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, with the goal of first matching household-level balance sheet moments before aggregating up to evaluate macroeconomic implications. 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 (see e.g. Parker et al., 2013). Second, many households hold minimal liquid wealth, despite oftentimes holding sizable stocks of illiquid wealth simultaneously (see e.g. Campbell, 2006; Kaplan et al., 2014). Due to 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 not 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]

Is this recently dominant modeling paradigm consistent with the data on household borrowing? We test the ZHtM framework by adopting the tools of household finance. Specifically, while the macroeconomic literature has often justified this 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. Instead, 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. In this paper, we adopt such a portfolio-choice-based approach by investigating households' propensity to revolve high-interest credit card debt. We document that this propensity is larger than predicted by the ZHtM paradigm, discuss how to realign heterogeneous-agent models with the borrow-

[1] See Kaplan and Violante (2021) 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).

ing data, and then aggregate up to evaluate the implications of credit card borrowing for macroeconomic policy.

As a first step, we examine credit card borrowing in the data. Borrowing decisions reveal households' marginal intertemporal price of consumption, and hence shed light on the intertemporal consumption choices that are at the core of macroeconomics and finance (Zinman, 2015). Using the Survey of Consumer Finances (SCF), we document that more than 50% of households with a credit card revolve high-interest credit card debt. That is, the majority of households with a credit card choose to carry an interest-bearing balance from one billing cycle to the next. Moreover, households with measured net liquid wealth of roughly zero also exhibit similarly large borrowing propensities. Viewed from the perspective of household portfolio-choice decisions, such active "participation" in credit card borrowing reveals the extent to which households willingly incur the high marginal price of consumption that credit card borrowing entails (the median credit card rate is 16% in our sample).

The overall borrowing propensity that we observe empirically is much larger than typically predicted by conventional heterogeneous-agent models.[3] Despite this large extensive margin of high-cost borrowing, however, we find on the intensive margin that households are generally quite far from hitting their credit limit and instead borrow only intermediate amounts (e.g., the median revolving balance is roughly $2,500). That is, most borrowers are not constrained at a kink in their budget set (neither the zero-liquid-wealth kink nor their credit card limit), and hence their credit card borrowing decisions reveal their marginal valuation of borrowing. Combining these findings, our empirical analysis provides a third stylized fact about household balance sheets: households exhibit high extensive margin, but modest intensive margin, usage of credit card debt. We also use credit bureau data from Experian to document a fourth stylized fact: revolving credit card debt is persistent.

The pervasiveness of credit card borrowing in the data is inconsistent with the conventional ZHtM modeling paradigm, which is instead built on the premise that many households have high MPCs because they are constrained due to their eschewal of high-cost debt.

[3]Many heterogeneous-agent models impose hard no-borrowing constraints that (unrealistically) prohibit borrowing completely. Of models that allow for unsecured borrowing, examples include Kaplan et al. (2018) which predicts that 15% of households will borrow (at a borrowing wedge of 6%), and Kaplan and Violante (2014) which predicts that 26% of households will borrow (at a borrowing wedge of 7.5%).

This empirical tension presents a theoretical challenge: despite constrained, hand-to-mouth, households being the canonical modeling tool that economists use to generate realistic MPCs, our empirical findings suggest that a new theory is needed.

We then turn to a theoretical analysis and ask whether present bias can improve consumption-saving models' joint fit of household borrowing and MPCs. In contrast to standard exponential time preferences, present-biased preferences are time inconsistent and induce a predisposition for immediate gratification (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 specific applications to high-cost borrowing (e.g., Meier and Sprenger, 2010; Kuchler and Pagel, 2021; Allcott et al., 2022; Laibson et al., 2022a). 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, 2022).

To make progress on the empirical tension 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 generate large consumption responses. Combining our two propositions, the role of present bias is to get households to revolve intermediate levels of high-cost debt, and households in this indebted state display large MPCs.

We next show that credit card borrowing has important implications for how households respond to macroeconomic policy, a central concern 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, since larger wealth shocks can leave households debt-free and hence willing to consume more rapidly. 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 decline rapidly in the size of a liquidity injection. 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, since it implies that even large stimulus checks can generate sizable spending responses.

Our model with present bias also yields novel predictions about households' dynamic response to fiscal stimulus. Specifically, 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 quickly thereafter. 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 debt when stimulus checks were received (as marked by the vertical dashed lines). But, what is perhaps less recognized is that debt paydown was only 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. To the extent that credit cards are short-term variable-rate products that move with monetary policy – a pattern which is broadly true following the 2009 CARD Act (Nelson, 2022; Grodzicki, 2023)[4] – present bias will reshape the channels through which monetary policy operates. Specifically, 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 follow-

[4]In particular, many credit cards are variable-rate products with an interest rate based on the prime rate.

ing 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 interest rates have risen alongside the federal funds rate over the past year.

(a) Revolving Credit Card Balances (b) Credit Card and Federal Funds Rates

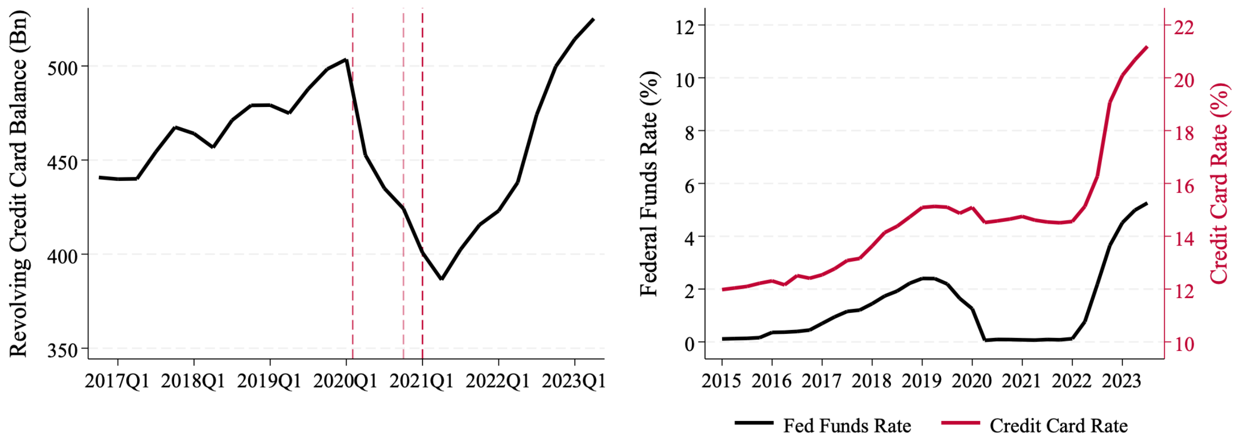

Figure 1: **Revolving Credit Card Balances and Interest Rates.** The lefthand panel plots aggregate revolving credit card balances (black curve; data from the Y-14M report for large banks only), using vertical dashed lines to mark the timing of the three rounds of stimulus payments. The righthand panel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

To introduce readers to consumption-saving models with present bias, we initially conduct both our household-level and macro-policy analyses in a stripped-down cake-eating model with a credit card. We end by presenting a richer model with illiquid (equity-like) assets and stochastic income to show that the insights developed in our simple model continue to hold. This richer model also clarifies that present bias differs from simply high impatience, as our model with present bias produces realistic levels of illiquid wealth accumulation alongside credit card borrowing.

The remainder of this paper proceeds as follows. Section 2 reviews the heterogeneous-agent literature to provide a basis for our empirical tests. Section 3 presents our empirical analysis, and documents the pervasiveness of high-cost borrowing in the data. Our theoretical analysis begins in Section 4, where we use a simple 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 heterogeneous-agent model with stochastic income and illiquid assets. Section 6 concludes.

2 ZHtM: A Brief Review of the Literature

To ground our empirical analysis, we start by briefly reviewing the 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 may 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 this paper we focus on the "soft borrowing constraint," which is the kink that arises at zero liquid wealth whenever households face a wedge between the interest rate on borrowing versus saving. Soft constraints inhibit borrowing by making debt costly, but they do not rule out borrowing completely. While it is also common for models to take the borrowing wedge to infinity and thus impose a "hard borrowing constraint" that explicitly prohibits any borrowing, this approach is not intended to be realistic for the majority of U.S. households that have quick access to bank credit (e.g., through their credit cards). For these households, hard constraints at zero liquid wealth are best interpreted as a simplifying assumption that captures the essence of soft constraints, particularly if soft constraints are rarely breached.

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 literature in household finance that documents the *pervasiveness* of

[5]Foundational work in this literature includes Cochrane (1989), Zeldes (1989), Deaton (1991), Carroll (1992, 1997), and more recently Kaplan and Violante (2014). For a small set of recent papers that also provide a richer exploration of the theoretical mechanisms at play, see Auclert et al. (2018), Aguiar et al. (2020), Carroll et al. (2021), Kaplan and Violante (2021), and Achdou et al. (2022).

[6]E.g., Johnson et al. (2006), Parker et al. (2013), Agarwal and Qian (2014), Broda and Parker (2014), Cloyne and Surico (2017), Havranek and Sokolova (2020), Ganong et al. (2020), and Fagereng et al. (2021).

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

high-cost borrowing.[8] While these two literatures have largely developed separately from one another, a contribution of our paper is to bring them more closely together.

A "Portfolio Choice" Based Framework. To justify the 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]

In this paper, we instead start with the observation that the ZHtM framework presumes not only that households hold zero net liquid wealth, but also that they bunch at zero liquid wealth precisely to avoid revolving high-cost debt. This is, in practice, a portfolio-choice prediction that ZHtM households do not take short positions in high-cost unsecured debt products such as credit cards.

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.[10] 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 choose not to borrow because the cost r^{cc} is too high. Critically, this constrained ZHtM agent will also have an MPC of 1, because if they are given ϵ more liquidity at time t then

[8] See e.g. Ausubel (1991), Agarwal et al. (2015), Fulford and Schuh (2015), Zinman (2015), Keys and Wang (2019), Kuchler and Pagel (2021), and reviews in Beshears et al. (2018) and Gomes et al. (2021).

[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] For simplicity we use discrete time here, though our later theoretical analysis will be expressed in continuous time (starting in Section 4).

the first inequality in (1) implies that they will optimally consume that liquidity now.

Alternatively, if we observe that an agent is actively revolving a credit card balance then this means they are not constrained at the zero-liquid-wealth kink. 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 face a marginal price of consumption of r^{cc}.

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 to not 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 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?

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.[11] We adjust all nominal figures to 2019 dollars.

Our measure of pre-tax income comes directly from the SCF summary extract file. For after-tax income, we use the NBER TAXSIM program to calculate federal tax liabilities, and then subtract an additional 5% for state taxes. A household's liquid assets are defined as the sum of liquid transactions account balances, cash, and government and corporate bonds, minus revolving credit card debt.[12] Illiquid wealth is defined as the remaining SCF wealth

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

[12] Our measure of liquid wealth follows Kaplan et al. (2018). The SCF does not include data on cash holdings, so cash holdings are imputed from the Survey of Consumer Payment Choice.

categories that are not included in liquid wealth.[13]

Our definition of credit card debt again simply follows the SCF summary extract file. 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%.[14] 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.[15]

SCF Sample Selection. We now describe our SCF sample criteria. To begin, we follow Kaplan and Violante (2014) and drop the top 5% of households by net worth.[16] We also drop retired households, since retirees face additional economic considerations that are not well captured by our stationary consumption-saving model with a calibrated labor-income process.[17] While these restrictions will be important in Section 5 when we calibrate our model to match SCF wealth moments, they have little effect on our credit card borrowing estimates. 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 also impose two additional restrictions on our overall SCF sample: we drop unbanked

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

[14] Excluding promotional 0% balance-transfer cards is a conservative restriction because holding a balance typically voids the grace period, meaning that any new purchases on that card will immediately incur interest at the non-promotional rate (even if those purchases are paid off at the end of the billing cycle).

[15] 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.

[16] We make this restriction because the calibrated heterogeneous-agent model that we build in Section 5 will not feature the sorts of richer income processes and heterogeneous wealth returns that are needed to describe such high net worth households (see e.g. Gabaix et al., 2016; Benhabib and Bisin, 2018).

[17] We drop households where the head is 68 or older, or neither the head nor spouse is in the labor force. Retirees face a different earnings profile than workers, and their consumption decisions are complicated by health and bequest factors that require specialized models beyond what we study here (e.g., Yogo, 2016).

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).

In our SCF sample, 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 holding both a bank account and a credit card,[18] supply-side restrictions often inhibit lower-income/wealth households from accessing these financial products.[19] Since the typical ZHtM framework assumes that households have easy access to both a liquid checking/savings account and a higher-cost unsecured borrowing account like a credit card, our filtering of unbanked and underbanked households ensures that our 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 balance sheets are inconsistent with the ZHtM framework we are evaluating.

