, our setup for asset illiquidity is stylized, and we view additional enrichments focused both on expanding the space of illiquid assets (e.g., homes in addition to retirement accounts) and the realism of those assets (e.g., carefully modeling the tax treatment of equities) as interesting future research steps.[71]

We set the retirement rate $\lambda^R = \frac{1}{45}$ to generate an average working life of 45 years (Kaplan et al., 2018). When households retire, we follow the specification of Maxted et al. (2024) and assume that households consume a deterministic income flow (earned at a 75% replacement rate) plus a return of r on their total wealth. This gives an exponentially discounted retirement value of $v^R(x) = \frac{u(0.75\bar{y}+r\times(b+a))}{\rho}$.[72]

	Description	Value	Target / Source
Preferences			
β	Short-run discount factor	0.84	(see Section 5)
ρ	Long-run discount rate	3.17%	(see Section 5)
γ	Risk aversion	1.5	Lee et al. (2021)
Income			
-	Income process	(see text above)	Floden and Lindé (2001)
Liquid Asset			
r	Risk-free rate	1%	Maxted et al. (2024)
ω^{cc}	Credit card borrowing wedge	15.18%	SCF
$b^{cc-limit}$	Credit card limit	-0.25	Kaplan et al. (2018)
ω^{payday}	Payday borrowing wedge	361%	Typical payday loan rate
Illiquid Asset			
r^a	Return on illiquid asset	5%	Gomes and Michaelides (2005)
σ^a	Volatility of illiquid asset	18%	Gomes and Michaelides (2005)
λ^a	Illiquid asset adjustment rate	12	Kaplan and Violante (2022)
-	Illiquid asset transaction cost $\chi(\cdot)$	(see text above)	U.S. DC pension plan
Other Structural Assumptions			
λ^R	Retirement rate	$\frac{1}{45}$	Kaplan et al. (2018)
-	Retirement functional form	(see text above)	Maxted et al. (2024)

Table 11: **Model Calibration.** This table presents the calibration that we use in our two-asset heterogenous-agent model in Section 5.

[71] Relatedly, see Di Tella et al. (2024) for an exploration of how a two-account model such as this can be used to address asset pricing facts in addition to facts about household-level consumption behavior.

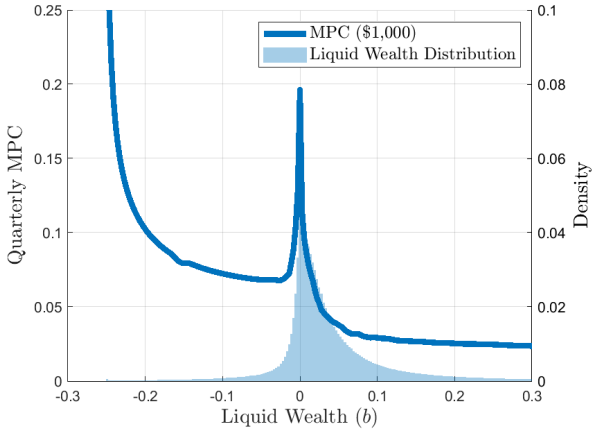
[72] Note that we do not actually model households in retirement, but we assume a simple terminal value to provide a realistic retirement-saving motive during working life.

B.4 Additional Analysis of Heterogeneous-Agent Model

$\beta = 1$ Calibrations. Section 5 focuses on the $\beta < 1$ case, since the two $\beta = 1$ calibrations that we consider do not provide as good of a fit to the micro data on credit card borrowing and wealth accumulation (see Table 4). For more on the $\beta = 1$ cases, Figure 14 below replicates the analysis in Figure 7 for the two $\beta = 1$ calibrations. Perhaps unsurprisingly, it turns out that both $\beta = 1$ calibrations also produce elevated MPCs. But, they each do so in ways that are inconsistent with the facts about household finances documented in Section 3.

For the calibration with $\beta = 1$ and $\rho = 4.08\%$, the average quarterly MPC (MPX) is 7.0% (19.5%). As the lefthand panel of Figure 14 shows, however, only 19% of households in this calibration carry any credit card debt. Instead, most of the elevated average MPC is driven by the large mass of ZHtM households at, or just to the right, of the zero-liquid-wealth kink. As discussed throughout Section 3, this grouping of households is at odds with the data on household borrowing behavior. For the calibration with $\beta = 1$ and $\rho = 14.20\%$ in the righthand panel of Figure 14, the average quarterly MPC (MPX) is 21.1% (58.8%). While it's not too surprising that a model with such a large discount rate can generate large MPCs, this calibration also (counterfactually) generates essentially no wealth accumulation on average. It's also interesting to note that even though this calibration matches the 52% borrowing propensity observed in the SCF, it still produces a large mass of ZHtM households that is inconsistent with the evidence in Table 2.

