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# Revolving versus Convenience Use of Credit Cards: Evidence from U.S. Credit Bureau Data

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**Abstract**

Credit card payments and revolving debt are important for consumer theory but a key data source—credit bureau records—does not distinguish between current charges and revolving debt from the previous month. We develop a theory-based econometric methodology informed by survey evidence to estimate the likelihood a consumer is revolving each quarter. We validate our approach using a new survey linked to credit bureau data. For likely revolvers: (1) 100 percent of an increase in credit becomes an increase in debt eventually; (2) credit limit changes are half as salient as debt changes; and (3) revolving status is extremely persistent.

JEL Codes: C81, D14, G51

Key Words: Credit cards, revolving, convenience use, credit bureau

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# 1 Introduction

Understanding credit card use is an important part of modern consumer theory. The literature has focused on the use of credit cards to provide liquidity to buffer income and expenditures shocks, and it is easy to see why. Figure 1 shows that debt on revolving accounts rose from 0 to 9 percent of disposable personal income over three decades, then dropped by almost one-third after the Financial Crisis. What this accumulation of debt and the accompanying changes in credit tell us have been central to the literature (Gross and Souleles, 2002; Agarwal et al., 2017; Gross et al., 2020; Chava et al., 2019; Aydin, 2015; Fulford and Schuh, 2017). Understanding why and when consumers revolve credit card debt from month-to-month is a central focus of several puzzles in consumer finance (Bertaut et al., 2009; Laibson et al., 2003; Agarwal et al., 2009). Yet roughly half of people with credit cards use them solely for the “convenience" of making payments, taking advantage of interest-free short-term debt by re-paying their bill in full every month.[1] Failing to account for the difference between convenience and revolving uses can give a misleading picture of consumer financial management (Johnson, 2007; Zinman, 2009b), money demand (Schuh and Briglevics, 2014; King, 2004; Akhand and Milbourne, 1986), and payment choice (Zinman, 2009a; King and King, 2005).

Credit bureau data have become one of the most important sources of information on consumer credit available to researchers at policy and academic institutions. Credit bureau data collected from financial institutions give a comprehensive view over time of an individual consumer’s credit cards and other debts, such as mortgages or auto loans, so they are a key source of nationally representative statistics on credit use at the individual and aggregate level. However, financial institutions (furnishers) report the total credit card debt owed by a consumer at the time of reporting, which is the sum of current-period credit card charges plus unpaid debt revolved from the previous period (if any). Thus, credit bureau data do not directly identify convenience debt (current charges)

[1] See statistics in reports from the Survey of Consumer Finances (SCF) and Survey of Consumer Payment Choice (SCPC). "Convenience users" are also sometimes called "transactors." One reason for convenience use is the discount earned from rewards, which steers consumers toward credit cards (Ching and Hayashi, 2010). This credit card fee-reward system generates regressive transfers among consumers (Schuh et al., 2010).

and revolving debt separately, a point made recently by Agarwal et al. (2018), among others.[2]

To overcome this shortcoming, we develop a theory-based econometric methodology informed by survey evidence that derives an estimate of the likelihood a given consumer in credit bureau data is revolving or not. The approach is broadly applicable to help policy and research organizations with access to credit bureau data better understand a key facet of consumer credit use. We then use our estimates to study whether convenience users and revolvers react differently to changes in credit limits, a central question in the literature examining consumer credit use, and thus provide a comparison of the relative empirical importance of credit limits and debt.

We estimate a finite mixture model based on intertemporal choice theory, which suggests that debt dynamics of revolvers and convenience users should differ in important ways. Convenience users do not revolve their current charges across periods, so the evolution of their debt mimics that of all consumption, which in its simplest form would follow a martingale process. The debt of revolvers, on the other hand, acts like a negative asset with significant persistence and a strong impact of credit limits. We combine this theory observation with information on revolving by age and credit utilization in the credit bureau data and surveys to estimate the finite mixture model. Together, these pieces provide an estimate of the likelihood an individual is revolving based on his or her credit and debt dynamics, age, and credit utilization. We examine different specifications of dynamics for revolvers and conveniences users and choose the model that best predicts revolving in the Making Ends Meet Survey linked to the Consumer Financial Protection Bureau's (CFPB's) credit bureau data. Our approach provides better separation between credit card uses in the survey data than a model using age and utilization alone.

[2]Other data sources do distinguish between revolvers and convenience users, but are limited in other ways. Highly restricted bank account data provides information on whether an individual credit card account is revolving, but do not provide information on the consumer as a whole (see, for example, Gross and Souleles (2002), Grodzicki and Koulayev (2019), Agarwal et al. (2017, 2018), reports using the JPMorgan Chase Institute data such as Farrell and Greig (2017)). Seeing only the cards an individual holds at a single institution is quite limiting: the Survey of Consumer Payment Choice (SCPC) shows the average consumer holds more than three cards. More detailed information is available on the select consumers willing to let a personal financial management apps collect transactions data across accounts. (See, for examples, Gelman et al. (2014), Baker (2018), and Olafsson and Pagel (2018)). Publicly available survey data like the SCPC and Survey of Consumer Finances (SCF) contain self-reported revolving status, but do not have the rich dynamics and frequency of account level data and have difficulty matching more comprehensive data (Zinman, 2009b).

Using our estimates, we make three central empirical findings. First, for consumers who are likely to be revolvers, 100 percent of an increase in credit limit becomes an increase in debt eventually. This large pass-through from credit to debt is similar across credit utilization levels and across age, conditional on revolving. Convenience users are much less sensitive to changes in their credit limits. When we estimate the impact of a change in credit on all consumers, we closely match estimates of exogenous changes to credit that do not distinguish between revolvers and convenience users (Gross et al., 2020; Chava et al., 2019).

Our second finding is that changes in credit for revolvers have about half the impact of changes in debt. In standard intertemporal accounting, a decrease in credit and an increase in debt have identical impacts on liquidity (after accounting for interest payments). We show how this observation implies a relationship between the coefficients on past debt and credit limits. Yet many people may not know or pay attention to their credit limit unless they are actually at the limit, or they may view credit limits as a soft constraint which can be increased with a phone call. Credit limits may thus be much less "salient" than debt in affecting intertemporal behavior. We find that for revolvers, limits are between one third and one half as salient as debt on average. For convenience users, changes in credit are only 6 percent as salient as debt.

Third, our estimates further suggest that revolving is very persistent. About 20 percent of high probability revolvers transition to being low probability revolvers after four years. This finding is consistent with the limited survey evidence and with Grodzicki and Koulayev (2019) who show that revolving episodes on individual credit card lines are quite persistent as well. Our work complements theirs by looking at the entire consumer, but having to infer revolving rather than observing it directly.

Overall, our empirical findings suggest that revolvers and convenience users react quite differently to changes in credit, so policies are likely to have very different effects for these two populations. A large literature uses credit bureau or similar data to understand credit card use and the impacts of various policies. There is often significant variation in estimated impacts over time and for different populations. Some of this variation may be from combining different populations of credit card users over time or be from differences in the fraction of revolvers captured by the local average treatment effect.[3] Our results suggest that underlying the population average effect of a change in credit are (at least) two populations with very different relationships to changes in credit. In complementary work with an explicit dynamic structural model, Fulford and Schuh (2017) show that at least two populations—one impatient and willing to revolve, one patient and willing to save—are necessary for intertemporal consumption models to fit the course of credit card debt over the life-cycle and the persistence of credit utilization.

A small literature examines the differences between credit card revolvers and convenience users, generally using surveys to understand the correlates between revolving and convenience use. King (2004) uses the Survey of Consumer Finances (SCF) to examine the impact of credit cards on money demand. Tan et al. (2011) examine the propensity to revolve using a survey in Malaysia. King and King (2005) examine the tradeoff between debit and credit cards using the SCF. Sprenger and Stavins (2010) examine credit card debt and payment choices. Zinman (2009a) examines the decision to use a debit or credit card, the relative price of which depends on whether someone is revolving because revolvers start paying interest immediately, while convenience users benefit from a grace period.

Perhaps the clearest, more basic policy implication of our work is the benefit of expanding and refining credit bureau data and similar data sources to directly measure and distinguish between revolving and convenience use so researchers do not need to rely on econometric inference. Efforts such as the Making Ends Meet Survey used here or Stavins (2020) who merges the SCPC with credit bureau data at the consumer level to examine how debt balances and the decision to use debit cards differs for revolvers, are a step in this direction.

[3] See, for example, Chava et al. (2019) who used exogenous variation in credit limits to examine the pass-through from credit to debt and finds relatively large pass-through, but also significant heterogeneity. Gross et al. (2020) examine the increase in credit card limits and credit card debt following the aging off of a bankruptcy flag from credit reports to understand the marginal propensity to consume over time. Brown et al. (2015) examine the substitution patterns between home equity and credit cards and find it varies over time. Some of the heterogeneity examined by Pence (2015) when discussing Brown et al. (2015) may be from the mix of revolving and convenience populations. Similarly, Fulford and Stavins (2019) find significant variation in the impact of mortgage acquisition on credit card borrowing, but cannot distinguish revolving debt from payment debt.

## 2 The data

Our data come from credit bureaus, which are national consumer reporting companies (NCRC) that receive and maintain information about all kinds of credit activity from financial institutions for nearly all consumers. Equifax, Experian, and Transunion are the three main U.S. credit bureaus. In recent years, credit bureau data have been made available to researchers and policy makers in anonymized form that protects the confidentiality of consumers.

Although they contain a rich array of information, credit bureau data represent only a subset of the comprehensive records maintained by banks or other creditors about individual consumer accounts. An NCRC is a data aggregator that relies on data “furnishers”—typically the creditor—to collect and report information on the individual “tradelines” for each consumer. For credit cards, the tradeline information typically includes the total amount owed (current charges plus unpaid debt from last period, if any), the credit limit, whether the account is current, and whether the account was current in the past. Furnishers typically provide updates to credit card tradelines monthly and the updates may coincide with a consumer’s billing cycle. The NCRC combines the tradelines reported from many furnishers with information it maintains at a consumer level.

For this paper, we used the CFPB’s Consumer Credit Panel (CCP). The CCP is an anonymized 1-in-48 sample of all credit bureau records from one of the three main U.S. credit bureaus. In the CCP, we observe a panel of credit reports every quarter; our analysis uses quarterly data from 2012 to 2019. The large size of the data makes it computationally impractical to examine within-person dynamics on the entire CCP, so we conduct our analysis on a 5 percent sub-sample of the CCP. Our analysis data set restricts to consumers with an open card at some point during the sample period and contains approximately 250,000 consumers per quarter and nearly 12.8 million consumer-quarter observations. Of these, only 9.3 million consumer-quarter observations have an open credit card because consumers gain and lose credit cards frequently (Fulford, 2015a). We combine all credit card tradelines together to form a consumer-level panel that gives a the total credit card debt of each consumer over time.