We are left with a final sample that captures 71% 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 our analysis sample.

There is a related reason to drop these households: the SCF lacks coverage of many of the borrowing margins that households without credit cards instead utilize (e.g., pawn shop loans; Zinman, 2015). So, had we kept households without credit cards in our SCF sample, this would have caused us to underestimate their true borrowing propensities.

To be clear, we are by no means claiming that unbanked and underbanked households are unimportant for macroeconomic dynamics. In fact, we model unbanked and underbanked households explicitly as separate household-blocks in our quantitative model in Section 5. But, as our findings therein suggest, to the extent that such households may be important

[18]On credit cards, note of course that using a credit card need not imply that the household revolves a balance on that card. Benefits of credit card usage include convenience, fraud protection, and discounts such as cash-back. Credit cards also help build credit history, which is important since households typically need at least one active tradeline within the past six months to have a credit score. So, by not having a credit card now, households may struggle to get bank credit in the future if the need arises (FDIC, 2017).

[19]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, 2022).

for the economic question at hand, they should be studied via differentiated models that account for their limited access to traditional consumer financial products.

Supplement: Experian Consumer Credit Panel. We supplement our SCF analysis with Experian credit bureau data. This has two benefits. First, its panel dimension allows us to study the persistence of credit card borrowing. Second, the Experian dataset is a much larger sample than the SCF, and is administrative rather than survey data. Credit bureau data also has its drawbacks, however, which is why we use it as a supplement to the SCF.[20]

Our Experian panel contains a random sample of one million U.S. consumers from 2013 through 2022. Key credit card variables include total balances due, payments, and credit limits. Note that credit card issuers provide credit bureaus with payment data for only a subset of account-months (see e.g. CFPB, 2020). So, Experian internally imputes missing payments to provide a complete panel. These observations are then presented to us as monthly averages at a quarterly frequency.

To align our definition of (revolving) credit card debt in the Experian panel with our definition in the SCF, we aggregate credit cards at the individual level and then define credit card debt as the balances remaining after subtracting payments from balances due. Since our data is quarterly, we can identify if an individual revolves a balance at some point in a given quarter, but we cannot tell in which specific cycle(s) a balance was revolved. Additionally, because payment data is partially imputed, our analysis using credit bureau data should be interpreted with a measure of caution.

Appendix A.3 provides further details on the credit bureau data. While we focus on the complete quarterly panel in the main text, we also have granular account-level data at a monthly frequency (though with incomplete and potentially nonrepresentative payment histories). Appendix A.4 presents a robustness analysis using the monthly data.

[20] In particular, (i) we have a much more limited picture of households' overall balance sheets, (ii) the data is at the individual rather than household level, and (iii) credit card payments are only partially reported, so our identification of households' revolving status is imperfect (described further below).

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 a mean before-tax income of $95,999 and a mean after-tax income of $69,003. Households are measured to hold an average of $19,020 of liquid wealth alongside $273,133 of illiquid wealth, though there is also pronounced heterogeneity. 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 highly prevalent in the SCF, and occurs at much higher levels than predicted by many heterogeneous-agent models (see footnote 3).[21]

	Mean	SD	10th	25th	50th	75th	90th
Before-tax income	95,999	94,313	24,778	43,092	73,406	121,474	187,448
After-tax income	69,003	65,356	21,302	34,643	54,956	85,770	127,831
Liquid wealth	19,020	63,053	-11,422	-1,526	3,260	18,815	58,726
Illiquid wealth	273,133	469,704	-3,297	18,081	114,429	344,606	816,930
Has high-interest CC debt	0.519	-	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 Liquid Wealth. Next, we zoom in on the borrowing of households with minimal measured liquidity. Since the key premise of the ZHtM paradigm is that there exists a large set of households that are constrained at the zero-liquid-wealth kink by their avoidance of credit card debt, we ask whether the low-liquidity households that have previously been identified as ZHtM are, in fact, eschewing high-cost debt.

[21]While it may seem surprising that 52% of households revolve high-interest credit card debt, this estimate is consistent with other analyses using alternative data sources. In the Federal Reserve's 2019 Survey of Household Economics and Decisionmaking (SHED), 52% of households with at least one credit card report carrying a balance in the past 12 months (FRB, 2020). The Atlanta Fed's 2019 Survey of Consumer Payment Choice (SCPC) reports that 47% of credit card adopters carried an unpaid balance over the past month, with a median unpaid balance of $1,500 (Foster et al., 2020). At the account level, the CFPB's biannual report finds using Y-14 data that around 60% of accounts revolved a balance in 2019, and that the effective interest rate (which accounts for promotional rates) on those accounts was over 15% (CFPB, 2021).

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. Similar to the analyses in Kaplan and Violante (2014) and Kaplan et al. (2018), these low-liquidity households are typically viewed as capturing the ZHtM share in heterogeneous-agent models. However, a sharper test of the ZHtM paradigm looks not only at (fuzzily measured) net liquid wealth, but also at credit card debt. 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.

	Within One Month	Within Two Weeks	Within One Week
Share of Preferred SCF Sample	0.209	0.116	0.067
Proportion (within) with high-interest CC debt	0.495	0.516	0.516
	(0.011)	(0.016)	(0.022)
Share of Overall SCF Sample	0.359	0.250	0.175

Table 2: **Credit Card Borrowing by Low-Liquidity Households.** This table considers households with measured liquid wealth that is within one month's, two weeks', or one week's pay of zero liquidity. 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 choices, we find that around 50% of households with roughly zero measured liquid wealth also report that they are borrowing on a high-interest credit card. That is, despite these households holding (fuzzily measured) 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.

A second takeaway is that there are fewer low-liquidity households in the preferred SCF sample than in the overall SCF sample. As emphasized above, this gap highlights the risks of ZHtM identification being confounded by households that are not well captured by the SCF nor well described by models with credit card borrowing (see Appendix A.1 for more).

Intensive Margin of Credit Card Debt. Having thus far focused on the extensive margin of credit card borrowing, we now analyze the intensive margin. Here we use our Experian dataset, since its larger sample is particularly helpful when plotting distributions (our results are similar, though noisier, in the SCF — see Appendix Figure 11).

Conditional on individuals that revolve credit card debt, the lefthand panel of Figure 2 plots the distribution of credit card debt relative to credit limits. The righthand panel plots the distribution of credit card debt relative to income. The key takeaway from Figure 2 is that, even though consumers 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

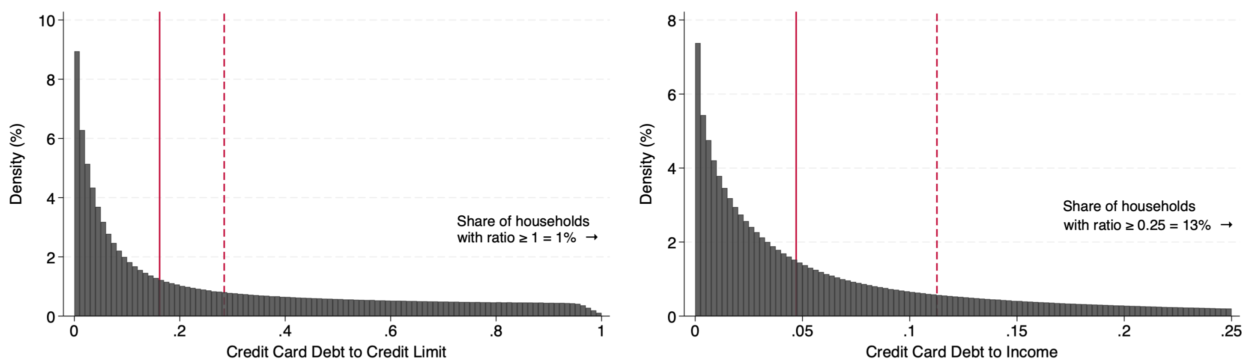

Figure 2: **Experian Data: Intensive Margin of Credit Card Borrowing.** For individuals that we measure as revolving credit card debt in our credit bureau data, the lefthand (righthand) panel shows how much credit card debt they revolve scaled relative to their credit limit (income). The median (mean) ratio of credit card debt to the credit limit is 0.162 (0.284). The median (mean) ratio of credit card debt to income is 0.047 (0.113).

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. We end by examining the persistence of credit card debt. We again use credit bureau data, since its panel dimension is needed. We ask: conditional on revolving credit card debt in quarter t, what is the probability of revolving credit card debt in quarter $t+1$, $t+2$, $t+3$, and $t+4$? As reported in Table 3, credit card debt is quite persistent. Conditional on revolving a balance in quarter t, there is a greater than 90% chance that a consumer is revolving credit card debt four quarters in the future.[22]

	Quarter $t+1$	Quarter $t+2$	Quarter $t+3$	Quarter $t+4$
Share still revolving	0.939	0.931	0.927	0.924

Table 3: **Experian Data: Persistence of Credit Card Debt.** Conditional on revolving credit card debt in quarter t, this table reports the probability of revolving credit card debt in one, two, three, or four quarters from quarter t.

We summarize our analysis of persistence 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 is persistent.*

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 – due to their avoidance of high-cost debt. However, we tested this key premise above and found that it fails empirically.[23]

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 borrowing-constrained. In our theoretical analysis to follow, we will show that present bias provides a path forward.

[22] See also the related empirical analyses in Grodzicki and Koulayev (2021) and Fulford and Schuh (2023). For even more evidence, though the SCF is not a panel it does ask households about their repayment tendencies. Among households with a high-cost balance, 26% answered that they "almost always" repay in full, 32% answered that they "sometimes" repay in full, and 42% answered that they "hardly ever" repay in full. This again suggests that revolving is broadly persistent, though with heterogeneity across households.

[23] Our findings are inconsistent not only with models that rely on binding soft borrowing constraints, but also with models relying on hard no-borrowing constraints. In short, the typical household's borrowing propensity will be poorly captured by models that assume away the possibility of such borrowing ex ante.

Why Present Bias? There are three empirical properties that jointly lead us to consider present bias as a potential path forward. 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 also find that despite the high extensive margin usage of credit card debt, borrowers simultaneously accumulate non-trivial stocks of illiquid wealth (Laibson et al., 2022a).[24]

To fit the first 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: $u'(c_t) = \delta(1 + r^{cc})\mathbb{E}_t [u'(c_{t+1})]$, where the median credit card interest rate r^{cc} reported in the SCF is 16%. That is, by revolving credit card debt, the median borrower is willingly foregoing a return on saving of at least 16%.

In a conventional model, this is a difficult condition to satisfy for the majority of households. One way to do so would be with a low discount factor δ, but this conflicts with the other two properties that borrowers often revolve only small amounts, and that borrowers have considerable illiquid wealth. Another would be for these households to expect large consumption growth so that $u'(c_t) \gg \mathbb{E}_t [u'(c_{t+1})]$, but this is unlikely for such a large set of the population.[25] Instead, the strategy that we pursue below is to generalize the Euler equation with present bias (Harris and Laibson, 2001).

While present bias is a natural way of generating this seemingly puzzling borrowing behavior (see Proposition 1 below), it is of course impossible to fully rule out other explanations. It is also unnecessary: our main results on fiscal and monetary policy (Sections 4.3 and 5.2) do not rely specifically on present bias. Rather, these sections examine how households' responses to fiscal and monetary policy change once households are modeled as revolving some credit card debt instead of being constrained at the zero-liquid-wealth kink.

[24] In our preferred SCF sample, high-interest revolvers have median (mean) net worth of \$80,685 (\$201,205).

[25] This simple Euler equation also ignores default, though default considerations are unlikely to be a key driver of borrowing for the large set of households that borrow only small amounts (and ex-post credit card charge-off rates were low from 2013 through 2019). Relatedly, while there is a literature in macroeconomics that bases unsecured borrowing rates on households' default probabilities (e.g., Chatterjee et al., 2007), this sort of pricing schedule generally implies – counterfactually – that the first dollar of credit card borrowing will cost (close to) the risk-free rate. That is, this type of model (counterfactually) removes the kink that arises at zero liquid wealth, and hence is ill-suited for the question that we explore in this paper of why so many households breach that kink in the first place.

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 three steps. First, we outline the continuous-time specification of present bias that we will use in this paper, known as Instantaneous Gratification (IG). Second, 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 key implications of credit card borrowing for fiscal and monetary policy. Third, in Section 5 we extend these insights to a calibrated heterogeneous-agent model with stochastic income and illiquid assets to show that our main results continue to hold in richer environments.

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).[26] The basic idea is that the continuous-time IG discount function is the limiting discount function that results from starting in discrete time and then shrinking the length of time that each self lives down to a single instant (Laibson and Maxted, 2022). In the continuous-time limit, for $t \geq 0$ 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." Standard exponential discounting is recovered by setting $\beta = 1$.