(a) $\beta = 1$ and $\rho = 4.08\%$



(b) $\beta = 1$ and $\rho = 14.20\%$

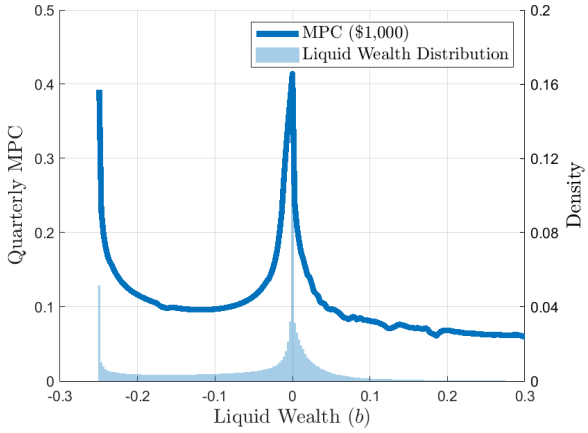


Figure 14: **MPCs and Liquid Wealth.** This figure replicates the analysis in Figure 7 for the two $\beta = 1$ calibrations.

Additional Results for $\beta < 1$ Calibration. Here we provide two additional results for the two-asset model with $\beta < 1$ from Section 5. First, Table 12 presents a fuller comparison of the wealth distribution in the model and in the data. Overall the model performs reasonably well at matching the wealth distribution both unconditionally and conditional on revolving status. However, the model underpredicts the wealth of households with credit card debt to some extent.

	10th	25th	50th	75th	90th
Panel A: Unconditional					
Data	-0.1	0.3	1.7	5.0	11.5
Model	-0.1	0.1	1.4	5.0	10.6
Panel B: Has High-Interest CC Debt					
Data	-0.2	0.2	1.1	3.4	7.6
Model	-0.2	0.0	0.3	2.5	6.5
Panel C: No High-Interest CC Debt					
Data	0.1	0.7	2.7	7.4	15.2
Model	0.2	1.0	3.2	7.5	14.2

Table 12: **Wealth Distribution in the Model and Data.** This table compares the wealth distribution predicted by the model to the corresponding total wealth moments reported in Tables 1 and 3 (scaled by average income of \$78,419).

Next, Figure 15 shows how the MPC and MPX vary with the size of a fiscal transfer (similar to the analysis in Figure 5). As discussed in Section 4.3, an implication of indebted saving behavior is that MPCs and MPXs remain elevated even for large stimulus checks. This effect is again illustrated in Figure 15 which shows, for example, that the average quarterly MPX remains above 20% for transfers up to roughly \$10,000.

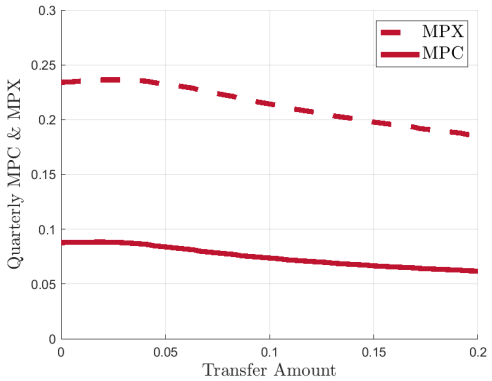


Figure 15: **Quarterly MPCs for Different Transfer Amounts.** This figure plots average quarterly MPCs (solid line) and MPXs (dashed line) across varying transfer amounts. To interpret magnitudes, recall that a transfer of 0.05, for example, corresponds to 5% of average annual income (average after-tax income is \$78,419 in our preferred SCF sample; Table 1).

MPCs and MPXs. In Section 5 we report MPCs and MPXs, where the MPX is imputed using the mapping provided in Laibson et al. (2022). The consumption-saving model in Section 5 makes predictions about notional consumption (i.e., utility-generating consumption flows). Durable goods drive a wedge between notional consumption and consumer spending, since durables generate a one-time burst of expenditure but a long-lasting flow of utility. Both the MPC and the MPX can be relevant concepts depending on the question at hand, which is why we report both in Section 5.

In more detail, Laibson et al. (2022) show that the mapping from MPCs to MPXs can be computed using the formula: $MPX_\tau(x) = \left(1 - s + \frac{\delta s}{r+\delta}\right) MPC_\tau(x) + \frac{s}{r+\delta} \times \frac{\partial}{\partial b}\mathbb{E}[c(x_\tau)|x_0 = x]$, where δ is the depreciation rate (calibrated to 22%) and s is the durable share (calibrated to 12.5%). While Laibson et al. (2022) argue that this mapping provides a good reduced-form fit of the data, they also emphasize that it relies on strong assumptions (most importantly, that durables are liquid) and hence should be interpreted with a measure of caution.