Not all credit bureau data used by research or policy institutions contain the same level of tradeline detail or frequency of reporting. Our approach is practical for credit bureau data that are at least quarterly and contain either all credit card tradelines separately or the sum of credit card tradelines at the consumer level. We calculated many of the results presented here in an earlier working paper (Fulford and Schuh, 2015) with similar credit bureau data (the Equifax/NY Fed Consumer Credit Panel available through the Federal Reserve System) and found only minor differences between results.

While the CCP and other credit bureau data give a complete picture of consumers' debts, credit bureau data do distinguish revolvers from convenience users directly. We use two surveys extensively that ask about revolving to gain more insight into how people are using and acquiring the debt we see in the CCP. We also compare some results to the Survey of Consumer Finances.

The CFPB's Making Ends Meet survey (MEM) is a survey of financial decision-making. The sampling frame for the survey is the CCP. This link allows us to compare the administrative credit bureau data to self-reported revolving status to validate our methodology. The survey was in the field in May and June 2019 and has 2990 respondents. The survey is weighted to be representative of consumers with a credit record, which, by definition, includes all consumers with a credit card. Initial results from the the survey and weighting are described in Fulford and Rush (2020).

The Survey of Consumer Payment Choice (SCPC) conducted by the Federal Reserve Bank of Atlanta examines how a nationally representative sample of consumers decides which payments instruments to use and how these consumers use them. The survey was part of the RAND American Life Panel from 2008-2014 and has been implemented using the Understanding America Study Panel since then. Recent waves of the survey have included slightly over 3,000 respondents (Foster et al., 2019).

# 3 Credit card use

There are three facets to credit card use: (1) whether someone has a credit card and thus "adopted" it as payment instrument; (2) whether someone uses that card to pay for expenditures; (3) whether someone pays off the debt incurred when the card is used for payment at the end of the billing cycle or "revolves" debt from month to month. People who use their cards only for payments are often called convenience users or transactors, because they are using the card as a convenient payment mechanism for transactions. Because the difference in use is central to our empirical examination, we briefly examine each of these elements of card use in turn.

Adoption of credit cards has been relatively stable the last 30 years. The share of consumers with a credit card has been approximately constant at around 70 percent since 1989 (Schuh and Stavins, 2015, p. 20). Information on how frequently credit cards are used is more recent. Pooling the SCPC from 2012 to 2017, 69.9 percent of respondents report having a credit card. Conditional on having a credit card, 83 percent of credit card adopters (58 percent of all consumers) use it for a transaction in the previous month. These respondents use it for 25.2 percent of transactions. Figure 2 shows the credit card adoption rate, overall population use rate, and share of transactions (conditional on adoption) over the life-cycle. Credit card adoption is increasing steadily over the life-cycle from around 40 percent in the early 20s to above 90 percent for those over 75. At any given age, the gap between adoption and payment use in the past month is about 10 percentage points.[4] Note that some of the people who did not use their card for a payment may nonetheless have some revolving debt on the card from previous transactions. Conditional on having a card, the share of all transactions using a credit card is fairly stable over the life cycle at around 25 percent.

What fraction of users in Figure 2 are revolving debt from month to month? In the CCP, a large fraction of consumers with an open credit card have positive debt at any given point in time. This large fraction is slightly misleading, however, because credit bureau data does not allow us to distinguish new charges from debt acquired previously. Some credit card users users pay off their entire balance every month. Others may roll debt over from one month to the next and so are using the revolving credit aspect of credit cards. Both have unpaid debt at any given point in time, so they are indistinguishable in the data.

Figure 3 shows the fraction in different age groups who reported that they revolve credit card

[4] We obtain a similar figure using the CCP to show the fraction of all accounts with an open credit card and with positive credit card debt by age.

debt from month to month (conditional of having a card) using the pooled 2012-2017 Survey of Consumer Payment Choice and the 2019 MEM. The point estimates of the surveys are generally close, and the confidence intervals generally include the other survey, so we discuss them jointly. Between the ages of 20-25 and 40-50, the fraction revolving debt increases from around 40 percent to around 60 percent. The fraction revolving proceeds to fall steadily, but even at age 70-75, around 40 percent of the credit card holding population reports revolving debt. Around 80 percent of the 70-75 year old population has a credit card (Figure 2), so a large portion of the population is borrowing at high interest rates even well into retirement age.

Figure 4 shows the fraction who report revolving in the MEM surveyby their credit card utilization rate (total debt/total credit card limit) in the CCP. The overall contours of revolving and utilization are clear from the figure: (1) most people using less than 10 percent of their credit limit are not revolving, (2) about 60 percent of people using between 10 and 30 percent of their credit report revolving; (3) around 80 percent of people with utilization greater than 30 percent report revolving. The survey evidence is similar to the fraction of credit card accounts that are revolving by utilization reported in Grodzicki and Koulayev (2019). Note that credit card accounts studied by Grodzicki and Koulayev (2019) are different from consumers because a consumer may have many cards.

In Figure 4, slightly less than 20 percent report revolving on a credit card despite having almost no credit card debt in the quarter of the survey (the 0-1 percent utilization group is predominantly 0 utilization). One reason may be the timing of the survey compared to the last credit card statement. When people answer the survey and the quarterly reporting of the CCP do not coincide exactly, so some people may have credit card debt at the time of the survey, but not as of the last reporting for the quarterly CCP. It is also possible that some people misunderstood the question.

We next examine the distribution of credit limits, debt, and utilization. The top two panels of Figure 5 show the distribution of credit card limits and credit card debt (both conditional on being positive) over age. The figures are on a log scale so changes in them are proportional to changes in credit utilization (conditional only on the limit being positive) in the bottom panel. Early in the life cycle, median credit card debt increases with credit limits and continues to increase until the age of 50. After age 60, credit card debt starts falling. The median 70- and 80-year-old has as much credit card debt as the median 20-30 year-old. Of course, some of that debt is convenience use, but it illustrates the extent to which credit is an integral part of the financial life of people across all ages, as well as the importance of credit limits.

Credit limits and debt combine to give the fraction of credit used, shown in the bottom panel of Figure 5. Consumers with zero debt have zero credit utilization, and so are included in utilization but are excluded from debt distribution, which includes only positive values. Median credit utilization falls continuously from age 20 to age 80. The median 20-year-old is using more than 30 percent of available credit, and median 50-year-old is still using nearly 30 percent of their credit. Credit utilization falls to below 20 percent only around age 70.[5]

Figure 6 shows a histogram of the credit utilization distribution over all ages that gives more detail than the quantiles. Around one quarter of the population is using below 10 percent of available credit. Above 10 percent, the distribution is then relatively flat between approximately 20 percent utilization and 80 percent utilization, with a hump just before 100 percent utilization. However, relatively speaking, a large portion of the population is not actively hitting its credit limit at any given time. Not being at a credit limit does not mean that credit limits do not matter, but does suggest that an important part of understanding how credit limits might matter is through the intertemporal budget constraint (Fulford and Schuh, 2017).

A useful way to read the histogram in Figure 6 is that there are, broadly speaking, two populations mixed together: a population that uses almost none of its credit, and a population that uses anywhere from 20 to 100 percent of its available credit about evenly. As we show in Figure 4, about 80 percent of people with 30 percent or higher utilization are revolving.

[5]These medians are somewhat lower than we reported in an earlier working paper (Fulford and Schuh, 2015) using the NY Fed/Equifax consumer credit panel. The NY Fed/Equifax CCP is also derived from a large sample of credit bureau data. It does not separately identify individual credit card trade lines. One reason may be that the definition of which accounts are general purpose credit cards may differ between the two data sets. The dynamics of credit card utilization and debt are nearly identical to Fulford and Schuh (2015).

# 4 Debt dynamics

This section applies insights from intertemporal consumption theory to derive some implications for how the debt of convenience users and revolvers should evolve. The basic idea is that convenience users are using their cards only for payments, so the credit bureau debt we observe should evolve in ways similar to consumption. We model convenience users as consumers with sufficient assets that they can smooth consumption effectively. Debt for revolvers, on the other hand, is a negative asset, so should evolve similarly to an asset. Because revolvers are borrowing, credit limits may occasionally bind for them, so we model them as buffer-stock consumers who care about available liquidity. Our goal throughout is to develop what existing theory suggests rather than extend the theory. We use these distinct dynamics in the next section to help separate revolvers from convenience users.

## 4.1 Debt for different kinds of users

Many of those with credit card debt in our data set are actually convenience users who are using credit as a convenient payment mechanism but plan to pay off their entire debt before being charged interest. Using the SCPC, Figure 3 shows that such convenience users are around 40 percent of the credit card-using population early in the life cycle, and that the proportion rises with age. By definition, convenience users charge some fraction $\omega_{i,t}$ of their consumption $C_{i,t}$ to their credit card each month:

$$D_{i,t} = \omega_{i,t} C_{i,t}, \tag{1}$$

where $D_{i,t}$ is credit card debt and $\omega_{i,t}$ may be stochastic and time varying.

For a revolver, debt changes from period to period according to the standard accounting accumulation equation:

$$D_{i,t+1} = (1 + r)(D_{i,t} - Y_{i,t} + C_{i,t}), \tag{2}$$

where $Y_{i,t}$ is income, $r$ is the interest rate, and $t$ is either age or time, two concepts that are indistinguishable for an individual. A revolver pays off debt if her income is greater than her consumption, and she accumulates debt if her consumption exceeds her income.

Equations (1) and (2) are accounting equations for different kinds of uses. They do not make assumptions about intertemporal behavior beyond assuming a known constant interest rate and that, for a borrower, the amount of debt represents the amount of wealth.[6] Even without putting additional structure on the evolution of income and consumption, the accumulation equation suggests that past debt impacts future debt for revolvers. The rest of this section takes these basic equations and puts more structure on preferences and income to derive estimating equations.

## 4.2 Debt for convenience users

Suppose sufficiently wealthy consumers who do not revolve on credit cards can perfectly smooth consumption up to shocks in the desire to spend (such as whether a consumer takes a vacation or buys a durable good in a given month). Then convenience use in equation (1) should vary only because of these expenditure shocks and the fraction of expenditures consumers charge on a card. Then a sensible equation describing convenience debt is :

$$D_{i,t} = \eta_i^C + f(age_{i,t}) + \epsilon_{i,t} \tag{3}$$

where $\eta_i^C$ is a fixed effect capturing consumer $i$'s level of consumption and tendency to pay for consumption with a credit card. The polynomial in age $f(\cdot)$ allows consumption, or the tendency to use a card, to vary with age.