Models with present bias also require an assumption about the extent to which agents are aware of their future present bias (O'Donoghue and Rabin, 1999, 2001). In this paper we assume sophistication, meaning that agents are fully aware of their future self-control problems. However, this is without loss of generality since there is an observational equivalence

[26] For other foundational work on present bias in continuous time, see e.g. Barro (1999), Luttmer and Mariotti (2003), Grenadier and Wang (2007), and Cao and Werning (2016).

between sophistication and naivete in the models studied below.[27]

Given that the limiting IG discount function has an arbitrarily short "now," IG preferences 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, which allows us to easily augment rich consumption-saving models with present-biased preferences. Specifically, Maxted (2022) shows that under IG preferences, the policy and value functions of a present-biased agent are affine transformations of the policy and value functions of an agent without present bias. Accordingly, the equilibrium behavior of a present-biased agent 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 behavior of an agent with present bias.[28]

A key benefit of this tractability is that, while other behavioral or non-behavioral enrichments may also potentially be able to generate elevated MPCs while simultaneously fitting the borrowing patterns identified in the SCF, present bias adds almost no additional computational complexity relative to a model without present bias.[29] This makes present bias a portable solution that can be utilized broadly in the heterogeneous-agent literature.

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, this section presents these insights in a stripped-down environment. A fuller model is then provided in Section 5 below.

[27] I.e., we could have instead assumed partial or full naivete and then calibrated a different β to get exactly the same policy functions as we use in the current paper under sophistication. See Maxted (2022) for details.

[28] 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.

[29] Though we do not know of any other particular solutions, one related direction is bounded rationality, which can help to generate large MPCs for households regardless of their liquid wealth (see e.g. Ilut and Valchev, 2020; Lian, 2021; Boutros, 2022; Thakral and Tô, 2022).

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 $\frac{-\bar{y}}{r+\omega^{cc}}$.

Equilibrium. We assume that the household has CRRA utility:

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

where γ denotes the coefficient of relative risk aversion. We also impose the restriction throughout that $\gamma > 1 - \beta$, which implies that the household's desire to smooth consumption (γ) is greater than their time inconsistency $(1 - \beta)$.[30]

For the case of 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). Following Harris and Laibson (2013), we restrict our focus here to Markov-perfect equilibria.[31] By doing so, the key benefit of IG preferences is that the intrapersonal equilibrium will be: (i) unique; and (ii) can be analytically characterized from the behavior of an agent without present bias.

[30] See Harris and Laibson (2013) for a discussion of this restriction. We will always set $\gamma \geq 1$, so this restriction never comes into play in practice in the current paper.

[31] This is the typical approach in the present-bias literature, though the weaker subgame-perfect refinement may introduce other interesting equilibria (Laibson, 1994; Bernheim et al., 2015).

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. The debiased exponential agent is what the present-biased agent would be if they were to stop being present biased.*[32] *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 (2022) here:[33]

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:*

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

Our earlier restriction that $\gamma > 1 - \beta$ means that $\frac{1}{\psi} > 1$. Thus, Lemma 1 implies that present bias increases consumption by a multiplicative factor of $\frac{1}{\psi}$. This result is intutive: present bias makes agents want to bring utility into the present, so present-biased agents overconsume 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 accumulate 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 below 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 $\rho = 2.5\%$. To

[32]The debiased exponential agent is introduced as a theoretical point of comparison for the present-biased agent. We do not intend to imply that this sort of "debiasing" is easy, or even possible.

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

introduce present bias, we set the short-run discount factor $\beta = 0.9$. Finally, we set the coefficient of relative risk aversion $\gamma = 1.5$. These parameters are all consistent with our calibration of the richer heterogeneous-agent model in Section 5 (additional details therein).

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 consumption functions is: $c(b) = \frac{1}{\psi}\check{c}(b)$. The righthand panel of Figure 3 shows the corresponding saving function, $s(b) = \bar{y} + rb + \omega^{cc}b^{-} - c(b)$. 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 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.

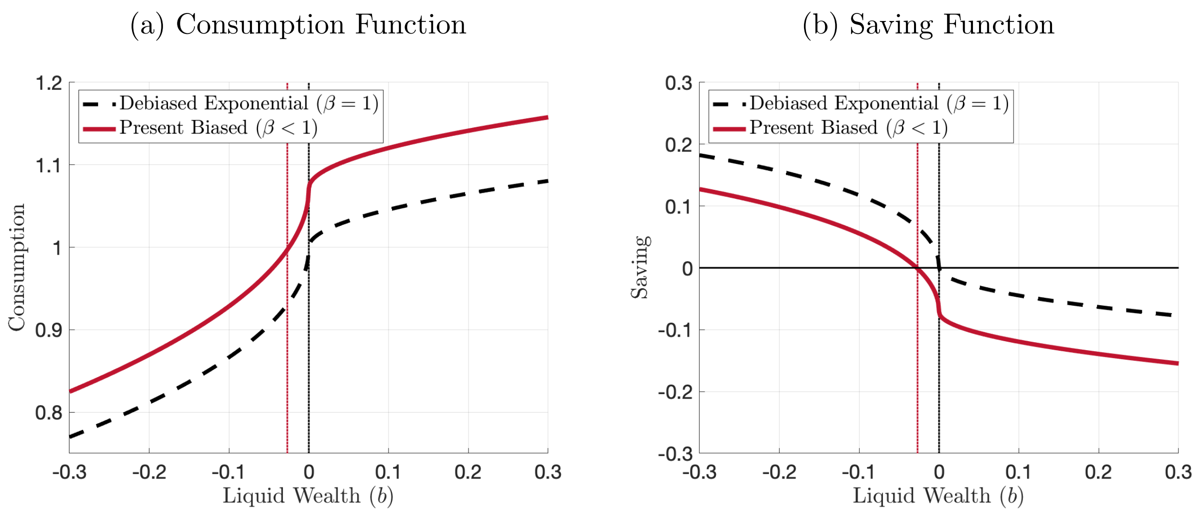

Figure 3: **Consumption and Saving Functions.** The lefthand panel plots the consumption function for the debiased exponential agent (dashed black curve) and the present-biased agent (red curve). The righthand panel plots the corresponding saving functions for the two agents. The dotted vertical lines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

Figure 4 presents quarterly MPCs around the soft borrowing constraint at $b = 0$ for both types of agents. We follow Achdou et al. (2022) in defining the MPC as the change in cumulative consumption over τ years following a liquidity injection of size χ:

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

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).

(a) Quarterly MPC: Small Shock (b) Quarterly MPC: Large Shock

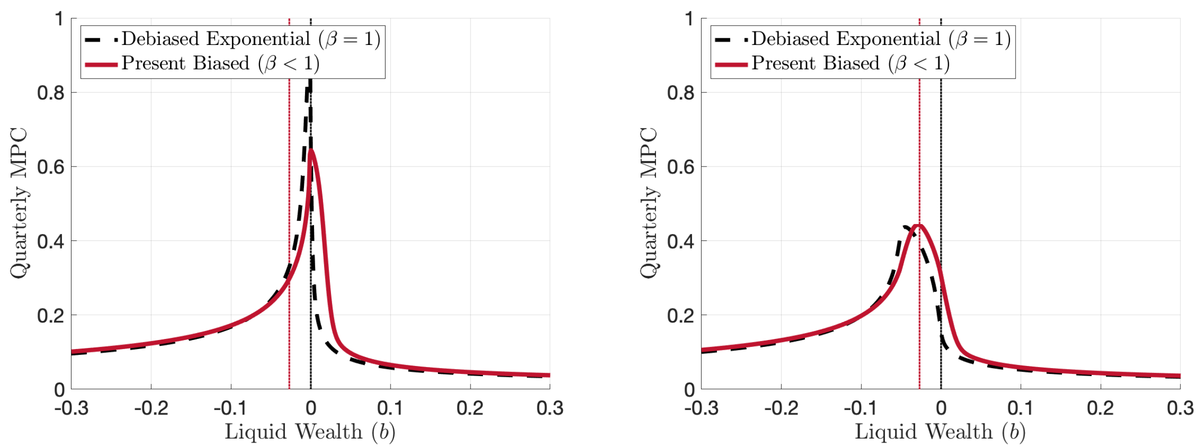

Figure 4: **MPCs out of Small and Large Shocks.** The lefthand panel plots the quarterly MPC out of a small wealth shock for the debiased exponential agent (dashed black curve) and the present-biased agent (red curve). The righthand panel plots the quarterly MPC out of a larger wealth shock that is 5% 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. We provide a brief description, and refer readers to Achdou et al. (2022, Appendix G.3 in particular) for a fuller theoretical analysis of the exponential agent's behavior.

Looking at Figure 3, the first point to highlight is that the debiased exponential agent will dissave whenever $b > 0$ since $\rho > r$, but will save whenever $b < 0$ since $\rho < r + \omega^{cc}$. At the soft borrowing constraint of $b = 0$, the debiased exponential agent optimally chooses to simply consume their flow income forever thereafter, $\check{c}(0) = \bar{y}$. Thus, the dotted black vertical line where $\check{s}(b) = 0$ occurs at $b = 0$. This means that the zero-liquid-wealth kink is an absorbing point for the debiased exponential agent.

The second point to highlight is that, since the soft borrowing constraint binds for the debiased exponential agent, their 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 at $b = 0$, as shown in the lefthand panel of Figure 4. This concavity also implies that the debiased exponential agent's MPC at $b = 0$ will decline as the shock gets larger, as illustrated in the righthand panel of Figure 4.

Overall, we see that the debiased exponential agent 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 understand 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 key 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 accumulate some amount of credit card debt in this simple model, as shown by the dotted red vertical line in Figure 3. This important implication of Lemma 1 is summarized below in our first proposition:

Proposition 1. *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 quite simple: 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 (2022). □

Proposition 1 shows that once $\beta < 1$, soft borrowing constraints no longer prevent borrowing completely. Thus, present bias provides a powerful mechanism for fitting the high extensive margin usage of credit card debt that we documented empirically in Section 3.

However, just because present-biased agents will accumulate some amount of credit card debt, this is not to say that they will necessarily max out their credit cards. The intuition follows from Figure 3, which shows that consumption drops off quickly once $b < 0$ due to the fact that consumption is now being funded through high-cost borrowing. So, while present-biased agents will persistently revolve some high-cost debt, their total debt levels can still be modest overall. Thus, present bias provides a natural means of fitting the high extensive margin but modest intensive margin borrowing patterns summarized in Stylized Fact 3.

Before continuing, we emphasize that the credit card borrowing behavior of present-biased agents is fundamentally different from that of exponential agents 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) they will get to the soft constraint 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 $\rho > r + \omega^{cc}$.[34] That is, 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. This underscores that Stylized Fact 3 poses a challenge to models without present bias.[35]

Present bias overcomes this issue. On the one hand, setting $\beta < 1$ prevents soft constraints from binding because agents overconsume at $b = 0$. However – and unlike the behavior of exponential agents – just because present-biased agents take on some high-cost debt, this does not necessarily imply that they will borrow as much as possible. Instead, the extent to which present-biased agents are willing to borrow depends on the level of β.

As mentioned in Section 3.3, another way to understand the difference between an ex-

[34]By generic, we are ignoring the two boundary cases of $\rho = r$ and $\rho = r + \omega^{cc}$.

[35]While richer models with stochastic income can generate some intermediate high-cost borrowing as a transitory state, note that: (i) such debt must be quite extensive and persistent (Stylized Facts 3 and 4), and (ii) 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 evidence in Table 2. Moreover, a model with $\beta = 1$ needs to also fit the fact that borrowers accumulate sizable stocks of illiquid wealth simultaneously (see footnote 24). As we will show in Section 5, since β can be calibrated to fit credit card borrowing while ρ can be calibrated to fit total wealth accumulation, this joint accumulation of credit card debt alongside illiquid wealth is again a natural pattern in the data to fit with present bias (Laibson et al., 2022a).

ponential agent's borrowing behavior and a present-biased agent's borrowing behavior is through the 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):

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

The lefthand side of (7) is the growth rate of consumption. For $\beta = 1$ we recover the standard continuous-time Euler equation of $\frac{\dot{c}_t}{c_t} = \frac{1}{\gamma}\left(\tilde{r}(b_t) - \rho\right)$. This Euler equation highlights why the model with $\beta = 1$ only allows for three possible long-run wealth outcomes, with the outcome 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 $\beta < 1$. In particular, we can interpret the term in brackets as the present-biased agent's "effective" discount rate, which varies with the slope of the consumption function, $c'(b_t)$.[36] Setting $\dot{c}_t = 0$ in (7), an absorbing point for the present-biased agent can arise whenever $\Big[\rho + (1-\beta)c'(b_t)\Big] = \tilde{r}(b_t)$. Since $c'(b)$ varies over the state space and particularly around $b = 0$ (discussed further below), intermediate amounts of credit card borrowing will be easier to obtain for $\beta < 1$.