Details of Figure 8. Starting from the model's steady state, we simulate the three rounds of stimulus checks that were disbursed to U.S. households around April 2020, January 2021, and March 2021. For each EIP, we calculate the stimulus amount that we feed into the simulation by dividing the total payment at each round (as reported by the IRS)[73] by the number of U.S. households in 2020 (126.8 million).[74] The resulting payment per household for the three rounds are \$2,141, \$1,116, and \$3,166. After simulating the model from 2020 to 2023, we take a quarterly snapshot of credit card debt in the model (converted to an aggregate dollar amount) and compare it to the data (also measured quarterly).

We make two adjustments to make the simulation more comparable to the data. First, to synchronize the pre-COVID period in the data with the steady state in the model, we detrend the data by subtracting an extrapolated linear trend fitted to the pre-COVID period. Second, we scale the model-predicted credit card debt amount in order to account for sample differences between the model and the data. Specifically, since the Y-14 data that we use only captures large banks with total consolidated assets of \$100 billion or more, we first

[73] https://www.pandemicoversight.gov/news/articles/update-three-rounds-stimulus-checks-see-how-many-went-out-and-how-much

[74] https://www.census.gov/library/publications/2024/dec/c2020br-10.html

scale down the model-predicted estimates by the ratio of large bank credit card balances to total credit card balances (the scaling factor is 0.92). We next adjust the model-predicted estimates by the ratio of all credit card debt to high-interest credit card debt in the SCF, since our model only captures high-interest credit card debt (the scaling factor is 1.18). Lastly, we multiply our model-predicted average estimate by 126.8 million $\times$ 74%, since we assume that 74% of all households have a credit card (given that our preferred SCF sample captures 74% of the overall SCF sample).

B.5 Heterogeneous-Agent Model: Discussion of Limitations

Despite being enriched with two assets and stochastic income, the heterogeneous-agent model presented in Section 5 is still a relatively stylized model. For instance: our assumption that log income follows an AR(1) process is a simplification, as discussed recently for example in Ganong et al. (2024); our treatment of the illiquid asset as a DC retirement account abstracts from housing, which is an important source of wealth for many households; we ignore preference heterogeneity. In this section we discuss some of the main ways in which the model in Section 5 is incomplete, which we hope will guide future research on the sorts of model enrichments that can continue to improve the model's fit of the micro data.

To begin – and as already discussed in the main text – our policy analysis on the implications of credit card borrowing is presented in partial equilibrium. Guided by the results in Section 4.3, we view a full general equilibrium analysis as an important future research step.

Our two-asset model also has some flaws in terms of matching the micro data on household finances. Although the model performs reasonably well at fitting the total wealth of households with and without credit card debt, its fit of these conditional moments is not perfect. In particular, Table 5 and Appendix Table 12 show that the model generates too little wealth for households with credit card debt, and too much wealth for households without. The model also generates too little credit card debt on the intensive margin, largely because the model misses the right tail of credit card balances shown in the righthand panel of Figure 2. In the SCF, average credit card debt relative to average income is 0.14, whereas average credit card debt in the model is 0.053.[75] Relatedly, the model predicts a strong

[75]This average looks only at households with credit card debt. As discussed in Appendix A.2, credit card

negative relationship between average credit card debt and illiquid wealth, which is not immediately apparent in the SCF. The model predicts that, conditional on having non-zero illiquid wealth, average credit card debt drops to 0.022. That is, the model predicts that households with credit card debt will tend to liquidate their illiquid wealth in order to repay that debt, which prevents households with illiquid wealth from also accumulating large credit card balances. Larger fixed costs to accessing illiquid wealth – which are particularly realistic for home equity – may help to resolve this inconsistency.

Our model also misses to some extent on the decomposition of average wealth into its liquid and illiquid components (though as discussed above, liquid wealth is difficult to measure precisely in the data). In the SCF, average liquid wealth is 0.2 and average illiquid wealth is 3.7 (both scaled relative to average income). In the model, the breakdown between average liquid and illiquid wealth is 0.0 and 3.9, respectively. Some of this difference is likely due to the fact that withdrawals from the illiquid asset are not particularly costly in the model (in terms of both money and effort), and hence there is little reason for the households in our model to accumulate large liquid-wealth buffers.