Alternatively, if the Permanent Income Hypotheses (PIH) holds for convenience users, then following a change in income, consumption should adjust to the annuity value of the change in income. See Hall (1978) for the original formulation, Deaton (1992) for an extended discussion of the preferences and environment necessary for consumption to follow a martingale, and Blundell

[6]For the complicated consequences of relaxing this assumption, see Fulford (2015a).

et al. (2008) for a more recent version that incorporates the life cycle and uncertainty. Then:

$$\Delta D_{i,t+1} = \eta + f(age_{i,t}) + \epsilon_{i,t}. \tag{4}$$

Because consumption behaves as a martingale with drift, so does convenience debt. Equation (4) allows permanent shifts up or down of convenience debt, while equation (3) allows the individual effect to capture permanent consumption and assumes all further shifts are transitory. By omitting limits, we are implicitly assuming that convenience users are not credit constrained. Convenience users are typically using only a small fraction of their available credit (see Figure 4).

## 4.3 Debt for credit revolvers

We model revolvers as buffer-stock consumers who may be constrained by their limit occasionally. The existence of an occasionally binding credit limit induces concavity into the consumption function (Carroll and Kimball, 2001). Following Aiyagari (1994), the available liquidity or cash-at-hand, is $W_t = Y_t + B_t - D_t$, which is just the sum of current income $Y_t$ and the current credit limit $B_t$ minus previously accumulated debt $D_t$. Given the available resources, consumers must decide how much to consume today and how much to consume tomorrow. The consumption function may vary with age as expectations of future income change (Carroll, 2001), and so:

$$C_{i,t} = C_t(W_{i,t}) = C_t(Y_{i,t} + B_{i,t} - D_{i,t}). \tag{5}$$

Notice that using cash-at-hand inherently treats credit limits as equivalent to liquid savings within the consumption function. This assumption does not imply that credit limits are necessarily binding this period for revolvers, but instead that revolvers take into account the fact that by consuming more and increasing their debt, they are reducing their available cash-at-hand for the future.

In expectation, the assets of buffer-stock consumers will tend to return to an individual specific focal cash-at-hand $W_i^*$ where liquidity is neither increasing or decreasing.[7] Appendix A.1 shows

[7] Deaton (1991) introduces the focal point. See Jappelli et al. (2008), Fulford (2015b) for recent empirical exami-

that taking an expansion of the consumption function around the individual focal point and solving for debt in the accumulation equation yields:

$$D_{i,t+1} = \mu_i + \mu_t + g(\text{age}_{i,t}) + \alpha D_{i,t} + \beta B_{i,t} + \epsilon_{i,t}, \tag{6}$$

where $\alpha = (1+r)(1-M)$, $\beta = (1+r)M$, and $M$ is the marginal propensity to consume out of cash-at-hand at its steady state. A log-linear approximation of the consumption function around the individual specific focal point gives:

$$d_{i,t+1} = \mu_i + \mu_t + g(\text{age}_{i,t}) + \alpha d_{i,t} + \beta b_{i,t} + \epsilon_{i,t}, \tag{7}$$

where lower case indicates logs, $\alpha = (1+r)(1-m)$, $\beta = (1+r)m/\bar{\nu}$, and $m = C'(W^*)/C(W^*)$ is the elasticity of consumption with respect to changes in cash-at-hand measured at the steady state of cash-at-hand and $\bar{\nu}$ is average credit utilization.

This expansion provides several useful predictions about the relationship between debt and the credit limit. While the model assumes that credit limits matter, it is possible the credit limit is not an important constraint on consumer choices. The consumer may not find credit limits salient, particularly if they are not binding today. Alternatively, the consumer may be able to raise the limit easily, so it may not represent a true constraint. Similarly, the model does not allow for alternative assets so when the consumer is borrowing she must not be saving. In reality, consumers do keep a small amount of liquid assets (Gross and Souleles, 2002; Fulford, 2015a), and some have substantial illiquid assets. If these assets are substitutes for consumer credit, the credit limit will not matter as much. Then, a simple test for whether the credit limit matters for consumption and debt is $\beta > 0$.

More generally, in this framework of available liquidity, an increase in debt has nearly the same impact on liquidity as a decrease in the credit limit because both affect cash at hand. The accumulation equation approximations predict that $\alpha + \beta = (1+r)$. This prediction is useful

nations. Fulford (2015b) discusses the underlying preferences that might change the individual specific focal point.

for understanding the economic content of the model and its empirical implications. While credit limits may not matter, debt certainly does because it directly affects the intertemporal budget constraint whether or not credit limits ever bind. Put differently, while the consumer has to decide whether to adjust behavior when the credit limit changes and may decide to ignore changes that are not binding today, creditors can make ignoring debt extremely costly. While $\beta > 0$ implies that credit constraints matter, if $\beta = (1 + r - \alpha)$, then changes in debt have the same impact as changes in assets or income.

There are several reasons credit might be less salient than assets. Credit limits may not be reported well by banks and creditors to consumers. Consumers may not always know or remember their credit limits. And the volatility of credit limits may make them less valuable to consumers than a savings or checking account with more stable value (Fulford, 2015a). If credit is less salient than assets, a change in credit will have a smaller impact than a change in debt or income. We can back out an estimate of salience by assuming that only a fraction $\sigma B_{it}$ of credit in accumulation equation (2) matters for consumption decisions. Then, $\alpha + \beta/\sigma = (1 + r)$ and given estimates of $\alpha$ and $\beta$ and an appropriate interest rate $r$, the salience of credit compared to assets is:

$$\sigma = \frac{\beta}{(1 + r - \alpha)} \tag{8}$$

from equation (6) and:

$$\sigma = \frac{\beta\bar{\nu}}{(1 + r - \alpha)} \tag{9}$$

from equation (7) in logs where $\bar{\nu}$ is average credit utilization.

# 5 Separating convenience users from revolvers

In this section, we take the modeling insights from the previous section and use them to help divide the CCP into revolvers and and convenience users. The estimates take in the evolution of revolving over age (Figure 3) and utilization (Figure 4) and then add the prediction of who is revolving based on individual debt dynamics using the implications of the previous section. The basic idea is to use the data to separate the population statistically into those who at a given period are more likely to be convenience users and those who are more likely to be revolvers. We employ a Finite Mixture of Regressions model (Faria and Soromenho, 2010), sometimes also called a latent class model, depending on the discipline and application. McLachlan and Peel (2000) provide a more complete treatment. We examine several different specifications of the dynamics for convenience users and revolvers to understand which give the best predictions.

## 5.1 The EM algorithm

Because we cannot observe directly who in the credit bureau data is a convenience user, the observed data represent a combination of revolvers and convenience users. Each observation is one or the other, but we cannot observe this latent class. However, we can construct a model of the separate paths of debt for convenience users with density:

$$f_C(D_{i,t}|D_{i,t-1}, X_{i,t}; \theta^C, \sigma^C),$$

and for revolvers with density:

$$f_R(D_{i,t}|D_{i,t-1}, X_{i,t}; \theta^R, \sigma^R),$$

where the density functions are conditional on past debt, other observables $X_{it}$ and parameters to be estimated. Then the joint density of the data is:

$$H(D_{i,t}|D_{i,t-1}, X_{i,t}; \Theta) = p^C f_C(D_{i,t}|D_{i,t-1}, X_{i,t}; \theta^C, \sigma^C) + (1 - p^C) f_R(D_{i,t}|D_{i,t-1}, X_{i,t}; \theta^R, \sigma^R),$$

where $p^C$ is the unconditional probability that any observation is from a convenience user, which is not directly observable. Since the mixing probabilities $p^C$ are unobserved, maximizing the sum over all $i$ and $t$ of $\ln H$ requires also maximizing over the unobserved probability $p^c$. Even if the underlying parameters of the revolver and convenience user models are easy to estimate, this problem is very difficult to maximize jointly. Instead, the standard approach is to use the Expectation Maximization (EM) algorithm which alternates between estimating the parameters for revolvers and convenience users conditional on $p^C$, and $p^C$ conditional on the parameters.

The algorithm works as follows: We start round $j$ of the algorithm with an estimate of the probability that each observation is a convenience user: $w_{i,t}^{j,C}$, where $p^{j,C}$ is the average over all $i$ and $t$ of $w_{i,t}^{j,C}$. We take the initial $w_{i,t}^{0,C}$ from the predictions of a logit model of convenience use in the MEM survey based on credit utilization and age.[8] Then, estimation proceeds in two steps: (1) with $w_{i,t}^{j,C}$ as weights, we use Weighted Least Squares to estimate each of the models for convenience users and revolvers independently; and (2) we update the weights and $p^{j+1,C}$ using Bayes' rule based on the new estimates from each model. Thus, for each iteration $j$,

$$w_{i,t}^{j+1,C} = \frac{p^{j,C} f_C(D_{i,t}|\theta^{j,C})}{p^{j,C} f_C(D_{i,t}|\theta^{j,C}) + (1 - p^{j,c}) f_R(D_{i,t}|\theta^{j,R})},$$

and $p^{j+1,C}$ is the average of the new posterior weights for each observation. The two steps alternate until the overall likelihood converges.

For each underlying model described below, we model the densities of the residuals as normally distributed and require the conditional likelihood for a convenience user to follow the same conditional likelihood of a being a convenience user in the MEM survey based on age and utilization. Then the density for a convenience user is:

$$f_C(D_{i,t}|D_{i,t_1}, X_{i,t}; \theta^C, \sigma^C) = p_{MEM}^C(\text{age}_{it}, \nu_{it}) \phi(D_{i,t}|D_{i,t}, X_{it}; \theta^C, \sigma^C),$$

where $\phi(\cdot)$ denotes the density of the normal distribution with mean determined by the particular convenience model and variance $(\sigma^C)^2$. Revolvers follow the same structure. We estimate $p_{MEM}^C(\text{age}_{it}, \nu_{it})$ using a logit model with a cubic for age and utilization. Figures 7 and 8 show

[8] We have also taken the initial probabilities as uniformly distributed between 0 and 1 and found that the initial value does not affect convergence of the estimation.

the estimated fractions of revolving (which implies the complementary fractions of convenience use) over age (Panel A) and utilization (Panel B) using the MEM surveyestimates of $p^C_{MEM}$, and compares them with the corresponding estimates from the MEM survey and SCF logit models.

## 5.2 Estimated models of credit use

This section reports the results of estimating several possible models of credit use with the EM algorithm. Table 3 shows five joint models of revolving and convenience use. For each model, we calculate the average probability across all consumer quarters of revolving. For comparison, the mean self-reported revolving status across consumers with credit cards in the MEM survey is 51 percent. We also calculate the mean squared difference between the probability of revolving predicted by the model for consumers in the MEM survey during the quarter of the survey and their self-reported revolving status. We calculate the full model for the entire CCP sample, but can only compare the self-reported status to the MEM respondents.

Even within a user type, consumers may have very different preferences, so all of the models allow individual specific effects. In practice, due to the size of the data set and the iterative nature of the algorithm, we removed the individual and time effects first by regressing each variable on individual and year fixed effects and then using the residuals to estimate the credit-use models. All models include a cubic polynomial in age.