For more, Appendix Figure 15 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 behavior 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 $r < \rho$, 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 also as $b \uparrow 0$.*

[36] Intuitively, since the current self knows that future selves will overconsume, the willingness of the current self to set aside a marginal dollar of savings depends on the propensity of future selves to (over)consume out of that dollar (Harris and Laibson, 2001). This propensity is determined by the slope of the consumption function. When the consumption function is steep and $c'(b)$ is elevated, the current self will be less willing to save and hence will act as if they are relatively more impatient. See Maxted (2022) for derivation details.

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 $\beta < 1$. $\square$

Proposition 2 provides the key result that explains why MPCs can still be elevated even though households are unconstrained once $\beta < 1$.[37] 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 $b = 0$ (as discussed in Section 2). 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 upon breaching the soft constraint and starting to take on high-cost debt, a pattern we refer to as *indebted saving behavior*.

Before using Proposition 2 to interpret the MPCs shown in Figure 4, one caveat is needed. Proposition 2 characterizes the slope of the consumption function $c'(b)$, which is the instantaneous MPC. So, the results in Proposition 2 about $c'(b)$ will not map perfectly into the cumulative MPC defined in equation (6) and presented in Figure 4. Nonetheless, the results in Proposition 2 still demonstrate the key intuitions at play.

Using Proposition 2 as a guide, we now examine how present bias affects MPCs, as 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.[38]

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

[38] It is worth flagging an interesting and 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.

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*, which goes in the opposite direction to the $\beta = 1$ model, illustrates some of the nuances of indebted saving behavior. In particular, small wealth shocks that leave agents with a high-cost debt burden will generate only muted short-run consumption responses. But, bigger wealth shocks that alleviate that debt more fully will hence leave agents freer to consume at a more rapid rate.

In addition to these MPC size effects, 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 constrained at $b = 0$, their consumption function is concave and hence the MPC out of positive shocks will be smaller than the MPC out of negative shocks. But when $\beta < 1$ and households are positioned to the left of $b = 0$, now the consumption function is convex and hence the MPC out of positive shocks will be larger than the MPC out of negative shocks (Appendix Figure 16 provides an illustration). This indebted saving effect is consistent with the empirical evidence in Baugh et al. (2021), who find in account-level data that taxpayers frequently increase consumption following the receipt of a tax refund, but do not decrease consumption following a tax bill.[39]

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. Moreover, the paydown and sharp recurrence of revolving credit card debt around the COVID-19 recession (see Figure 1 and further discussion below) provides us with a new, untargeted, fact that is again consistent with the present-bias model. Though the analysis above is intentionally stylized for pedagogy, we will show in Section 5 that these insights continue to hold in a richer economic environment.

[39]Similarly, Sokolova (2023) finds in an MPC meta-analysis that the MPC is larger out of income gains than losses. However, note that Fuster et al. (2021) find the opposite effect in survey data: households report that they will cut spending more following losses than they will increase spending following gains.

4.3 Applications to Fiscal and Monetary Policy

Now that we have shown how present bias induces credit card borrowing, we turn to discussing the implications of this behavior for fiscal and monetary policy.

Credit Card Debt and Fiscal Policy. One key takeaway from the MPC size effect discussed above is that present bias increases the scope for fiscal policy to remain potent, because it implies that larger stimulus checks can still produce meaningful consumption responses. This is illustrated in Figure 5, which shows how the quarterly MPC varies based on the size of the liquidity injection (with agents starting from their respective steady-state wealth level). While the MPC declines quickly when $\beta = 1$, it remains elevated over much larger transfers when $\beta < 1$. Empirically, it is commonly found that households' spending responses remain elevated even for large liquidity injections (e.g., Kueng, 2018; Fagereng et al., 2021; Sokolova, 2023), and adding present bias helps to reconcile consumption-saving models with this feature of the data.[40]

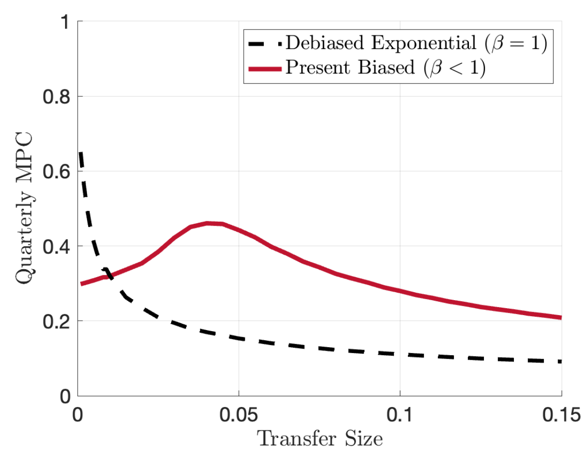

Figure 5: **Quarterly MPCs for Different Transfer Amounts.** This figure plots the quarterly MPC for the debiased exponential agent (dashed black curve) and the present-biased agent (red curve). Prior to receiving the liquidity injection, each agent starts from their respective steady-state (absorbing)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

[40]Present bias is complementary to other mechanisms that have recently been explored to increase households' spending response to large transfers, such as durable adjustment frictions (Beraja and Zorzi, 2023).

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 15). This prediction is consistent with the lefthand panel of Figure 1, and we discuss this prediction further in Section 5.2 below.

Finally, we find that present bias affects the "intertemporal MPCs" that discipline the general equilibrium propagation of fiscal stimulus (Auclert et al., 2018). For example, Appendix Figure 17 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.[41] 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 model 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 one-time rate cut. For any liquid wealth level b, the present-biased agent and the debaised exponential agent have exactly the same consumption elasticity, which follows directly 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.

Starting with the exponential agent (black dot), in the long run they sit constrained at exactly $b = 0$ and therefore 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 shows that the direct response to monetary policy depends critically on whether

[41] 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.

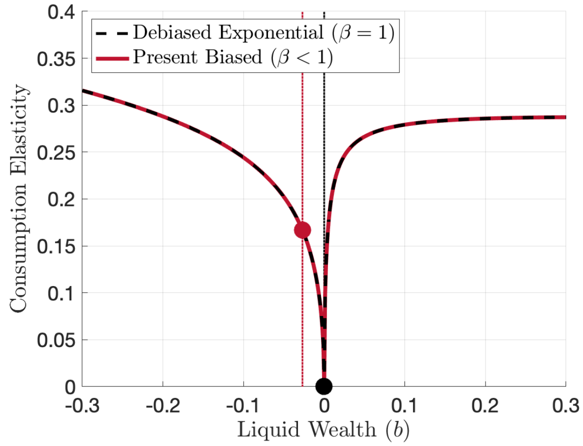

Figure 6: **Consumption Response to Rate Cut.** For each level of liquid wealth b, this figure plots the consumption response to an interest rate cut for the debiased exponential agent (dashed black curve) and the present-biased agent (red curve). The dotted vertical lines mark the absorbing states for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

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, our calibration with 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,[42] the indebted saving behavior detailed in Proposition 2 means that MPCs remain elevated when agents have some credit card debt. Instead, the main takeaway from the analysis here is that a model in which households typically carry intermediate levels of high-cost debt (Stylized Fact 3) and have elevated MPCs (Stylized Fact 1) will feature an important role for both direct and indirect responses to monetary policy. While a full general equilibrium analysis is an important next step for future researchers, the goal of Figure 6 is to highlight that credit card borrowing can have important implications for the channels through which monetary policy operates.

Finally, we note that the simple exercise in Figure 6 above assumes that there is 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,

[42]For more, see e.g. Werning (2015), Kaplan et al. (2018), Auclert (2019), and Slacalek et al. (2020).

1991). This 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 levels observed empirically.

5 Extension to Enriched Heterogeneous-Agent Model

We now extend the insights from Section 4 to a richer heterogeneous-agent model that features illiquid assets and stochastic income, similar to the continuous-time model of household balance sheets in Kaplan et al. (2018). Our analysis remains in partial equilibrium.

5.1 Present Bias in an Enriched Heterogeneous-Agent Model

The Household Balance Sheet. Each household faces idiosyncratic income risk, which we assume follows a calibrated finite-state Poisson process. We denote a household's time-t income flow by y_t.

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. Note that this generalizes the setup relative to the stylized model above, as borrowing wedge $\omega(b)$ can now depend on b.[43] 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 $\underline{b} = \frac{\min\{y\}}{r+\mathcal{W}(\underline{b})}$.[44]

In addition to the liquid asset, we now give households access to an illiquid asset a. Many households hold a large share of their wealth in assets that are relatively risky and illiquid, and introducing an illiquid asset allows the model to capture this key feature of household balance sheets (Campbell, 2006; Kaplan and Violante, 2014). The illiquid asset a offers an expected return of r^a and has a volatility of σ^a. We follow Kaplan et al. (2018) and assume

[43] $\omega(b)$ 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.

[44] As mentioned in footnote 28, borrowing constraint $\underline{b}$ cannot bind in equilibrium for the results of Maxted (2022) to hold. However, this is a relatively weak assumption in practice because we have placed no restriction on how onerous borrowing wedge $\omega(b)$ can become as households borrow more.

that the asset is illiquid because adjustments to a require a flow transaction cost of $\chi(d, a)$, where d represents flow deposits to the illiquid asset (or withdrawals if $d < 0$). Households cannot take short positions in the illiquid asset ($a_t \geq 0$).

To summarize, each household's balance sheet evolves as follows:

$$db_t = \big(y_t + rb_t + \mathcal{W}(b_t)b_t^- - d_t - \chi(d_t, a_t) - c_t\big)\, dt \tag{8}$$

$$\frac{da_t}{a_t} = \left(r^a + \frac{d_t}{a_t}\right) dt + \sigma^a dZ_t, \tag{9}$$

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

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 restrict our focus to Markov equilibria.

The Effect of Present Bias on Policy Functions. The enriched 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_t, and illiquid deposits/withdrawals d_t. Starting with 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 (2022) again applies with the key property being that asset allocation policy function $d(x)$ is independent of β:

Lemma 2. *Let $\check{d}(x)$ denote the asset allocation policy function of the debiased exponential agent. The present-biased agent and the debiased exponential agent have the same asset allocation policy function: $d(x) = \check{d}(x)$.*

As above, these results imply that we can use a simple two-step algorithm to recover the behavior of a present-biased agent from that of the debiased exponential agent.

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 15.13%, consistent with households' self-reported borrowing rate in the SCF. The illiquid asset is modeled as a diversified stock index, and has a risk premium of 4% and a volatility of 18% (Gomes and Michaelides, 2005). We calibrate the income process following Guerrieri and Lorenzoni (2017). We continue to set the coefficient of relative risk aversion $\gamma = 1.5$.[45]

To calibrate long-run discount rate ρ and short-run discount factor β we use two calibration targets. First, we target a mean total wealth level of 4.23, since the average wealth to average income ratio reported in Table 1 for our preferred SCF sample is 4.23 ($\frac{273{,}133+19{,}020}{69{,}003}$). Second, we target that 52% of households revolve credit card debt, again consistent with our estimate of high-cost credit card borrowing in Table 1.

One more assumption must be made to simulate the model. Since we treat the illiquid asset a as a diversified stock index, Brownian shock dZ is common across all households. To account for the fact that aggregate wealth will move around over time based on these common shocks, we solve the Kolmogorov forward equation under the assumption that $dZ_t \equiv 0$. That is, households consider asset risk when determining their policy functions, but we then study one specific shock sequence over which asset-return shocks never materialize.[46]

Table 4 reports our calibration of β and ρ. We set $\beta = 0.90$ to fit credit card borrowing, and $\rho = 2.51\%$ to generate average total wealth of 4.23. Our model also roughly matches the decomposition of 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 0.28 while average illiquid wealth is 3.96 (both scaled relative to average income). In the model, the breakdown between liquid and illiquid wealth is 0.23 and 4.00, respectively.

[45] While $\gamma = 1.5$ is representative of typical values in this literature, finance models often utilize much higher risk-aversion parameters.

[46] Since we calibrate our model to match SCF-reported wealth from 2013 through 2019, another reasonable approach would be to feed in a sequence of shocks that replicates U.S. stock market performance leading up to that period. We choose to set shocks to 0 for simplicity.