Finally, our modeling of the credit card environment is stylized. We abstract from default, and we assume that all households face the same credit card interest rate and credit limit. Papers such as Chatterjee and Eyigungor (2024), Dempsey and Ionescu (2024), and Herkenhoff and Raveendranathan (2024) provide a richer treatment of the credit card market.[76] Our analysis also focuses entirely on the U.S. context. While households in some countries have comparable levels of credit card borrowing, households in others borrow far less (Badarinza et al., 2016). An examination of the underlying drivers of these cross-country differences is likely to prove interesting for future research.

We also encourage future research to enrich the modeling of underbanked and unbanked households. As discussed throughout the main text, accounting for households' differential access to consumer financial products is an underexplored topic in the heterogeneous-agent literature. Our analysis in Section 5.2 provides only a preliminary treatment.

borrowing in the SCF is scaled up to account for underreporting.

[76] More broadly, for a rich emerging literature on the IO of credit card markets see also papers such as Nelson (2022), Guttman-Kenney and Shahidinejad (2023), Benetton and Buchak (2024), Matcham (2024), and Wang (2024).

B.6 Underbanked and Unbanked Households: Additional Details

Calibration Target: Nonbank Credit Usage. Because the SCF has limited coverage of nonbank credit, we use the FDIC National Survey of Unbanked and Underbanked Households to determine the borrowing propensity of underbanked and unbanked households. We use the 2015, 2017, and 2019 survey waves, and condition on households that (i) do not have a credit card, and (ii) are in the labor force.[77] On this sample we calculate the share of households that used a nonbank credit product in the past 12 months, where nonbank credit includes payday loans, pawn shop loans, auto title loans, refund advance loans, and rent-to-own. We calculate the nonbank borrowing propensity both for underbanked households that do have a bank account (but do not have a credit card), and for unbanked households that have neither a bank account nor a credit card.

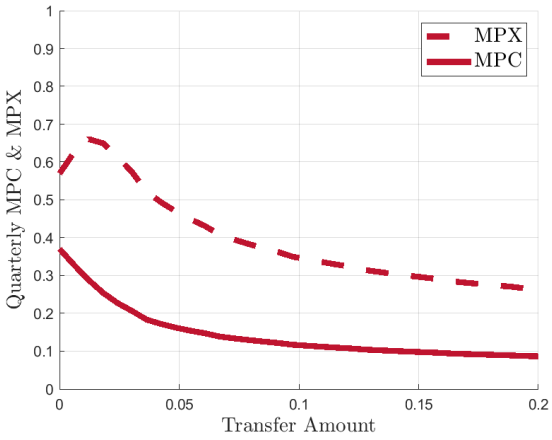
Model Calibration Details. The model calibration for underbanked and unbanked households is broadly similar to the calibration for banked households detailed in Appendix B.3. We make three changes to the externally calibrated parameters. First, average income for underbanked households is $41,158, and average income for unbanked households is $25,622.[78] Second, we set the liquid return r to -2% for unbanked households. Third, we assume that underbanked and unbanked households use payday loans for borrowing, so we set the borrowing rate to 362% (see Appendix B.3 for details). Finally, note that our recalibration procedure makes the simplifying assumption that there are no transitions between being unbanked, underbanked, or banked. While such transitions may be important they are beyond the scope of this paper, which attempts only a preliminary analysis.

Additional Results. Figure 16 replicates Figure 15 for underbanked and unbanked households. Relative to banked households, the key difference here is that underbanked and unbanked households are more likely to be on the concave part of their consumption function, and hence the MPC declines more quickly with respect to the transfer size.

[77] This second restriction is roughly equivalent to our dropping retired households in the SCF analysis.

[78] To exclusively sort SCF households into unbanked versus underbanked for this calibration, we include all households without a bank account as unbanked. Underbanked households are the remaining households that do have a bank account, but do not have a credit card.

(a) Underbanked



(b) Unbanked

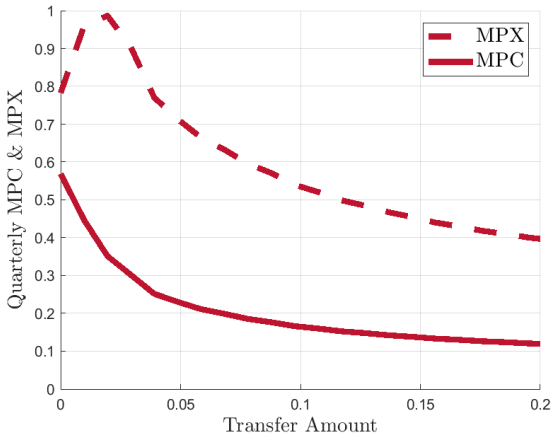


Figure 16: **Quarterly MPCs for Different Transfer Amounts.** This figure replicates the analysis in Figure 15 for underbanked and unbanked households.

Appendix References

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