The five model specifications provide a range of diverse options to discern which approach to handling stationarity and dynamics best fits the data. The key differences among the specifications are:

- Model 1 takes logs of credit card debt and limit following equation (7) for revolvers and equation (4) for convenience users.[9] As shown in Figure 5, credit card limits and debt have very large values and very small values. Taking logs makes the assumption of normal residual variance more reasonable.

[9]To avoid discarding consumers with zero debt, the actual transformation is to add to each consumer with a credit card \$100 in credit card debt and limit.

- Models 2 and 3 do not transform debt and credit limits. Model 2 allows convenience use to follow a random walk with drift following equation (4), while in model 3 convenience use varies around an individual specific mean following equation (3). Both models follow equation (6) for revolvers.

- Models 4 and 5 instead divide debt by the credit limit to allow the dynamics of credit utilization ($\nu_{it} = D_{it}/B_{it}$) to vary across model type. Normalizing by the credit limit is a different way to make the decisions of consumers with very high and very low limits comparable but imposes restrictions on the impact of past debt and credit. Both models take revolvers as following a simple AR(1) process. For convenience users, Model 4 takes utilization as following a martingale while model 5 takes utilization as varying around an individual specific mean.

It turns out that the models make very different predictions and some perform quite poorly. Model 1 produces an average revolving status that is closest to the results of surveys. Model 2 under-predicts revolving while model 3 substantially over-predicts revolving. Both models 2 and 3 depart substantially from the MEM consumers self-reported revolving status as judged by the mean squared difference. With a common residual variance across consumers but large differences in credit limits and debt across consumers (see Figure 5), the models using untransformed dollar values do not appear helpful in distinguishing consumer uses.

In contrast, models 4 and 5 with credit utilization perform fairly well. Model 4 somewhat underpredicts revolving while model 5 somewhat overpredicts revolving. Models 1 and 5 have the best match to MEM self-reported revolving. Model 4 has a slightly better match than model 1, but over-predicts revolving overall.

To better understand how these models differ in their predictions, Figure 7 for model 1 and Figure 8 for model 5 show how these models compare across several dimensions. Panel A of Figures 7 and 8 shows the fraction of revolvers at different ages that come from the EM estimates (using the posterior weights for each observation) compared to a logit from the MEM survey (see also Figure 3) and a similar logit from the SCF. Panel B of both figures shows similar results over credit utilization. Both models match the distribution of revolving across utilization fairly well. Model 1 matches the MEM survey distribution of revolving across age much better than model 5. The similarity suggests that differences in dynamics among consumers in the CCP do not produce large differences across utilization.

The advantage of the Finite Mixture Model over simply using a prediction from a survey is that it takes into account individual dynamics. It can therefore make individual predictions that are distinct from what a logit fit from a survey would imply. Panel C of Figures 7 and 8 shows the density of the revolving prediction for people who respond that they are a revolver in the MEM surveyand not a revolver. The dashed line shows the density of the probability that some is a revolver based on a logit of age and utilization. Unsurprisingly, people who report being revolvers have a large density at a high probability of revolving and people who report not revolving have a high density at a low predicted probability of revolving. Note, however, that the logit also predicts some people who report not revolving have some probability of actually being a revolver based on their utilization. For example, a middle age person with 80 percent utilization may report not revolving, but the logit suggests based on other similar people, that this person is likely to revolve.

The Finite Mixture Model estimates help differentiate people by putting more weight on predictions that someone either is or is not a revolver with high probability in Panel C. Adding the dynamics thus helps provide more separation. Panel C thus suggests that the Finite Mixture Model using debt dynamics has more predictive power than just using age and utilization alone.

Panel C in Figures 7 and 8 provides some insight into why model 5 has a better mean squared difference from MEM, despite substantially over-predicting revolving. If the algorithm perfectly predicted survey responses, all of the density in Panel C would be at zero for survey not-revolvers and at one for survey revolvers. The estimates in both models put more weight closer to zero and one than the logit and more weight contradicting the survey responses. Model 1 contradicts MEM respondents somewhat more than model 5, putting somewhat higher density in predicting that self-reported non-revolvers are revolving and the reverse.

While both model 1 and model 5 provide a reasonable fit, we take model 1 as our base model for examining how revolvers and convenience users differ. Model 5 does not produce qualitatively different estimates, but its over-prediction of revolving suggests it is less accurate.

# 6 How are revolvers and convenience users different?

This section uses the Finite Mixture Model predictions in the previous section with model 1 as a baseline to examine differences between revolvers and convenience users. We start by comparing average utilization and examine what the estimates say about transitions from revolver to convenience user. Then, using the revolving probabilities as weights, we examine how individual debt and credit dynamics differ. We expect that our methodology has additional applications, but these areas are continuing questions in understanding credit card use.

## 6.1 Average utilization

Panel D in Figures 7 and 8 show the average utilization of revolvers and convenience users by age for models 1 and 5 using the converged weights to estimate utilization as a local polynomial function of age. In both models, conditional on still being a revolver, average utilization declines slowly from around 60 percent in the 20s to 50 percent in the 60s and then more quickly after that. The average utilization of convenience users also declines slowly. An important factor explaining the overall decline in utilization is the decline in the fraction of revolvers, as the population slowly shifts from the top line of revolvers to the bottom line of convenience users.

## 6.2 Revolving transitions

A recurring question in understanding consumer credit is how long people spend borrowing. If a sizable portion of the population uses credit to smooth over shocks, then borrowing should be transitory. However, some consumers may be revolving for long periods due to preferences such as impatience or present bias, a "debt spiral," or other explanations not found in the benchmark life-cycle model. Because few surveys have a panel dimension and credit bureau data cannot distinguish between revolving and convenience use, it has been difficult to understand revolving persistence. Grodzicki and Koulayev (2019) examine revolving episodes in a data set that includes only single credit card lines that are not linked across consumers. Even considering single lines, the average revolving episode is quite long.

The EM algorithm produces a posterior weight of revolving for each consumer-quarter. This weight is the Bayes rule update of the likelihood that the consumer-quarter observation comes from the revolver model or the convenience user model. These weights can change for a consumer over time as utilization or the debt and limit dynamics change. For example, if a consumer's utilization drops significantly, the algorithm would suggest that the likelihood of revolving is lower.

Treating these model-based likelihoods as probabilities of revolving, we examine how consumers transition from a high revolving probability (revolving probability above 75 percent), medium probability revolvers (25 percent to 75 percent), to low revolving probability (less than or equal to 25 percent). Table 2 shows that in any given quarter, 45 percent of accounts are high probability revolvers, 25 are medium probability, and 30 percent low probability revolvers. Taking the average revolving probability over all the quarters we observe a given consumer, 27 percent of consumers have an average probability of revolving greater than 75 percent over all quarters we observe them, 66 have a medium probability on average, and 6 percent have a low probability on average.

High probability revolving status is very persistent. Table 2 shows the transition matrix from high, medium, and low revolving probability. Conditional on being a high probability revolver, 71 percent are still high probability revolvers in one year, 67 percent in two years, and 63 percent in four years. Almost all of the transition is into medium probability status, rather than to a low probability of revolving; 20 percent of high probability revolvers have become low probability revolvers after four years. Conversely, a low probability revolver today is a low probability revolver 45 percent of the time in one year, 42 percent in two years and 40 percent in four years. Thirty percent of low probability revolvers have transitioned into high probability revolvers after four years.

These probability transitions compare well to the limited survey evidence on overall revolving transitions. The SCPC had a repeat sample over several years. Using consumers who appear in more than sample, we calculate that 82.7 percent of self-reported revolvers in one year are also revolvers in the next year. Similarly, 87.5 percent of convenience users report being a convenience user in the next year.

Put together, our estimates suggest that somewhat more than half the population is a high probability revolver at a given time and this population generally stays a high probability revolver for a long time. A somewhat smaller proportion of the population is consistently a high probability convenience user. The medium probability revolvers do not generally stay medium probability revolvers: after four years 28 percent are high probability revolvers and 35 percent are low probability revolvers. In reality, these medium probability consumers are either revolving or not. The intermediate probability reflects that their debt dynamics, utilization, and age do not place a high posterior weight on either model.

## 6.3 Debt dynamics

This section examines how debt changes for an individual and how these changes are related to changes in credit and debt in the past. The basic specification is a variant of model 1,

$$\ln D_{it} = \theta_i + \theta_t + f(\text{age}_{it}) + \alpha \ln D_{it-1} + \beta \ln B_{i,t-1} + \epsilon_{it}, \tag{10}$$

with individual-specific levels of log credit card debt ($\theta_i$) and common time shocks ($\theta_t$) in addition to the age polynomial ($f(\text{age}_{it})$). The coefficient $\beta$ on the lagged credit limit determines how quickly a shock to credit card debt ($\epsilon_{it}$) dissipates back to the individual long-term effect given by $\theta_i + \theta_t + f(\text{age}_{it}) + \beta \ln B_{it}$. The effect of a change in credit limits is $\beta$ within one quarter, and $\beta/(1-\alpha)$ in the long term. In more advanced specifications we allow $\alpha$ and $\beta$ to change with age and with credit utilization so that, for example, older people or those close to using all of their available credit may react differently to a change in the limit.

In most specifications, we include those with zero debt by giving everyone \$100 in both credit and debt so that, rather than being undefined, these individuals are included as having nearly zero debt (we still exclude individuals with zero credit). The functional form in equation (10) with logs excludes consumers who have zero debt in the current or previous period because the log of zero is undefined. Equation (10) therefore estimates the response of those with debt to changes in limits conditional on having debt and a positive credit limit.

Table 3 shows the results of estimating several variations of equation (10). Column 1 shows the base specification, column 2 gives everyone \$100 in credit and debt and so includes those with no current debt. At the bottom of the table we calculate the long-term impact of a permanent increase in credit $\beta/(1-\alpha)$. Columns 3 and 4 weight by revolving probability, while column 5 weights by convenience probability. Table 4 shows similar estimates without taking logs for robustness.

On average across all consumers and adjusting for age, the pass-through of credit into debt occurs rapidly—nearly 75 percent in the long term in Table 3. Pass-through is somewhat larger in column 2 including card holders with zero debt, and in column 1 of Table 4 without taking logs.

These results for all consumers mask important differences between revolvers and convenience users. For revolvers, nearly 100 percent of a change in credit becomes debt eventually. Column 4 of Table 3 shows the estimated effects of debt and credit changes for revolvers. Debt returns to its steady state more slowly than when estimated over all credit users, as one would expect. The immediate impact of credit is lower, but the long-term impact of a change in credit for revolvers is nearly 100 percent due to the persistence of debt. In fact, in column 4 the long-term pass-through is 99.3 percent. In contrast, the pass-through is much lower for convenience users in column 5. This finding is the same when not taking logs in Table 4— the pass-through is 99.2 percent in the long term for revolvers (column 2), but much lower for convenience users.