Table 4 also reports the average marginal propensity to consume (MPC) and average marginal propensity for expenditure (MPX). Following Laibson et al. (2022b), the MPC is a measure of the notional consumption response to a liquidity shock (defined in equation (6)), whereas the MPX instead captures the response of expenditure.[47] 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. Regardless of which measure is used, our model generates sizable responses to liquidity injections. The average quarterly MPC is 11.8% and the average quarterly MPX is 31.4%, both of which are consistent with typical estimates in the literature.[48]

	Data	Model
Discount Function		
β	-	0.90
ρ	-	2.51%
Calibration Targets		
Has high-interest CC debt	52%	52%
Total wealth	4.23	4.23
Consumption and Expenditure		
Quarterly MPC	-	11.8%
Quarterly MPX	-	31.4%

Table 4: **Summary Statistics for Calibrated Model.** This table provides summary statistics for our calibrated heterogeneous-agent model with present-biased households.

Reconciling Theory and Data: Borrowing and MPCs. The key takeaway from this enriched heterogeneous-agent framework is that present bias continues to resolve the tension summarized in Section 3.3. Namely, our model with present bias generates elevated aggregate MPCs while also inducing borrowing patterns consistent with Stylized Facts 3 and 4.

Looking first at the distribution of credit card debt, Figure 7 below plots the liquid wealth distribution (bars) as well as the average quarterly MPC (solid line) and MPX (dashed line)

[47]We follow the mapping from model-based notional MPCs to MPXs that is provided in Laibson et al. (2022b) (further detailed in Appendix B.4). The MPX is often the more relevant concept empirically, since it is easier to measure expenditure than notional consumption. Additionally, the MPX is often the more relevant concept for macroeconomic policy, since consumer expenditure is what enters GDP.

[48]For a small transfer, estimated quarterly MPCs are generally in the range of 15-25%. Estimated quarterly MPXs are two to three times larger (see e.g. Laibson et al., 2022b). Though the MPC and MPX that we report in Table 4 are slightly below these empirical ranges, our model's aggregate MPC/MPX will increase in Section 5.3 once we additionally model unbanked and underbanked households.

conditional on liquid wealth. While a large proportion of households have close to zero liquid wealth, these households are not exactly constrained at the zero-liquid-wealth kink and instead revolve modest amounts of credit card debt, consistent with Stylized Fact 3. Looking next at these households' MPCs and MPXs, we continue to see that their indebted saving behavior leads to elevated MPCs/MPXs, consistent with Stylized Fact 1.

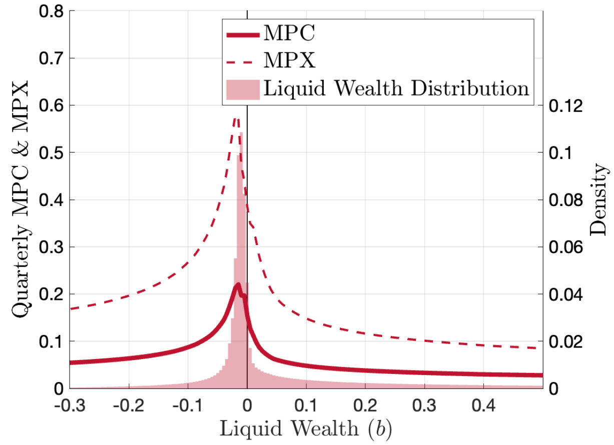

Figure 7: **MPCs and Liquid Wealth.** The lines plot average quarterly MPCs (solid line) and MPXs (dashed line) conditional on liquid wealth. The bars show the liquid wealth distribution.

Turning to the persistence of credit card debt, Figure 8 plots the persistence of high-cost borrowing in the model and in the data (reproduced from Table 3). Despite our model being stylized with respect to the sorts of idiosyncratic spending shocks that households face, it nonetheless does quite well in matching the persistence of credit card debt that we documented in Stylized Fact 4.

Finally, we emphasize that 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 matching the large average total wealth level of more than four-times income that we see in the SCF. Thus, by capturing the tension between acting impatiently and acting patiently that is inherent in household balance-sheet moments, present bias can improve heterogeneous-agent models' fit of key empirical properties of household finances (Laibson et al., 2022a).

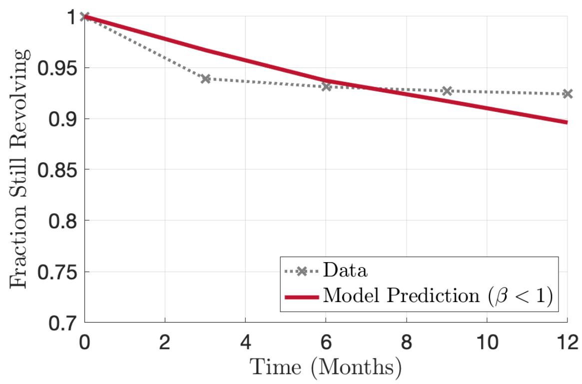

Figure 8: **Persistence of Credit Card Debt.** This figure plots the persistence of credit card debt in the data (dotted gray curve; reproduced from Table 3), and the corresponding persistence in the model (red curve).

Aside: $\beta = 1$ Calibrations. While our model with present bias can jointly fit MPCs, credit card borrowing, and total wealth accumulation, we briefly mention that – just as in Section 4 – the model without present bias ($\beta = 1$) does not provide a good description of the data. In particular, while we can match the total wealth moment of 4.23 with $\beta = 1$ and $\rho = 3.10\%$, only 8% of households revolve credit card debt in that case. Alternatively, we can match our 52% borrowing moment with $\beta = 1$ and $\rho = 12.72\%$, but then households' total average wealth is -0.07. That is, the $\beta = 1$ model does not match the tension between acting impatiently and acting patiently that is key for fitting the data. Further description of these $\beta = 1$ calibrations is provided in Appendix B.4.

5.2 Applications to Fiscal and Monetary Policy

Credit Card Debt and Fiscal Policy. Starting with fiscal policy, Appendix Figure 19 plots the average quarterly MPC and MPX as a function of the size of a liquidity injection (similar to the analysis in Figure 5 above). As discussed in Section 4.3, an important effect of indebted saving behavior is that MPCs and MPXs remain elevated even for large stimulus checks. This effect is again illustrated in Appendix Figure 19, which shows, for example, that the average quarterly MPX remains above 25% for transfers up to roughly $10,000.

Relatedly, we can now return to Figure 1 and use our calibrated model to provide a back-of-the-envelope simulation of how credit card borrowing responds to the EIPs that were received around the COVID-19 recession. This simulation is presented in Figure 9 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 then trace the subsequent evolution of credit card debt.

While this is only a stylized exercise,[49] there are two clear takeaways. First, our present-bias model predicts that credit card borrowing is a recurrent state, and hence policymakers should expect for the debt-relief benefits of liquidity injections to only be transient. This also relates to our MPC finding above: even though each household receives a large transfer of over \$6,500 in our simulation, they spend that extra liquidity relatively quickly. Second, while our model broadly fits this period, the fit is not perfect. In particular, it's interesting to note that our model with present bias predicts a rebound in credit card debt that is actually slower than what we see in the data, again highlighting how rapid that rebound was.[50]

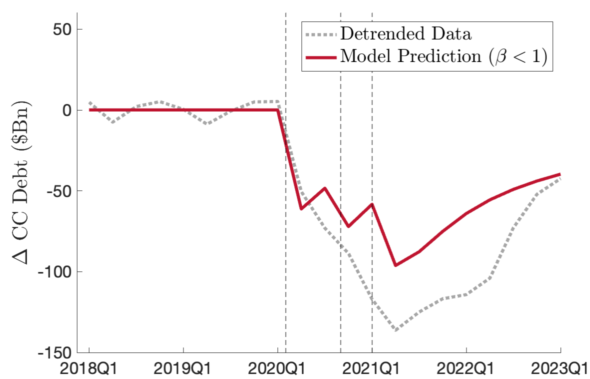

Figure 9: **Paydown-Rebound of Credit Card Debt.** This figure plots the detrended path of revolving credit card debt around the COVID-19 recession (dotted gray curve; see Figure 1), and the corresponding path of credit card debt predicted by the model (red curve). Simulation details are provided in Appendix B.4.

Figure 9 also suggests an important methodological point relating to how economists measure the spending response to fiscal policy. One common approach is to survey households about whether they intend to use a stimulus check to "mostly spend," "mostly save,"

[49] Simulation details are provided in Appendix B.4. This is a stylized exercise in that we are intentionally ignoring many important economic considerations of the period, such as the large unemployment spike in 2020, the added difficulty of purchasing various goods during lockdowns, extended UI, mortgage forbearance programs (Lee and Maghzian, 2023), etc.

[50] The imperfect fit should in some sense be expected, as we are abstracting from many economic considerations of the period. Additionally, one reason that our model misses to some extent the magnitude of the paydown is that it has too little credit card debt ex ante (partly due to our conservative calibration), and hence there "isn't enough" debt for the typical household to pay off upon receiving their stimulus checks.

or “mostly pay off debt.”[51] However, given that credit card borrowing is often a recurrent state, our model suggests that these survey questions may be difficult to interpret. Consider, for example, a typical household with liquid wealth of $b_0 = -0.02$ that receives a small fiscal stimulus. In the model, this household immediately uses this stimulus to repay a portion of its credit card debt. But, it is ambiguous as to whether this household should report that it uses the stimulus check to repay debt or to spend, since this same household also has a quarterly MPX of over 50%. That is, by paying down its credit card, this household also increases its willingness to spend. Thus, a novel lesson implied by our model with persistent and recurrent credit card debt is that survey designs should incorporate the fact that debt-repayment and spending may not be mutually exclusive, even over short horizons like one quarter. Relatedly, and as highlighted by Figures 1 and 9, just because households report using a stimulus check to pay down their debt, policymakers should not necessarily expect for that additional buffer to remain for long.

Credit Card Debt and Monetary Policy. For monetary policy, Appendix Figure 20 repeats the monetary policy experiment of Section 4.3 in our calibrated heterogeneous-agent model. Relative to earlier models such as Kaplan et al. (2018) that feature a large set of constrained households who do not respond to rate changes, the key difference in our model with present bias is that households are now unconstrained and hence respond more directly to monetary policy. Overall, the aggregate consumption elasticity is 0.16, which is very similar to the consumption elasticity of the simple example in Section 4.3. More broadly, it is important for policymakers to be aware of – and have models consistent with – the large credit card borrowing propensities observed in the data, since monetary policy affects the interest rates that credit card borrowers face.

[51] Foundational work includes Shapiro and Slemrod (1995, 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. Examples include the U.S. Census Bureau’s Household Pulse Survey (Boutros, 2020; Garner et al., 2020), and the New York Fed’s Survey of Consumer Expectations (Armantier et al., 2020).

5.3 Extension to Underbanked and Unbanked Households

While this paper focuses primarily on fully banked households, we end by extending our analysis to underbanked households (without a credit card) and unbanked households (without a bank account nor a credit card). Banked households compose 71% of our overall SCF sample, while underbanked households compose 22% and unbanked households compose 7%. We summarize our procedure and findings here, with details in Appendix B.5.

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 lending for credit. We set the borrowing rate to 362%, which equates to a (inflation-adjusted) typical payday loan rate of 15% per two-week borrowing period.

We also internally recalibrate parameters ρ and β, as summarized in Table 5 below. Following our procedure above, we calibrate ρ to match average wealth of 1.92 for underbanked households and 0.82 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, pawn shop, and auto title loans) is limited, we calculate these targets using the FDIC National Survey of Unbanked and Underbanked Households (details in Appendix B.5).[52] For underbanked households we calibrate $\rho = 3.43\%$ and $\beta = 0.88$. For unbanked households we calibrate $\rho = 4.88\%$ and $\beta = 0.91$. Given the very high interest rates that typify nonbank credit, our calibration suggests that

[52]Our calibration targets are likely to be lower bounds on underbanked and unbanked households' usage of credit, since even this FDIC Survey does not capture all forms of credit that households may use (e.g., checking overdrafts; Stango and Zinman, 2014).

both types again require $\beta < 1$ to match the observed borrowing propensities.

	Underbanked		*Unbanked*	
	Data	Model	Data	Model
Discount Function				
β	-	0.88	-	0.91
ρ	-	3.43%	-	4.88%
Calibration Targets				
Has nonbank debt	12%	12%	16%	16%
Total wealth	1.92	1.92	0.82	0.82

Table 5: **Discount Function Calibration for Underbanked/Unbanked Households.** This table gives the discount function calibration for underbanked and unbanked households.

Next, Figure 10 replicates the analysis in Figure 7 for underbanked and unbanked households. Despite having $\beta < 1$, we now see much less borrowing due to the very high cost that borrowing entails. 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.