The last row in Tables 3 and 4 calculates the salience of credit limit changes. The calculation assumes that any departures from this relationship are due to credit limits being less binding or salient than debt and calculates how much less important credit limits are using equations (9) and (8).

This salience calculation matters empirically for several reasons. First, it is an approximation of the extent to which credit limits bind; if a change in credit limits has zero salience, credit limits are not effectively binding behavior. Second, in an intertemporal budget calculation, the credit limit is a binding constraint that enters much the same way debt does so changes in credit look much like changes in debt in terms of their effect on the budget constraint. Yet credit is variable (Fulford, 2015a) and many people may not know their limits. Others may think of limits as "soft" constraints that can be increased simply by contacting the bank. Still others just may not care much about their limits. The salience calculation combines all of these reasons into a single number that asks: relative to the effect of debt, how much less impact does the credit limit have?

For revolvers, who might actually hit their limit, credit is half as salient as debt (columns 3 and 4 of Table 3 and column 2 of Table 4) using an interest rate of 14.07 percent.[10] Once again, this result varies significantly between revolvers and convenience users. For convenience users, credit is only approximately 6 percent as salient as debt (column 5 in Table 3 and column 3 of Table 4). This division suggests that, in general, changes in credit have by far their largest impact on revolvers. Fulford and Schuh (2017) make a similar observation through estimating a structural model of revolving.

We can also allow the response of debt to past debt and current limits to vary flexibly with credit utilization and age.[11] Because the coefficients from such a regression are difficult to interpret on their own, Figure 9 shows the marginal effects for revolvers evaluated over ages 20 to 70 and utilization from 0.1 to 1. We restrict this examination to revolvers using the posterior weights from model 1.

[10]The average Federal Reserve G-19 series for commercial bank interest rate on credit card plans, accounts assessed interest; not seasonally adjusted from May 2004 through May 2019 on an annual basis. We use the implied monthly (compounded) rate in the calculation.

[11]We estimate the following functional form for $\alpha$ and an identical one for $\beta$:

$$\alpha(\text{age}_{it}, \upsilon_{it-1}) = \alpha + \alpha_0\upsilon^{(0)}_{it-1} + \alpha_1\upsilon^{(1)}_{it-1} + \alpha_2\upsilon_{it} + \alpha_3\upsilon^2_{it-1} + \alpha_4\upsilon^3_{it-1} + \alpha_5\text{age}_{it} + \alpha_6\text{age}^2_{it} + \alpha_7\text{age}^3_{it} + \alpha_8\upsilon_{it-1} * \text{age}_{it} + \alpha_9\upsilon^2_{it-1} * \text{age}_{it} + \alpha_{10}\upsilon_{it-1} * \text{age}^2_{it} + \alpha_{11}\upsilon^2_{it-1} * \text{age}^2_{it},$$

where $\upsilon^{(0)}_{it}$ is 1 if utilization is 0, and 0 otherwise, $\upsilon^{(1)}_{it}$ is 1 if utilization is greater than 1.1 and 0 otherwise, and $\upsilon^2_{it} = \upsilon_{it} * \upsilon_{it}$. Note that, like the credit limit, the credit utilization rate is measured as the credit limit at the end of the period divided by the debt at the beginning.

Several important changes with age and credit utilization for revolvers are clear from Figure 9. First, the marginal effect of the credit limit is fairly similar to the average effect in Table 3 except at the lowest utilization rates. Second, the sum of the estimated credit effect and estimated debt effect is nearly constant and close to one at any age or utilization rate, which implies a relatively constant and high salience of credit for revolvers at all ages. Third, the long-term effect of credit on debt is large and relatively constant across ages and utilization rates. Panel (C) calculates the long-term effect at each age and utilization (essentially dividing the marginal effect at each age in panel (A) by one minus the marginal effect of debt in panel (B)). Young people reach that long-term state faster, but for all revolvers the long-term effect of credit on debt is nearly 100 percent. Fourth, the effect of utilization is extremely nonlinear at any age. The effects of credit and past debt are nearly identical for those using between 0.1 and 0.7 of their credit, but then change rapidly as individuals get closer to using all of their credit. Apparently, credit utilization matters a lot only when the the consumer is close to her credit limit. Finally, age and credit utilization do not seem to interact. Excluding the age-credit utilization interactions would not change this picture appreciably because the different lines connecting credit utilization are nearly parallel for different ages.

## 6.4 Credit dynamics

We next examine whether there is an important feedback mechanism from debt to credit. Table 5 shows the impact of past credit and debt on current credit. Allowing for individual specific means in credit, deviations from the long term are fairly persistent, with 91 percent of a deviation still existing within a quarter. Debt has a small negative impact on credit in column 1 and a small positive impact in column 2 which includes those with zero debt. Over the long term, averaging over all consumers, a permanent 1 percent increase in debt results in a 5 percent fall in credit in column 1 or a 3 percent increase in credit in the long term. This small positive effect is explained by substantial heterogeneity by type of consumer as shown in columns 3 and 4. An increase in debt is associated with a fall in credit for convenience users and a relatively substantial increase on average for revolvers.

## 6.5 Utilization dynamics

This section examines how credit utilization changes from quarter to quarter parametrically for different types of users. In previous work (Fulford and Schuh, 2015), we showed that moving to a parametric specification does not seem to matter on average because the conditional expectation functions are surprisingly linear. Table 6 shows how utilization this period is related to utilization in the previous period using regressions of the form:

$$\upsilon_{it} = \theta_t + \theta_a + \theta_i + \beta \upsilon_{it-1} + \epsilon_{it}, \tag{11}$$

where $\upsilon_{it} = D_{it}/B_{it}$ is credit utilization conditional on $B_{it} > 0$, age ($\theta_a$) and quarter ($\theta_t$).[12] All regressions use de-meaned data for included variables to absorb fixed effects rather than estimating them separately due to sample size.

The first column shows the population average effect. On average, a deviation from the individual mean diminishes at a rate of about 0.29=1-0.71 per quarter. And so, after a 10 percentage point increase in utilization 7 percentage points remain in one quarter, 2.5 percentage points in a year, and 0.64 percentage points after two years. The estimates in Table 6 emphasize that credit utilization for an individual is very stable. While there are deviations from the long-term mean, these dissipate quickly and are largely gone within two years.

The next two columns show analogous estimates for revolvers and convenience users. For revolvers, changes in utilization are somewhat more persistent. Convenience users, on the other hand, have almost no persistence in shocks to utilization.

# 7 Conclusion

Many consumer finance and counter-cyclical policy questions depend on how consumers respond to changes in credit or the price of debt. Yet credit bureau data that does not measure revolv-

[12]The combined age, quarter, and individual fixed effects are not identified. We drop one of each and use the normalization on the age effects discussed in section 6.4.

ing directly. Credit cards' mixed use as a payment instrument and a revolving debt mechanism confounds different populations and responses, making understanding mechanisms and the likely effect of policy difficult. By developing a method to separate revolvers and convenience users in the main, comprehensive source of information about debt and credit, we allow a deeper understanding of many of these questions.

Our methodology sheds light on some important questions about how revolvers and convenience users differ. Available credit appears to be the driving factor of debt for revolvers in both the short and long term. Separating convenience users from revolvers, we find that for revolvers an increase in credit is followed by a nearly 100 percent increase in debt over the long term. For those revolving debt, long-term credit and debt are closely related; we calculate that for revolvers changes in credit limits are half as impactful as changes in debt. In addition, those revolving are typically revolving for long periods of time.

Our analysis infers whether the consumer is revolving based on his or her utilization and debt dynamics for all cards combined, but the CFPB CCP contains information on each credit card held by an individual consumer. One interesting area for future research is to explore how consumers manage their card portfolio across multiple cards. For example, do consumers who are revolving maintain most or all of their balance on a single card? How do the number of cards of revolving and convenience users compare? How does utilization overall compare to utilization for each card and is this different for revolvers and convenience users.

Future research on the use of credit cards would be enhanced by improving and expanding the credit bureau data. Direct measurement of revolving versus convenience use is the most obvious data refinement that could shine a light on credit card use. Including comprehensive details on consumer management of their credit card debt by measuring monthly payments would enable researchers to derive even more insights and policy implications concerning revolving of credit card debt.

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# A Appendix

## A.1 Derivation of debt revolver accumulation equation

From equation (2) we have:

$$\frac{D_{i,t+1}}{1+r} - D_{i,t} + Y_{i,t} = C_{i,t}(Y_{i,t} + B_{i,t} - D_{i,t}).$$

Let $Y_{it} = P_{i,t}U_{i,t}$, where $P_{i,t} = E_{t-1}[Y_{i,t}]$ is the long-term or permanent component of income given age $t$, and $B^*_{i,t}$ is the expected credit limit at age $t$ for a given individual. Then define $D^*_{i,t}$ as the debt at which, given a credit limit $B^*_{i,t}$ and income realization $Y_{i,t} = P_{i,t}$, consumption is equal to income minus interest payments and so debt is not increasing or decreasing:

$$\frac{-rD^*_{i,t}}{1+r} + P_{i,t} = C_t(P_{i,t} + B^*_{i,t} - D^*_{i,t}).$$

Note that this is the Permanent Income Hypothesis consumption function in which all of permanent income and the annuity value of current wealth is consumed (Hall, 1978). A first-order expansion of $C_t(\cdot)$ around the point focal point $W^*_{i,t} = D^*_{i,t} - B^*_{i,t} - P_{i,t}$ then gives:

$$D_{i,t+1} \approx (1+r)M_{i,t}B_{i,t} + (1+r)(1-M_{i,t})D_{i,t} + M_{i,t}Y_{i,t} + \text{[Constant]},$$

where $M_{i,t} = C'_{i,t}(W^*_{i,t})$ is the marginal propensity to consume out of liquid cash-at-hand at its steady state. If $M_{i,t}Y_{i,t}$ and the constant can be well captured by individual fixed effects, age effects, and year effects, then a regression of the form:

$$D_{i,t+1} = \mu_i + \mu_t + g(\text{age}_{i,t}) + \alpha D_{i,t} + \beta B_{i,t} + \epsilon_{i,t},$$

where $M$ is the average of the $M_{i,t}$, $\alpha = (1+r)(1-M)$, $\beta = (1+r)M$, and $\epsilon_{i,t}$ captures the approximation error that represents unobserved income shocks not explained by age, individual, time, and differences from the average $\alpha$ and $\beta$. Note that $M_{i,t}$ may vary with age or overall credit utilization as well.