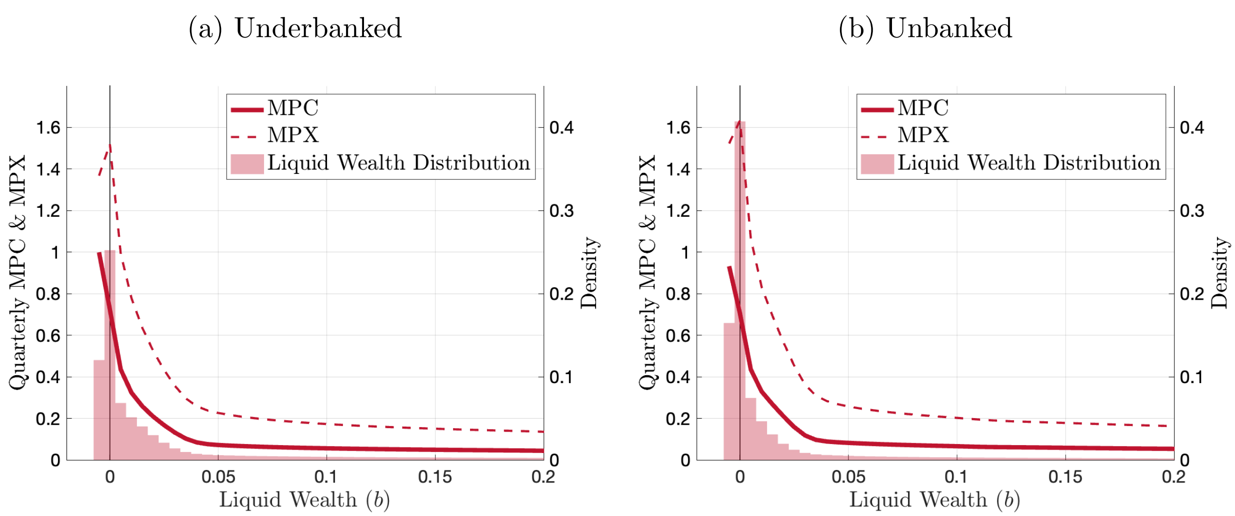

Figure 10: **MPCs and Liquid Wealth.** This figure replicates the analysis in Figure 7 for underbanked and unbanked households.

Putting It All Together: MPCs and Fiscal Policy. Finally, we aggregate the three household types to evaluate the overall MPC and MPX. In Table 6, we consider liquidity injections to each household in the economy of $1,000, $3,000, and $5,000. The second column reports the aggregate quarterly MPC (MPX), and the subsequent columns decompose the relative contribution to the MPC of banked, underbanked, and unbanked households.

	Aggregate		*MPC Share*		
	MPC	(MPX)	Banked	Underbanked	Unbanked
$1,000 Transfer	17%	(45%)	52%	35%	14%
$3,000 Transfer	13%	(36%)	64%	26%	10%
$5,000 Transfer	11%	(31%)	67%	24%	9%

Table 6: **Quarterly MPCs for Different Transfer Amounts.** This table reports our model's aggregate MPC (MPX), and the contribution of each household-block to that MPC.

For a transfer of $1,000, the aggregate quarterly MPC (MPX) is 17% (45%), from which the relative contribution of banked, underbanked, and unbanked households is 52%, 35%, and 14%. For a transfer of $5,000, the overall quarterly MPC (MPX) is 11% (31%), from which the contribution of banked, underbanked, and unbanked households is 67%, 24%, and 9%. In all cases, the banked households that compose 71% of the population are also the largest contributor to the overall MPC. Moreover, this analysis shows that banked households' contribution increases as the transfer gets larger. The reason goes back to 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 highlight that present bias allows for fiscal policy to remain much more potent when enacted at large scales. Even for a large stimulus check of $5,000, our present-bias model predicts a sizable quarterly MPC of 11% and MPX of 31%. This prediction contrasts with ZHtM-style models. For example, in the canonical model of Kaplan and Violante (2014), the MPC drops from 20% for a $500 transfer (similar to our model) all the way down to 3% for a $5,000 transfer (almost four times smaller than our model's 11% MPC). Recall the policy response to the recent COVID-19 recession, where many households received well over $5,000 of EIP payments. For a policymaker trading off the benefits of shrinking the output gap against the costs of creating inflationary pressure, modeling the household consumption response correctly is key for getting the size of stimulus checks correct.

6 Conclusion

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

The prevalence of credit card borrowing that we observe in the data suggests several directions for future investigation. We highlight three. First, while this paper identifies present bias as a simple way of improving heterogeneous-agent models' fit of household borrowing patterns, our analysis here is only a first step. Second, our extension to underbanked and unbanked households points to the importance of building models that account for households' differential access to consumer financial products. Third, it will be interesting to explore how the continued development of new financial technologies in consumer credit markets influences household borrowing behavior.

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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 these 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 unbanked and underbanked households. These 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 these households compose a non-trivial share of the low-liquidity households in the raw SCF.

Table 7 below presents summary statistics for our overall SCF sample, and then for the two sets of households that we subsequently exclude: unbanked households, 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 37% 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-saving models that 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. 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 that are typically modeled.[53]

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	78,843	85,820	15,602	30,090	56,836	101,414	162,899
After-tax income	57,705	59,120	14,188	25,690	43,902	73,546	113,058
Liquid wealth	14,652	54,538	-7,500	0	1,313	11,630	42,785
Illiquid wealth	207,263	414,802	-5,970	5,212	60,400	241,700	640,563
Has high-interest CC debt	0.371	-	0	0	0	1	1
Panel B: Unbanked Households							
Before-tax income	23,859	17,333	8,043	12,259	20,060	30,544	43,092
After-tax income	21,365	13,696	7,676	11,646	19,009	28,518	37,641
Liquid wealth	3	2,907	-19	0	0	196	722
Illiquid wealth	17,503	69,006	-7,577	0	2,553	11,000	65,400
Has high-interest CC debt	0.0563	-	0	0	0	0	0
Panel C: Underbanked Households (No CC)							
Before-tax income	37,595	35,730	10,181	16,159	28,507	48,478	74,667
After-tax income	30,506	24,120	9,479	14,822	25,300	38,904	57,098
Liquid wealth	4,317	20,382	0	51	547	1,946	7,197
Illiquid wealth	48,228	139,178	-10,000	0	7,100	45,025	140,236
Has high-interest CC debt	0	-	0	0	0	0	0

Table 7: **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.

[53] Though unbanked households are unlikely to borrow on a credit card, more than 80% 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).[54] 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.

Robustness Checks. We provide three additional robustness checks on our empirical analysis in Section 3.2. First, Table 8 below replicates Table 2 from the main text, but bins households based on dollars of measured liquidity rather than the liquid wealth to income ratio. Results are comparable in both cases. Second, Figure 11 uses SCF data to plot the distribution of households' credit card debt relative to both their reported credit limit and to their income. Similar to Figure 2, this figure shows that households' debt levels are typically intermediate. Third, Figure 12 plots the credit card borrowing propensity for individual SCF waves. 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. Nonetheless, Figure 12 shows that we see similar (or even higher) levels of high-cost borrowing across all SCF waves.

	[0, \$5,000]	[0, \$3,000]	[0, \$1,000]
Share of Preferred SCF Sample	0.228	0.170	0.080
Proportion (within) with high-interest CC debt	0.471	0.468	0.488
	(0.010)	(0.011)	(0.016)
Share of Overall SCF Sample	0.402	0.346	0.227

Table 8: **Credit Card Borrowing by Low-Liquidity Households.** This table is similar to Table 2, but bins households based on dollars of measured liquidity.

[54] 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.

(a) Credit Card Debt to Credit Limit

(b) Credit Card Debt to Income

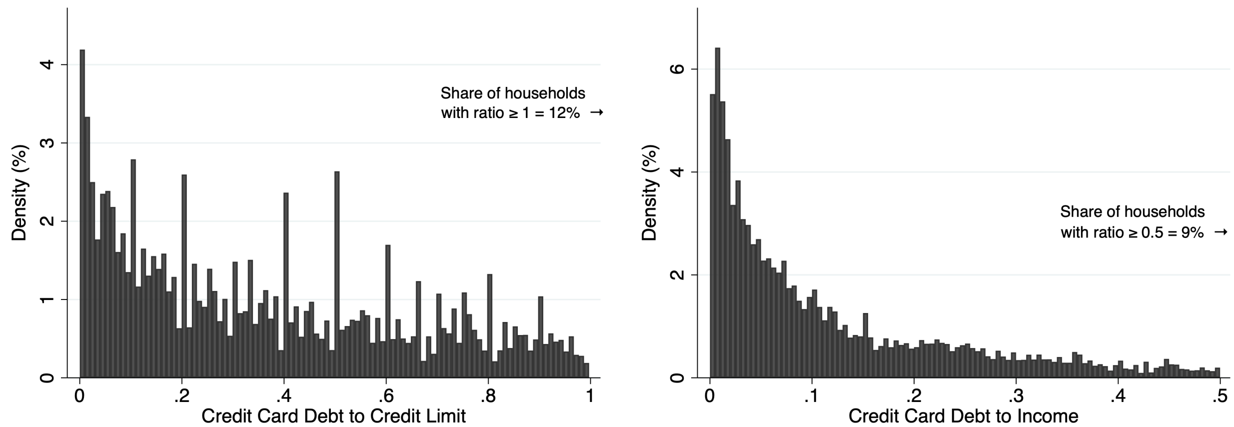

Figure 11: **SCF Data: Intensive Margin of Credit Card Borrowing.** This figure is similar to Figure 2, but uses SCF data. For households that report having high-interest credit card debt, the lefthand (righthand) panel shows how much credit card debt they revolve scaled relative to their reported credit limit (after-tax income).

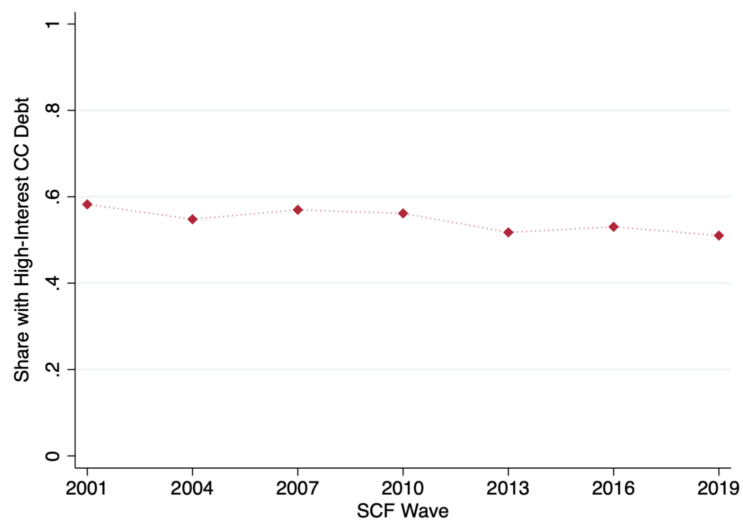

Figure 12: **Credit Card Borrowing Across SCF Waves.** For each SCF wave, this figure plots the share of households that report revolving high-cost credit card debt.

A.3 Experian Data: Additional Details

This section provides additional details about our credit bureau data from Experian. To align our definition of credit card tradelines with the definition used in the SCF, we aggregate three types of unsecured borrowing products: revolving bankcards, charge cards, and retail cards. Since 87% of consumers in our Experian sample have at least one credit card account, we restrict all our analyses to this subsample. Although we do not observe consumers' bank account ownership in the credit bureau data, most households with a credit card also have a bank account in the SCF, so we consider our Experian analysis sample close to fully banked.

Although the Experian data provides a comprehensive view of consumers' credit card debt, it has a few notable limitations. First, we cannot link family members within the same household, so all of our analyses are conducted at the individual level. Second, we cannot perfectly align our Experian sample with our preferred SCF sample, primarily because we do not observe age or labor force participation. Relatedly, we do not observe the interest rate that consumers pay on their credit card balances, so we cannot restrict our attention to high-interest credit card debt. Third, as mentioned in the main text and discussed further in Appendix A.4 below, many credit card issuers do not report payments to the credit bureaus, so payment data is partially imputed by Experian.

Appendix Table 9 presents summary statistics for our quarterly panel. All nominal figures are adjusted to 2019 dollars. The average estimated income is $53,243.[55] Though average income is well below our SCF estimate in Table 1, note that this should be expected because our Experian data is at the individual rather than household level. The average balance due is $6,039, and the average revolving balance (after payments) is $5,513. 83% of person-quarters carry a balance (meaning that a balance was revolved at least once during a quarter).[56] Despite this high extensive margin, recall from Figure 2 that the intensive margin is more modest and revolving balances tend to be significantly below credit limits.

[55] Experian's measure of income is an internal estimate, and hence is subject to measurement error. For more information, see https://www.experian.com/business/products/income-insight.

[56] Note that some of this revolving debt may be at a promotional 0% interest rate, since we do not observe credit card interest rates in our credit bureau data.