The assumptions necessary for the linear expansion in levels to provide a good approximation are strong, particularly comparing across many individuals with very different incomes and debt. A more flexible expansion involves taking logs and expanding around $D^*_{i,t}$, $B^*_{i,t}$, and $P_{i,t}$. Canceling constants and using the steady-state equation gives a first-order approximation:

$$\frac{D^*_{i,t}}{(1+r)} d_{i,t+1} - D^*_{i,t} d_{i,t} + P_{it} \ln U_{i,t} \simeq m_{it}(P_{i,t} \ln U_{i,t} + B^*_{i,t} b_{i,t} - D^*_{i,t} d_{i,t}),$$

where $b_{i,t} = \ln B_{i,t}$, $d_{i,t} = \ln D_{i,t}$, and $m_{i,t} = C'_t(W^*_{i,t})/C_t(W^*_{i,t})$ is the elasticity of consumption with respect to cash-at-hand at the steady-state cash-at-hand $W^*_{i,t}$. Rearranging gives:

$$d_{i,t+1} \simeq (1+r)(1-m_{i,t}) d_{i,t} + (1+r) m_{i,t} \frac{B^*_{i,t}}{D^*_{i,t}} b_{i,t} + (1+r)(m_{i,t}-1) \frac{P_{i,t}}{D^*_{i,t}} \ln U_{i,t}.$$

Defining $m = E[m_{i,t}]$ and $\bar{\nu} = E[\frac{D^*_{i,t}}{B^*_{i,t}}]$ as average credit utilization, then:

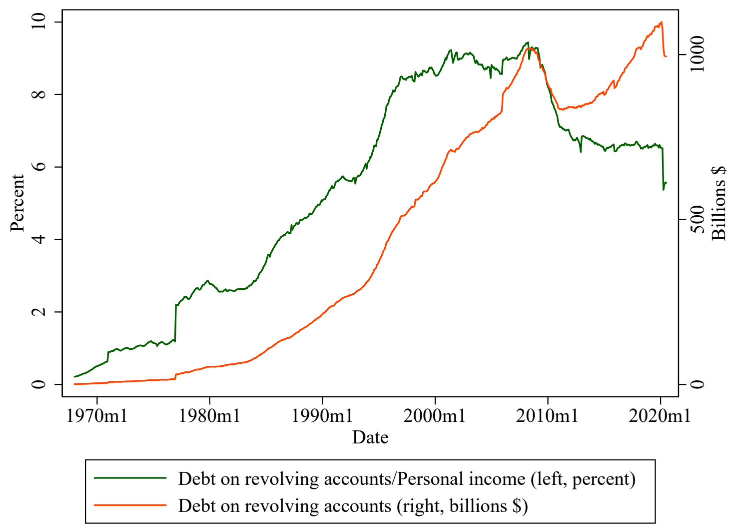
$$d_{i,t+1} = (1+r)(1-m) d_{i,t} + (1+r) m \frac{b_{i,t}}{\bar{\nu}} + \epsilon^s_{i,t},$$

where $\epsilon^s_{it}$ captures contains the idiosyncratic portion of the coefficients and the unpredictable income component. Following Blundell et al. (2008), suppose that idiosyncratic and age-specific drift factors are well-captured by an individual effect and age effects (or functions) so the approximation error is $\epsilon^s_{i,t} = \mu_i + \mu_t + g(\text{age}_{i,t}) + \epsilon_{i,t,}$. Then

$$d_{i,t+1} = \mu_i + \mu_t + g(\text{age}_{i,t}) + \alpha d_{i,t} + \beta b_{i,t} + \epsilon_{i,t},$$

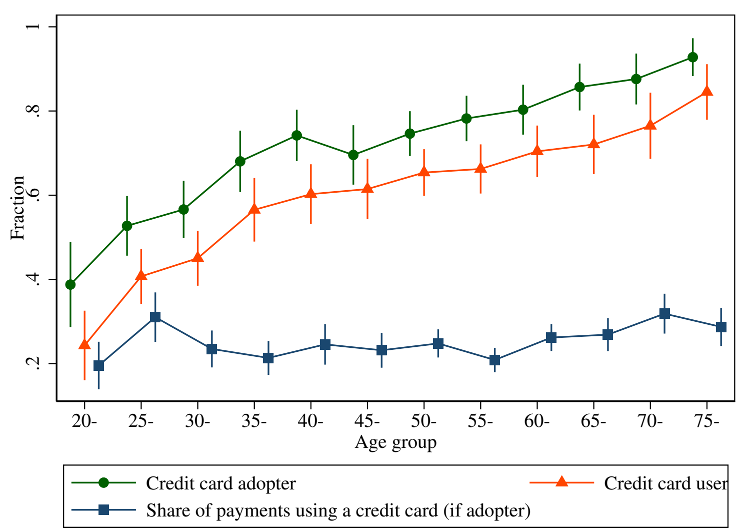
where $\alpha = (1+r)(1-m)$, $\beta = (1+r)m/\bar{\nu}$ and $E[\epsilon_{it}] = 0$.

Figure 1: Total debt on revolving accounts



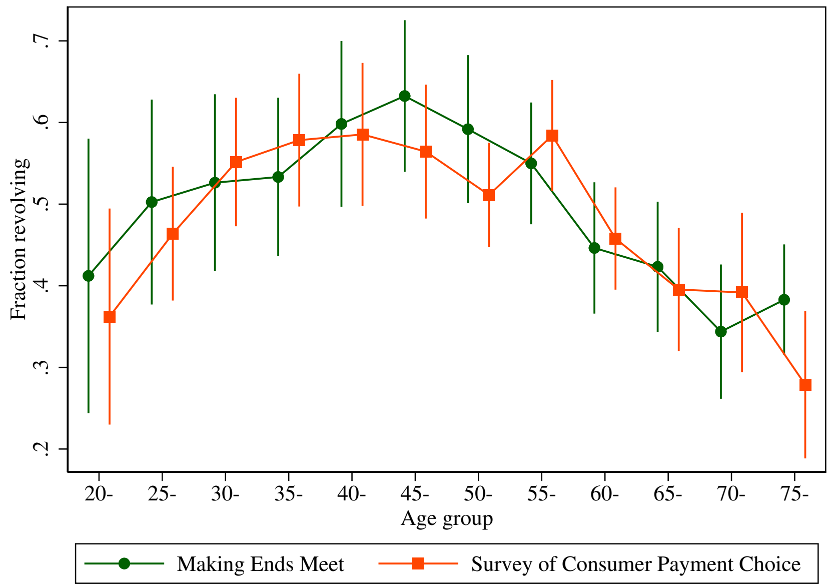

Source: Federal Reserve Bank of St. Louis FRED; Board of Governors G.19 Consumer Credit "Total Revolving Credit Owned and Securitized, Outstanding"; and Bureau of Economic Analysis Disposable Personal Income.

Figure 2: Credit card adoption and payments use by age from the SCPC



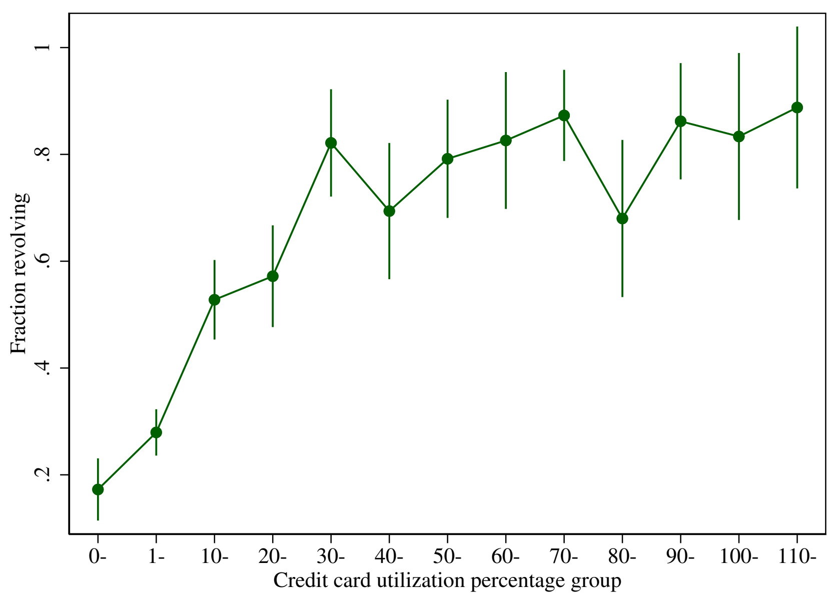

Source: Authors' calculations from the pooled 2012-2017 Survey of Consumer Payment Choice.

Figure 3: Fractions of consumers revolving by age, MEM and SCPC




Notes: Each dot represents the age-group mean from that survey (the surveys are offset so they can be cleanly distinguished). Bars are 95-percent confidence intervals. Source: Authors' calculations from the MEM survey and SCPC.

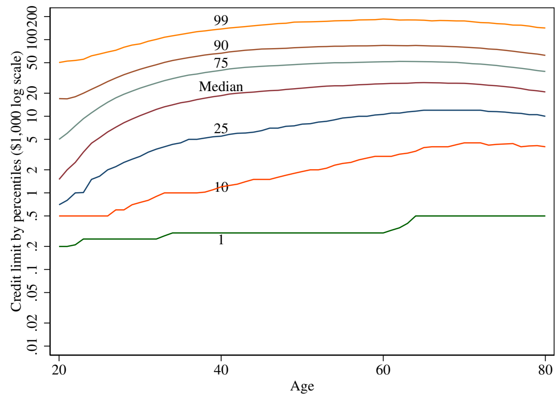
Figure 4: Fraction of consumers revolving by utilization, MEM



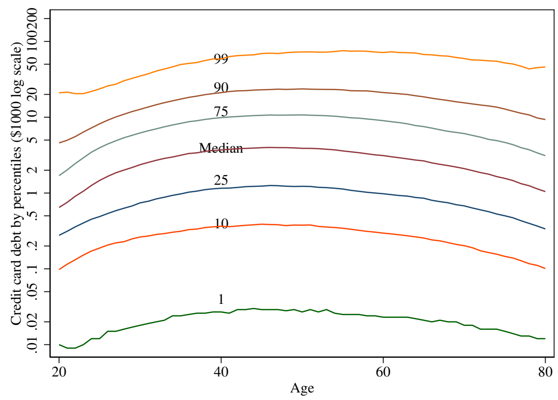

Notes: Each dot represents the mean for that utilization group from the MEM survey. Utilization is calculated using the CCP linked to that respondent. Bars are 95-percent confidence intervals. Source: Authors' calculations from the MEM survey.

Figure 5: Distributions of credit card limits, debt, and credit utilization by age

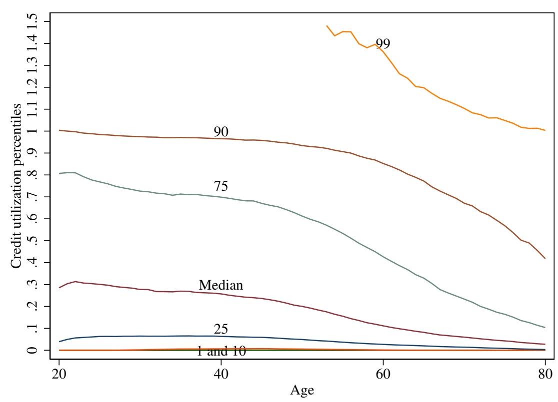
(A) Credit card limits




(B) Credit card debt

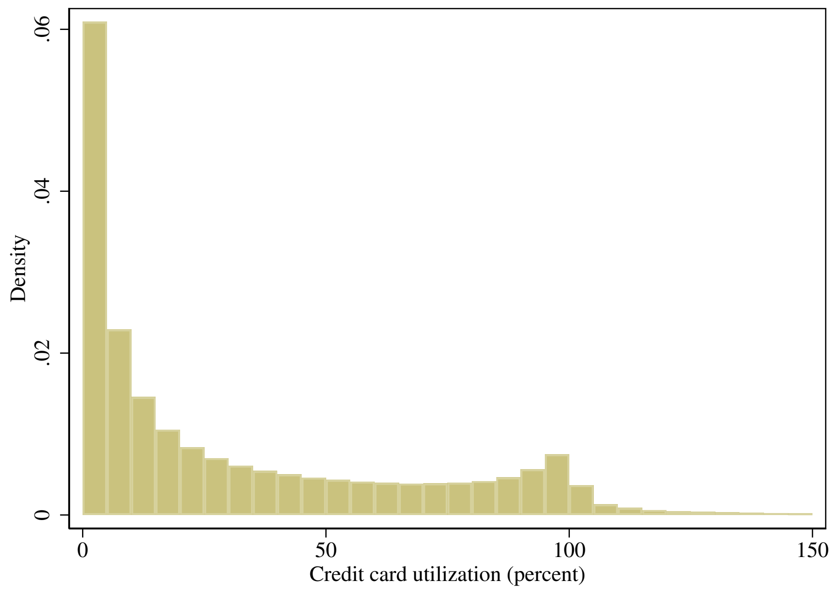



(C) Credit utilization



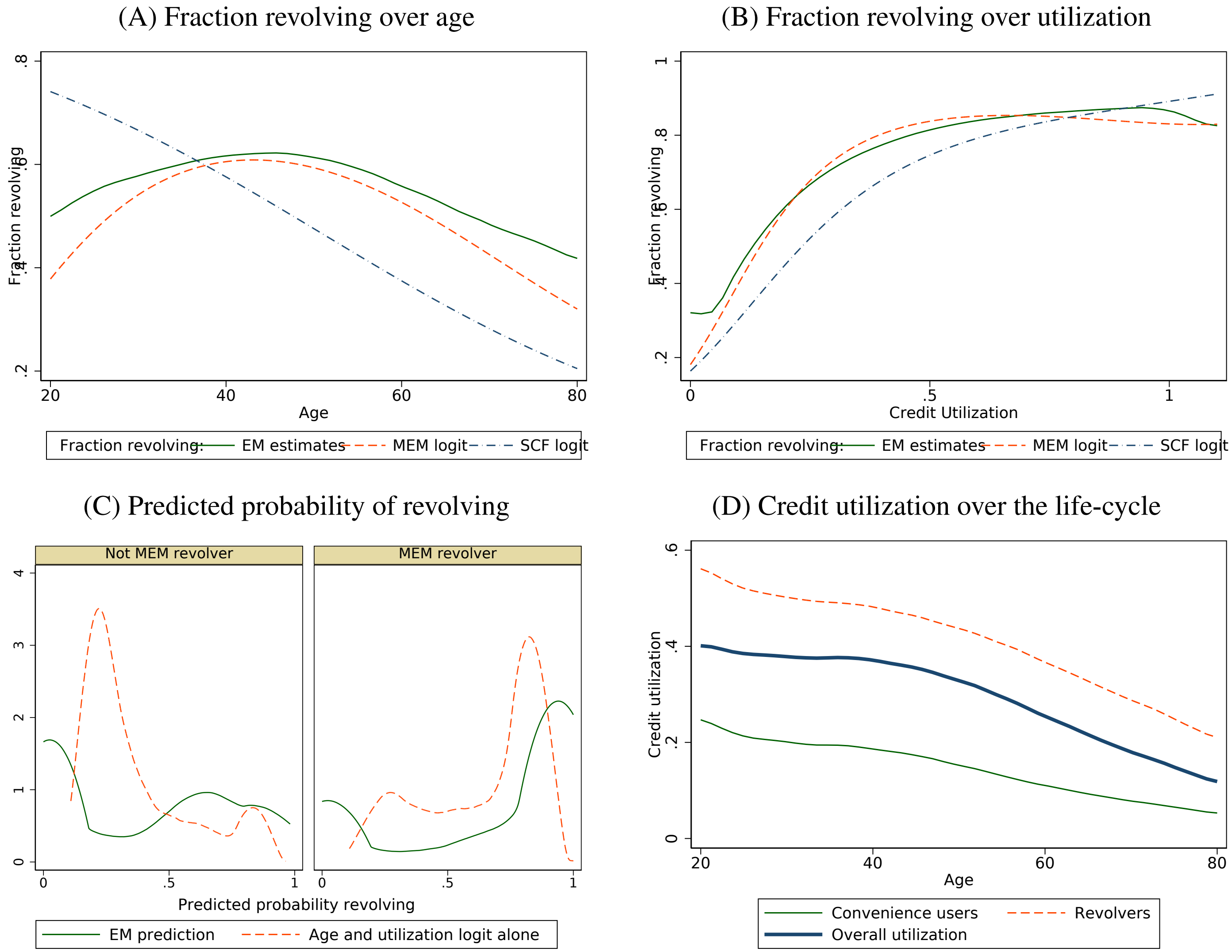

Notes: Each line is a percentile of the distribution of credit limits, debt, or utilization at that age, conditional on having a positive credit limit or debt on a log scale. For example, the 90th-percentile line shows that 10 percent of the population (with a positive credit limit) have a limit larger than that line. The 99th-percentile credit utilization is above 1.5. Source: Authors' calculations from the CCP.

Figure 6: Distribution of credit card utilization



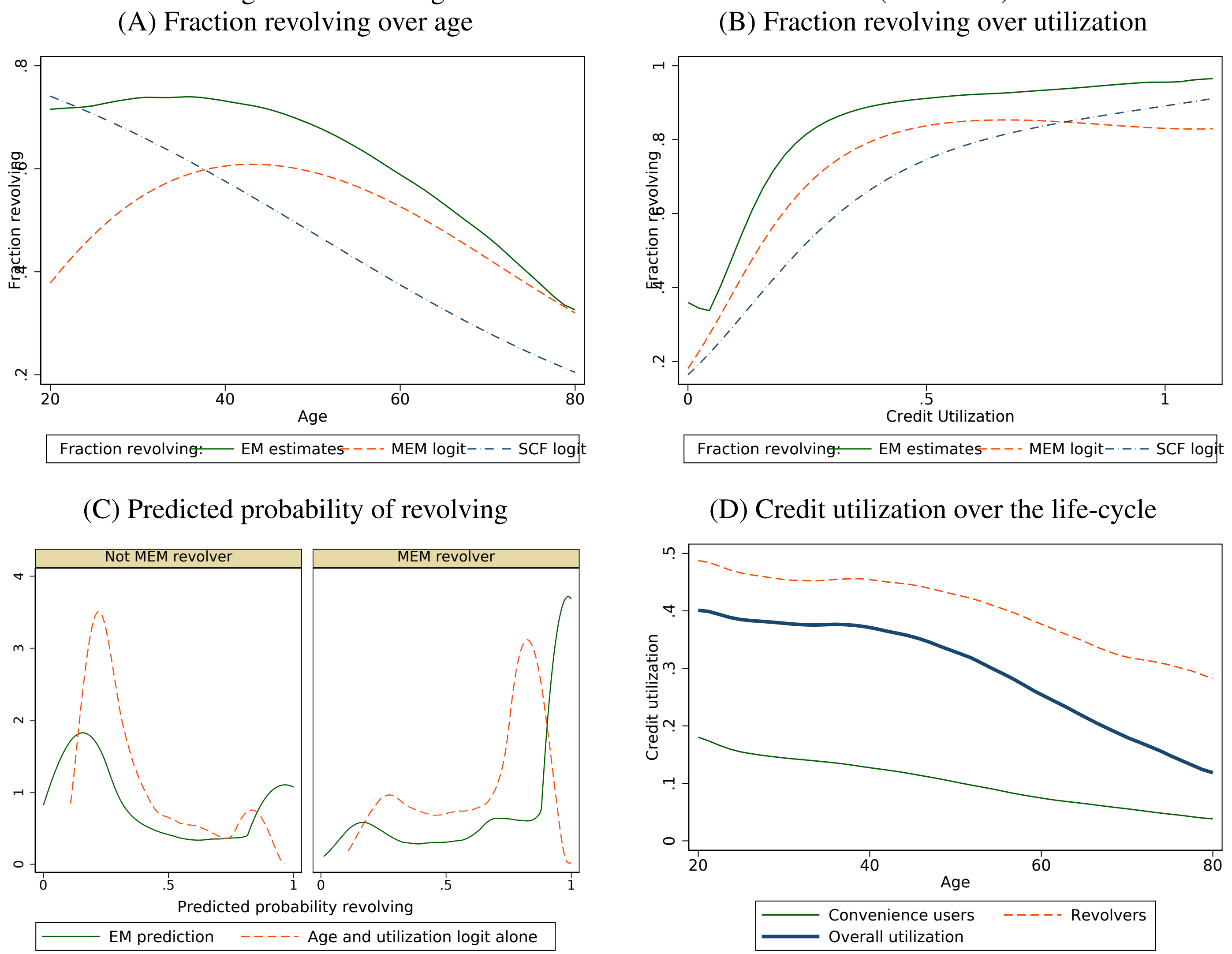

Notes: Shows the distribution of credit utilization (credit card debt/credit card limit if the the limit is positive). The histogram excludes utilization rates greater than 150 percent. Source: Authors' calculations from the CCP.

Figure 7: Revolving status from EM estimates of Model 1 (log transformation)




Notes: Sources: Authors' calculations from CCP based on the finite mixture model, and the MEM and SCF.