	Mean	SD	10th	25th	50th	75th	90th
Income estimate (individual)	53,243	30,677	26,299	33,132	44,429	63,994	90,292
Vantage score	715	95	577	647	731	798	821
CC balance due	6,039	10,795	30	483	2,189	6,719	16,132
Revolving CC balance	5,513	10,520	0	181	1,598	5,970	15,400
Has CC debt	0.826	-	0	1	1	1	1
Credit limit	31,300	35,290	1,366	6,008	20,125	44,451	75,895

Table 9: **Experian Sample Summary Statistics.** This table provides summary statistics for our Experian sample (mean, standard deviation, and 10th, 25th, 50th, 75th, and 90th percentile levels). See text for definitions of the variables summarized here.

A.4 Experian Robustness

While our analysis in the main text focuses on the quarterly data described above, we also have more granular account-level data at a monthly frequency. This section provides a brief overview of this monthly data, and uses it for a robustness analysis. As discussed in the main text, one important limitation of credit bureau data is that credit card payments are available for only a subset of account-months (see e.g. CFPB, 2020). Since missing payments are not imputed by Experian in the monthly data, we first restrict our sample to the subset of observations with non-missing payments, which constitutes 30% of the total sample. We then aggregate the remaining accounts at the consumer level.

One issue that we highlight is that credit card issuers' choice of whether or not to report payments is likely nonrandom (CFPB, 2020). For example, that CFPB report states: "unsecured revolving loan lenders may perceive the furnishing of actual payment data as a competitive disadvantage as this may enable competitors to use tradeline data to identify and poach their most profitable customers." Since credit card profitability is predominantly driven by revolving accounts (Adams et al., 2022), this suggests that our monthly sample is likely to be biased towards consumers that are *less likely* to revolve credit card debt.

Appendix Table 10 presents summary statistics for the resulting monthly panel. In line with the selection issues just discussed, our monthly sample is skewed toward consumers with higher income, higher credit scores, and lower balances. Despite this selection toward consumers with better credit profiles, we still find that 62% of person-months revolve a balance.

We next examine the intensive margin of credit card debt for this monthly sample.

	Mean	SD	10th	25th	50th	75th	90th
Income estimate (individual)	57,952	30,273	29,926	37,927	50,056	68,444	96,026
Vantage score	732	85	611	674	748	804	825
CC balance due	3,153	5,468	54	267	1,097	3,619	8,594
Revolving CC balance	2,499	5,114	0	0	377	2,690	7,509
Has CC debt	0.622	-	0	0	1	1	1
Credit limit	10,571	11,804	913	2,487	6,903	14,442	24,833

Table 10: **Experian Monthly Sample Summary Statistics.** This table replicates Appendix Table 9 for our monthly Experian sample.

Specifically, Appendix Figure 13 replicates Figure 2 from the main text on our monthly credit bureau sample. Results are broadly comparable, and in particular we still find that the intensive margin of credit card debt is much more modest than the extensive margin.

(a) Credit Card Debt to Credit Limit

(b) Credit Card Debt to Income

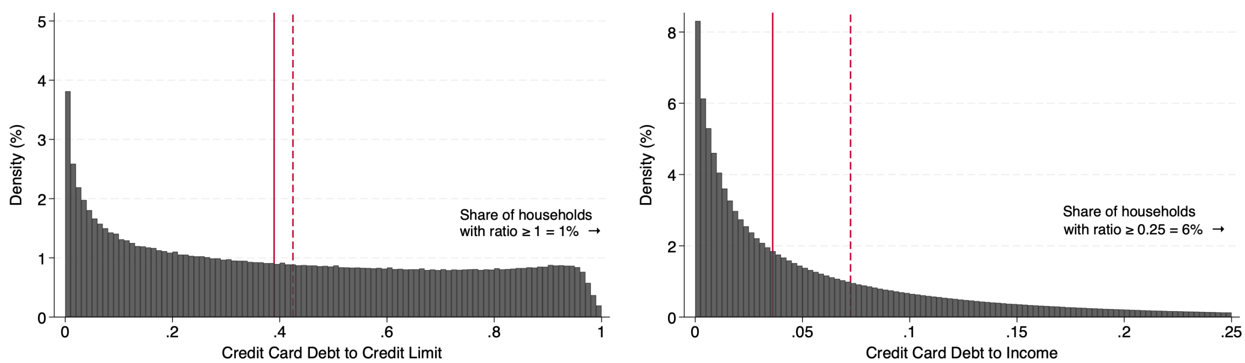

Figure 13: **Experian Monthly Data: Intensive Margin of Credit Card Borrowing.** For individuals that we measure as revolving credit card debt in our monthly data, the lefthand (righthand) panel shows how much credit card debt they revolve scaled relative to their credit limit (income). The median (mean) ratio of credit card debt to the credit limit is 0.389 (0.425). The median (mean) ratio of credit card debt to income is 0.036 (0.072).

Finally, we also examine the persistence of credit card debt using the monthly data. Appendix Figure 14 below plots the persistence of credit card debt in our monthly sample and in our heterogeneous-agent model (similar to Figure 8 in the main text). Although the persistence measured at a monthly frequency is somewhat lower than our quarterly estimates (which is unsurprising given the aggregated nature of the quarterly estimates), credit card debt still exhibits robust persistence with 86% of accounts still revolving after 12 months, again broadly matching the model's prediction.

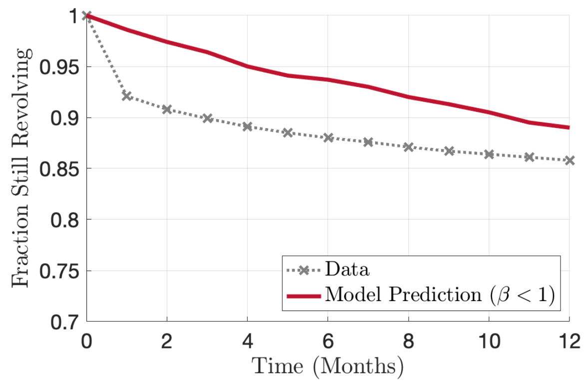

Figure 14: **Experian Monthly Data: Persistence of Credit Card Debt.** This figure plots the persistence of credit card debt in the data (dotted gray curve), and the corresponding persistence in the model (red curve).

B Additional Modeling Details and Results

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

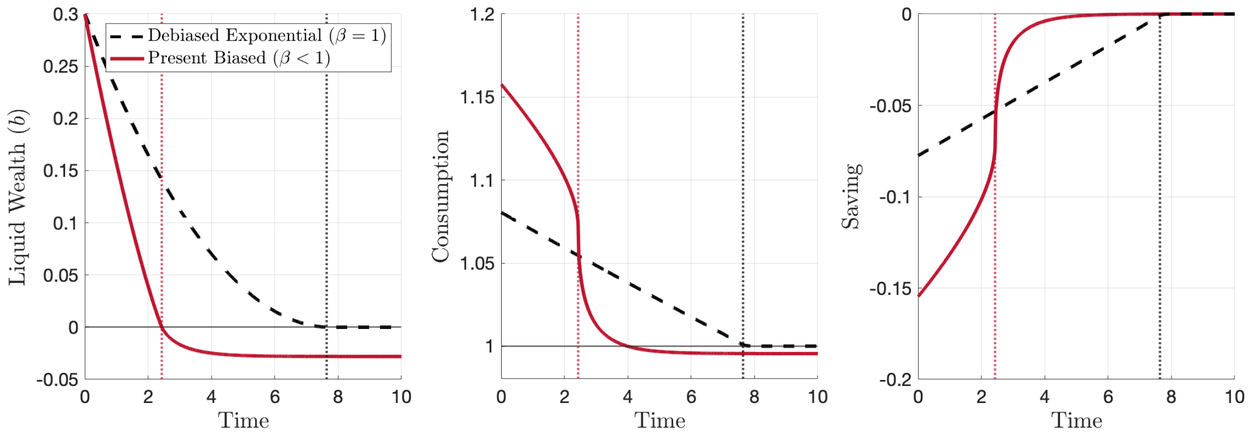

Figure 15: **Time Path of Wealth, Consumption, and Saving.** This figure plots the time path of liquid wealth (left), consumption (middle), and saving (right) for the debiased exponential agent (dashed black curve) and the present-biased agent (red curve). Wealth is initialized to $b_0 = 0.3$, and the 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 $b = 0$.

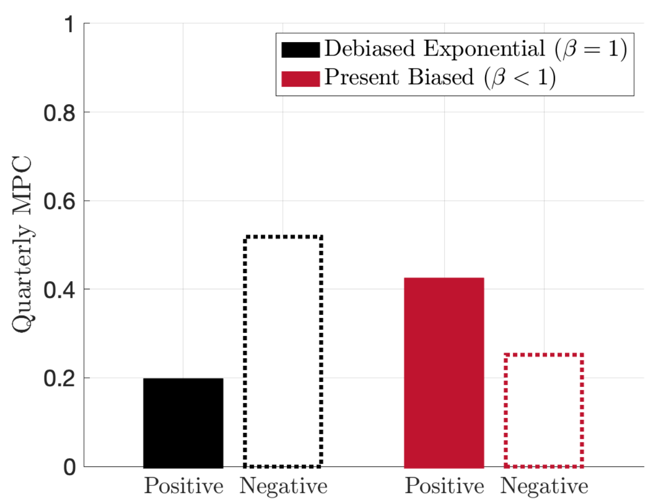

Figure 16: **MPC Sign Asymmetry.** This figure plots the quarterly MPC out of both a positive and a negative liquidity shock of $\chi = 0.03$ (i.e., 3% of annual income). The lefthand panel (black) plots the $\beta = 1$ case, and the righthand panel (red) plots the $\beta < 1$ case. Prior to receiving 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 $b < 0$.

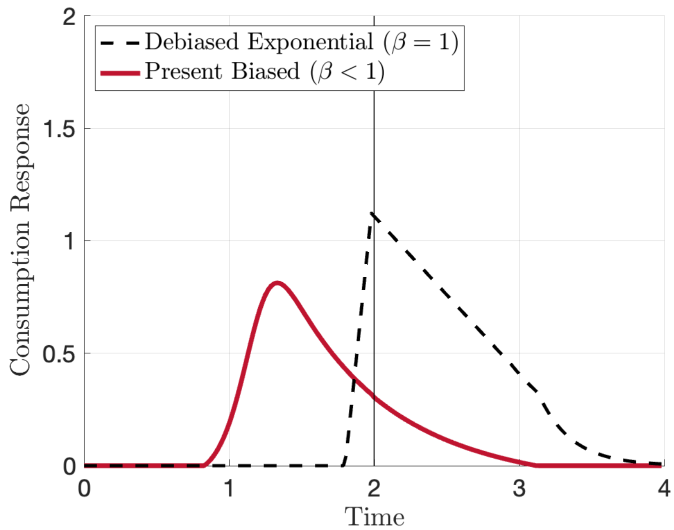

Figure 17: **Consumption Response to Future Wealth Shock.** This figure plots the consumption response to a wealth shock that occurs at time $t = 2$ for the debiased exponential agent (dashed black curve) and the present-biased agent (red curve). Prior to receiving news of the shock at time $t = 0$, each agent starts from their respective steady-state (absorbing) wealth level. The consumption response is scaled relative to the shock χ.

B.2 Footnote 37: Additional Details on $\beta r < \rho < r$ Case

Maxted (2022) 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 details on the calibration of the 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 additional 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.[57]

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

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 then convert to a continuous-time Ornstein-Uhlenbeck (OU) process following the method outlined in the Appendix of Laibson et al. (2021). Then, we discretize this OU process using standard 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 Laibson et al. (2021). For borrowing, we simply set the average borrowing wedge $\mathcal{W}(b)$ to a constant 15.13%. We could have introduced additional cost progressivity as households continue to borrow beyond a calibrated credit card borrowing limit, but in practice households do not typically borrow large amounts in our model so we opt for simplicity here. We set the borrowing wedge to 15.13% 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 0.87%.[58]

The risk premium on the illiquid asset is 4% with a volatility of 18%, following the calibration of Gomes and Michaelides (2005). Building on Kaplan et al. (2018), the functional form for the illiquid asset transaction cost function, $\chi(d, a)$, is as follows:

$$\chi(d, a) = \chi_0^+ d^+ + \chi_0^- d^- + \chi_1 \left(\frac{|d|}{a} \right)^{\chi_2} a. \tag{10}$$

In this transaction cost function, the terms $\chi_0^+ d^+$ and $\chi_0^- d^-$ characterize the linear cost associated with deposits (d^+) or withdrawals (d^-) from the illiquid asset. The third term $\chi_1 \left(\frac{|d|}{a} \right)^{\chi_2} a$ introduces convexity to ensure that d is finite and hence the illiquid asset a never jumps.[59] See Kaplan et al. (2018) for additional details.