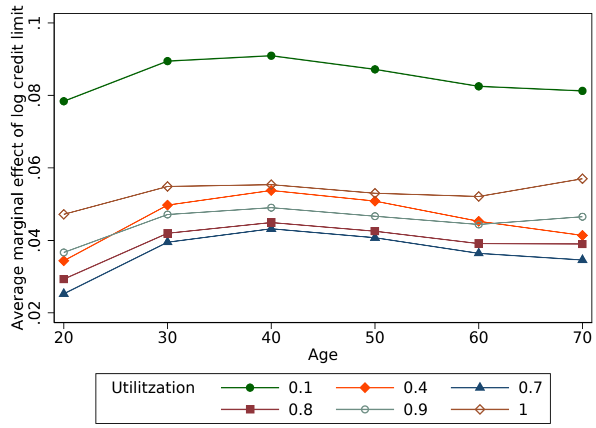
Figure 8: Revolving status from EM estimates of Model 5 (utilization)



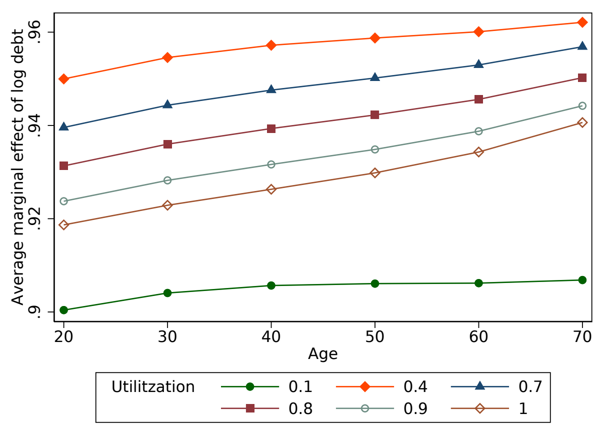

Notes: Sources: Authors' calculations from CCP based on the finite mixture model, and the MEM and SCF.

Figure 9: Average marginal effects of credit and previous debt on debt for revolvers

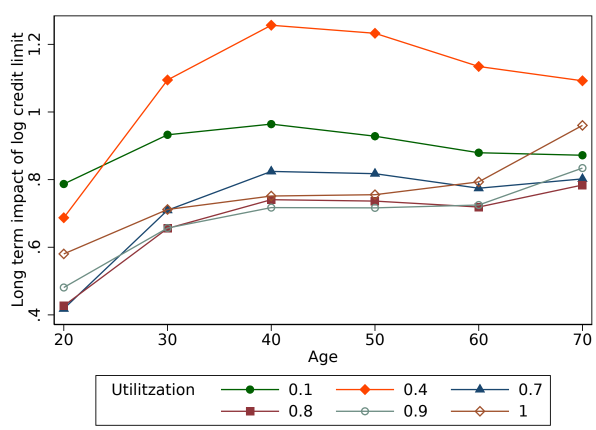
(A) Marginal effect of log credit limit on log debt next quarter




(B) Marginal effect of log debt this quarter on log debt next quarter




(C) Long-term effect of change in log credit limit on log debt




Notes: For panel (C) each point is calculated using the marginal effect in (A) divided by one minus the marginal effect in (B). Source: Authors' calculations from CCP based on a finite mixture model separating convenience users from revolvers.

Table 1: Specifications and comparison of finite mixture models

| | | Model | Quarters revolving (percent) | Mean squared difference from MEM |
|---|---|---|---|---|
| 1 | Revolver | $\ln D_{i,t} = \gamma^R X_{i,t} + \alpha \ln D_{i,t-1} + \beta \ln B_{i,t} + \epsilon^R_{i,t}$ | 56.6% | 0.278 |
| | Convenience | $\Delta \ln D_{i,t} = \gamma^C X_{i,t} + \epsilon^C_{i,t}$ | | |
| 2 | Revolver | $D_{i,t} = \gamma^R X_{i,t} + \alpha D_{i,t-1} + \beta B_{i,t} + \epsilon^R_{i,t}$ | 31.3% | 0.395 |
| | Convenience | $\Delta D_{i,t} = \gamma^C X_{i,t} + f(age_{it}) + \epsilon^C_{i,t}$ | | |
| 3 | Revolver | $D_{i,t} = \gamma^R X_{i,t} + \alpha D_{i,t-1} + \beta B_{i,t} + \epsilon^R_{i,t}$ | 86.6% | 0.439 |
| | Convenience | $D_{i,t} = \gamma^C X_{i,t} + \epsilon^C_{i,t}$ | | |
| 4 | Revolver | $\nu_{i,t} = \gamma^R X_{i,t} + \beta \nu_{i,t-1} + \epsilon^R_{i,t}$ | 45.4% | 0.323 |
| | Convenience | $\Delta \nu_{i,t} = \gamma^C X_{i,t} + +\epsilon^C_{i,t}$ | | |
| 5 | Revolver | $\nu_{i,t} = \gamma^R X_{i,t} + \beta \nu_{i,t-1} + \epsilon^R_{i,t}$ | 64.1% | 0.246 |
| | Convenience | $\nu_{i,t} = \gamma^C X_{i,t} + \epsilon^C_{i,t}$ | | |

Notes: Each model includes individual effects, time effects, and an age polynomial in $X_{i,t}$ and $\nu_{it}$ is credit utilization ($D_{it}/B_{it}$). "Quarters revolving" is the average over all consumer-quarters of the predicted probability of revolving. "Mean squared difference from MEM" is the mean of the squared difference between an indicator that is one if a consumer reports revolving in MEM surveyand the predicted probability of revolving. Source: Authors' calculations from CCP and the MEM survey.

Table 2: Transitions from probabilities consumer is revolving

| Probability revolver today: | Unconditional distribution | Probability revolver after: | One year | Two years | Four years |
|---|---|---|---|---|---|
| High | 44.62 | High | 71.18 | 67.42 | 63.31 |
| | | Medium | 11.6 | 13.96 | 16.34 |
| | | Low | 17.22 | 18.62 | 20.34 |
| Medium | 25.35 | High | 20.39 | 23.87 | 27.69 |
| | | Medium | 44.97 | 40.89 | 36.92 |
| | | Low | 34.64 | 35.24 | 35.39 |
| Low | 30.04 | High | 25.79 | 28.11 | 30.33 |
| | | Medium | 29.52 | 29.46 | 29.36 |
| | | Low | 44.69 | 42.43 | 40.31 |

Notes: High probability revolvers have a predicted probability of revolving greater than 75 percent, Medium probability is between 25 and 75 percent, and Low probability is 25 percent or less. Source: Authors' calculations from CCP.

Table 3: Regression results for Log Debt dynamics

| | Dependent variable: Log $\text{Debt}_t$ | | | | |
|---|---|---|---|---|---|
| | All | All | Revolvers | Revolvers | Convenience |
| | [1] | [2] | [3] | [4] | [5] |
| Log $\text{Debt}_{t-1}$ | 0.564*** | 0.672*** | 0.911*** | 0.952*** | 0.395*** |
| | (0.000298) | (0.000251) | (0.000116) | (8.50e-05) | (0.000315) |
| Log Credit $\text{Limit}_{t-1}$ | 0.244*** | 0.165*** | 0.0628*** | 0.0416*** | 0.248*** |
| | (0.000456) | (0.000344) | (0.000146) | (0.000112) | (0.000498) |
| Observations | 8,024,570 | 9,329,180 | 7,332,216 | 8,292,323 | 9,191,895 |
| R-squared | 0.442 | 0.561 | 0.934 | 0.962 | 0.250 |
| Demeaned | Yes | Yes | Yes | Yes | Yes |
| Zero included (add $100 to log) | | Yes | | Yes | Yes |
| Age polynomial | Yes | Yes | Yes | Yes | Yes |
| Long-term credit impact | 0.746 | 0.805 | 0.972 | 0.993 | 0.525 |
| Average utilization | 0.344 | 0.304 | 0.466 | 0.425 | 0.146 |
| Credit salience $\sigma$ | 0.188 | 0.148 | 0.293 | 0.299 | 0.059 |

Notes: Only includes observations with an open credit card. Columns with "Zero included=Yes" include observations with zero debt; in these regressions, all debt and credit limits are transformed by adding $100 before taking logs. Credit salience is $\sigma = \bar{\nu}\beta/(1 + r - \alpha)$ where $\alpha$ is coefficient on debt, $\beta$ on the credit limit, $\bar{\nu}$ is average credit utilization, and $r = (1 + 14.02/100)^{1/12}$. Source: Authors' calculations from CCP.

Table 4: Regression results for Debt dynamics

| | Dependent variable: $\text{Debt}_t$ | | |
|---|---|---|---|
| | All | Revolvers | Convenience |
| | [1] | [2] | [3] |
| $\text{Debt}_{t-1}$ | 0.827*** | 0.974*** | 0.497*** |
| | (0.000207) | (9.42e-05) | (0.000297) |
| Credit $\text{Limit}_{t-1}$ | 0.0272*** | 0.0182*** | 0.0340*** |
| | (0.000114) | (5.70e-05) | (0.000137) |
| Observations | 9,329,180 | 8,292,323 | 9,191,895 |
| R-squared | 0.734 | 0.959 | 0.314 |
| Demeaned | Yes | Yes | Yes |
| Age polynomial | Yes | Yes | Yes |
| Long-term credit impact | 0.850 | 0.992 | 0.514 |
| Credit salience $\sigma$ | 0.148 | 0.491 | 0.066 |

Notes: Credit salience is $\sigma = \beta/(1 + r - \alpha)$ where $\alpha$ is coefficient on debt, $\beta$ on the credit limit, and $r = (1 + 14.02/100)^{1/12}$. Source: Authors' calculations from CCP.

Table 5: Regression results for Log Limit dynamics

| | Dependent variable: Log Limit$_t$ | | | |
|---|---|---|---|---|
| | All | All | Convenience | Revolvers |
| | [1] | [2] | [3] | [4] |
| Log Debt$_{t-1}$ | -0.00485*** | 0.00297*** | -0.0137*** | 0.0330*** |
| | (0.000101) | (0.000114) | (0.000120) | (9.81e-05) |
| Log Credit Limit$_{t-1}$ | 0.908*** | 0.900*** | 0.821*** | 0.916*** |
| | (0.000159) | (0.000155) | (0.000190) | (0.000129) |
| Observations | 8,263,449 | 9,329,180 | 9,191,895 | 8,292,323 |
| R-squared | 0.839 | 0.835 | 0.725 | 0.915 |
| De-meaned | Yes | Yes | Yes | Yes |
| Zero included? | | Yes | Yes | |
| Age polynomial | Yes | Yes | Yes | Yes |
| Long-term debt impact | -0.053 | 0.030 | -0.077 | 0.393 |

Notes: Only includes observations with an open credit card. Columns with "Zero included=Yes" include observations with zero debt; in these regressions, all debt and credit limits are transformed by adding $100 before taking logs. Source: Authors' calculations from CCP.

Table 6: Regression results for Credit utilization dynamics

| | Dep. Variable: Credit utilization$_{i,t}$ | | |
|---|---|---|---|
| | All | Revolver | Convenience |
| Credit utilization$_{i,t-1}$ | 0.709*** | 0.879*** | 0.370*** |
| | (0.000235) | (0.000185) | (0.000287) |
| Observations | 9,168,829 | 8,274,886 | 9,168,829 |
| R-squared | 0.498 | 0.732 | 0.154 |
| Demeaned | Yes | Yes | Yes |

Notes: The sample includes observations when credit utilization is zero but excludes individual quarters when utilization is undefined (limit is zero) or utilization is greater than 5 (a very small fraction, see figure 6). All columns include age and year effects, with age effects normalized to have zero trend when fixed effects are included. Source: Authors' calculations from CCP.