Relative to Kaplan et al. (2018), our innovation here is to allow for differential linear components 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. In particular, we calibrate $\chi_0^+ = 0$ so that households can costlessly contribute a marginal dollar to the illiquid asset. We calibrate $\chi_0^- = 0.1$, meaning that a

calibrate a risk aversion of 2.

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

[59] Numerically, we calculate this term as $\chi_1 \left(\frac{|d|}{\max\{a, 0.01\}} \right)^{\chi_2} \times \max\{a, 0.01\}$ to ensure that the transaction cost at $a = 0$ remains finite.

marginal dollar of withdrawals costs a 10% penalty rate. This captures the typical 10% penalty tax rate charged to early withdrawals in the United States. For simplicity we set $\chi_1 = 1$ and $\chi_2 = 2$, which are roughly in line with Kaplan et al. (2018).

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 assume that they live for 15 more years, over which time they consume their income (earned at a 70% replacement rate) plus a return of r on their total wealth. This gives an exponentially discounted retirement value of $v^R(x) = \frac{u(0.7\bar{y}+r\times(b+a))}{\rho}(1-e^{-15\rho})$, similar to the specification of Laibson et al. (2021).[60]

	Description	Value	Target / Source
Preferences			
β	Short-Run Discount Factor	0.90	(see Section 5)
ρ	Long-Run Discount Rate	2.51%	(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%	Laibson et al. (2021)
ω^{cc}	Credit Card Borrowing Wedge	15.13%	SCF
Illiquid Asset			
r^a	Return on Illiquid Asset	5%	Gomes and Michaelides (2005)
σ^a	Volatility of Illiquid Asset	18%	Gomes and Michaelides (2005)
χ_0^+	Linear Component (Deposits)	0	U.S. DC Pension Plan
χ_0^-	Linear Component (Withdrawals)	0.1	U.S. DC Pension Plan
χ_1	Convex Component	1	-
χ_2	Convex Component	2	-
Other Structural Assumptions			
λ^R	Retirement Rate	$\frac{1}{45}$	Kaplan et al. (2018)
-	Retirement Functional Form	(see text above)	Laibson et al. (2021)

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

[60]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.** While our analysis in Section 5 focuses on the calibration that allows for $\beta < 1$, we now briefly describe alternate calibrations that fix $\beta = 1$ and calibrate ρ to match either total wealth of 4.23 or the credit card borrowing propensity of 52%.

These alternate calibrations are presented in Appendix Table 12 below. In the column labeled Model (Wealth) we calibrate ρ to match the total wealth moment, and in the column labeled Model (Borrowing) we calibrate ρ to match the borrowing moment. In either case, the model with $\beta = 1$ misses the untargeted moment substantially.

	Data	Model (Wealth)	Model (Borrowing)
Discount Function			
β	-	1	1
ρ	-	3.10%	12.72%
Calibration Targets			
Has high-interest CC debt	52%	8%	52%
Total wealth	4.23	4.23	-0.07
Consumption and Expenditure			
Quarterly MPC	-	9.4%	15.7%
Quarterly MPX	-	25.7%	41.9%

Table 12: **Summary Statistics for Calibrated $\beta = 1$ Model.** This table provides summary statistics for our calibrated heterogeneous-agent model with $\beta = 1$ households.

Finally, Appendix Figure 18 replicates the analysis in Figure 7 for our $\beta = 1$ calibrations.

(a) $\beta = 1$ and $\rho = 3.10\%$ (b) $\beta = 1$ and $\rho = 12.72\%$

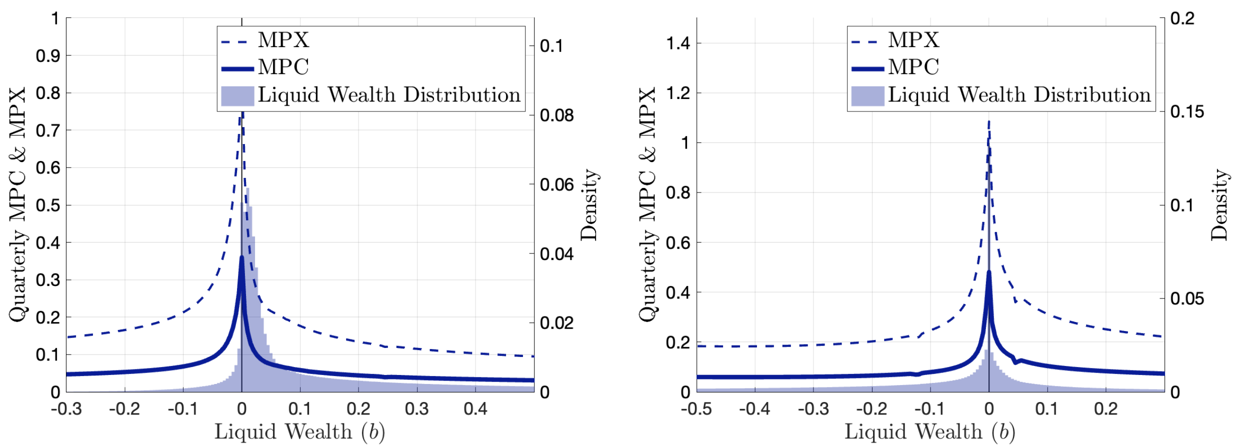

Figure 18: **MPCs and Liquid Wealth.** This figure replicates the analysis in Figure 7 for our two $\beta = 1$ calibrations.

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). Consumption-saving models like the one we built in Section 5 make predictions about notional consumption (i.e., utility-generating consumption flows). However, durable goods drive a wedge between notional consumption and consumer spending (as 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.

Credit Card Debt and Fiscal Policy: Details of Figure 9. Starting from the model's steady state, we simulate the three rounds of stimulus checks that were disbursed to U.S. households around March 2020, December 2020, and March 2021. For each EIP, we calculate the stimulus amount that we feed into our simulation by dividing the total payment at each round (as reported by the IRS) by the number of U.S. households.[61] The resulting payment per household for the three rounds are \$2,171, \$1,131, and \$3,212. After simulating our model from 2020 to 2023, we take a quarterly snapshot of credit card debt in our model (converted to an aggregate dollar amount) and compare it to the data (also measured quarterly).

We make two adjustments to our model's simulation to make it comparable to the data. First, to synchronize the pre-COVID period in the data with the steady state in our model, we de-trend 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 scale down the model-predicted estimates by the share of large banks in the credit

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

card market. We next adjust the model-predicted estimates by the ratio of all credit card debt to high-interest credit card debt in the SCF, as our model only captures high-interest credit card debt. Lastly, we scale the model-predicted estimates by the ratio of balances on all credit card accounts to balances on open accounts in the Experian data to account for the fact that our model excludes accounts that have been closed but still have a balance.

Credit Card Debt and Fiscal Policy: MPC Size Effect.

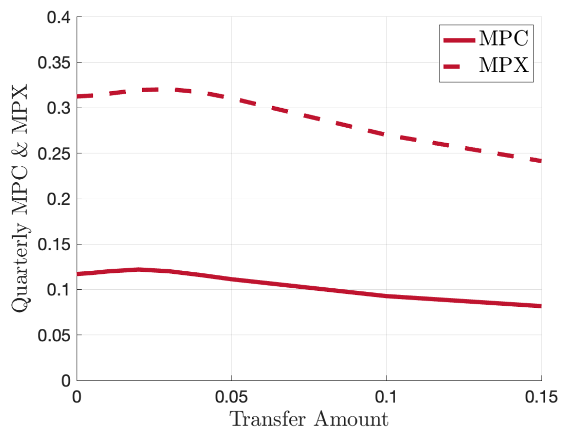

Figure 19: **Quarterly MPCs for Different Transfer Amounts.** This figure plots average quarterly MPCs (solid line) and MPXs (dashed line) across varying transfer amounts. To interpret magnitudes, recall that a transfer of 0.05, for example, corresponds to 5% of average annual income (average after-tax income is $69,003 in our preferred SCF sample; Table 1).

Credit Card Debt and Monetary Policy: Consumption Response.

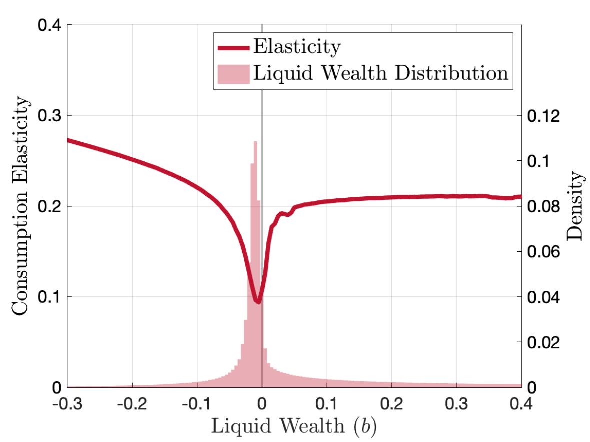

Figure 20: **Consumption Response to Rate Cut.** The line plots the elasticity of average consumption conditional on liquid wealth, and the bars show the liquid wealth distribution.

B.5 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.[62] 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 above in Appendix B.3. We make three changes to the externally calibrated parameters. First, average income for underbanked households is \$33,537 and average income for unbanked households is \$21,365. Second, we set the liquid return r to -2% for unbanked households. Third, since a typical payday loan rate is 15% per two-week borrowing period,[63] we set the borrowing rate to 362% for underbanked and unbanked households.[64] 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 21 replicates Figure 19 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. Turning to

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

[63] 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/

[64] 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.

monetary policy, Figure 22 plots underbanked households' consumption response to a rate change (similar to Figure 20). For unbanked households, there is no consumption response by construction since the cost of payday loans and the return on cash are insensitive to monetary policy.

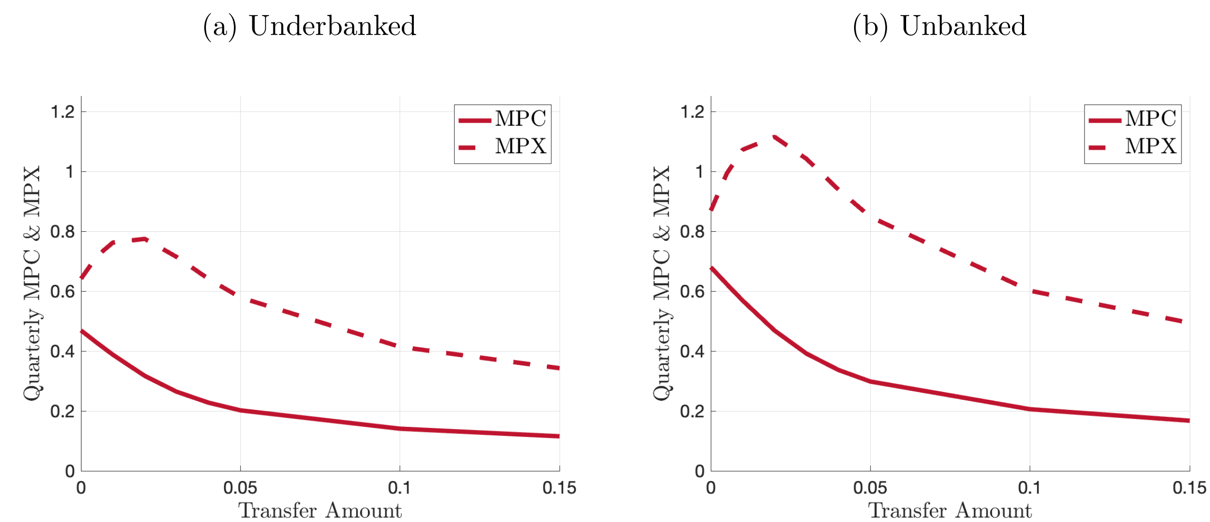

Figure 21: **Quarterly MPCs for Different Transfer Amounts.** This figure replicates the analysis in Figure 19 for underbanked and unbanked households.

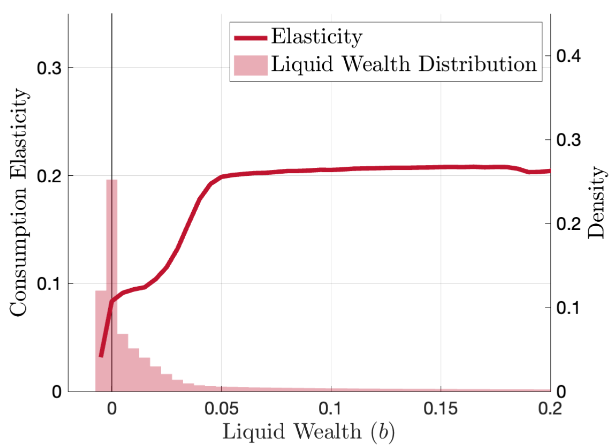

Figure 22: **Consumption Response to Rate Cut.** This figure replicates the analysis in Figure 20 for underbanked households.

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