

# Consumer revolving credit and debt over the life-cycle and business cycle

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## Abstract

Little work has examined how unsecured consumer credit, such as the limit on credit cards, varies over the life-cycle, and how consumers respond to changes in their ability to borrow over the short and long term. Using a large panel of credit accounts in the United States, we document large life-cycle variation in consumer credit. Credit limits increase rapidly early in life, growing by more than 400% between age 20 and 30. Debts grow almost as fast, however, and so credit utilization falls slowly throughout the life-cycle, only reaching 20% by age 70. Individual credit utilization is extremely stable despite the large life-cycle, business cycle, and individual volatility of credit. Stable utilization means that consumer debts are very sensitive to changes in credit limits. Dividing between those who revolve debts and those who use credit cards only for payments, we find that for revolvers nearly 100% of an increase in credit limits eventually becomes an increase in debts.

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# 1 Introduction

Credit and debts dominates the lives of most U.S. households and it is impossible to understand their consumption and savings decisions without understanding the credit available to them and the debts they have accumulated. To take several areas where credit and debts are central: Credit card borrowing is the primary source of short-term consumption smoothing for U.S. households since the average household has very little liquid savings (Fulford, 2015b). Credit cards have become an important method of payment, and so lacking access to credit limits payment options (Foster, Schuh, and Zhang, 2013; Schuh and Stavins, 2014). More than thirty percent of individuals between ages 20 and 60 have an auto loan at any given moment, and close to 50 percent of 20-25 year olds have a student loan (see figure 9). Paying down mortgage debt is the primary source of savings for the average household (Nothaft and Chang, 2005). Taken together, the price of credit is the relevant opportunity cost (Zinman, forthcoming) and the availability of credit the relevant constraint for the average household when it considers its short-term consumption smoothing, long-term wealth accumulation and housing consumption, payment choice, transportation, and human capital acquisition.

Despite the centrality of credit and debt in the financial lives of Americans, little is known about how credit changes in the short and long-term, and how changes in credit are related to changes in debts. While there is a large literature that considers which groups have access to credit and its cost, very little examines how credit or debts changes over time or with age. Yet consumer credit is extremely variable for individuals in the short term (Fulford, 2015a), and this variability fundamentally alters their savings and consumption decisions. How does changing credit over the business cycle, over the life-cycle, and for individuals relate to their debts?

To answer this question, we use the the Federal Reserve Bank of New York Consumer Credit Panel (CCP) which contains a 5% sample of every credit account in the United States from 1999-2014 from the credit reporting agency Equifax.<sup>1</sup> The panel nature of these data are crucial since

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<sup>1</sup>For most of the econometric work, we use a sub-sample of the full 5% sample since the smaller sample is much more straightforward computationally and our confidence intervals are extremely small. Using a sub-sample will also allows us to perform checks of specification search and model selection bias by performing the same analysis on a

they allow us to examine how short-term changes in credit and debt for an individual accumulate. The long panel then lets us examine how debt and credit evolve over the life-cycle from these short term changes. We supplement the CCP with the Survey of Consumer Payment Choice (Schuh and Stavins, 2014) and the Survey of Consumer Finances to draw a more complete picture. We focus on credit cards since these have observable limits and are widely held, but briefly examine other debts over the life-cycle.

Credit and debts show extreme life-cycle variation, much larger than the changes in income or consumption over the life-cycle (Attanasio et al., 1999). Between ages 20 and 30, credit card limits increase by more than 400%, and continue to increase after age 30, although at a slower rate. Credit card debt increases at nearly the same pace early in the life-cycle, as individuals use their new limits, and it is only after age 50 that the average credit card debt starts to decline. Other debts, such as mortgages and auto loans, show similar life-cycle variation, while student loan debt peaks early in life. However, these debts do not have readily measurable limits. Aggregate consumer credit and debts show large business cycle variation as well, again substantially larger than the comparable income or consumption movements. For example, the average credit card limit fell by approximately 40 percent over 2009.<sup>2</sup>

Despite this massive variation in credit and debts over the life-cycle and business cycle, credit utilization is remarkably stable. Credit utilization is the fraction of available credit an individual is using. Credit utilization has held steady at just over 30% for the entire period from 2000 to 2014, even as there have been large swings in both credit and debts. Similarly, despite the 400% gains in credit and debt early in life, credit utilization falls very slowly over the life-cycle. The mean credit utilization is 50% in the 20s and is still nearly 40% at age 50. Credit utilization only falls below 20% after age 70.

Individual credit utilization is extremely persistent as well, despite the individual volatility in

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different sample.

<sup>2</sup>See figure 1 and Ludvigson (1999) for a discussion of aggregate credit limit changes. Over the same period from their peak in approximately 2008 Q2 to the trough around 2009 Q2 both aggregate personal consumption and personal income fell by around 3.2% (see Federal Reserve Bank of St. Louis FRED, Personal Income and Personal Consumption Expenditure Series, <https://research.stlouisfed.org/fred2/>).

credit limits documented by Fulford (2015a). We show both non-parametrically and through regressions that deviations from individual credit utilization disappear quickly, as individuals rapidly return to their individual specific utilization. Credit utilization is not zero for most people suggesting a strong tendency to use some of available credit, and to return rapidly to that steady state utilization following a shock to credit or debt.

Central to understanding the relationship between credit and debts is that consumers use credit for distinct purposes. Some consumers use credit cards as a payment mechanism and pay their bills in full every month and are often called “convenience” users. Some consumers hold debt from month to month, and so are “revolvers.” We use simple consumption theory to help divide between convenience users and revolvers. For convenience users not close to their credit limits—as few are—reported debts are some fraction of consumption every month. If convenience users are smoothing their consumption well, then after allowing for trends with age and aggregate shocks to consumption and changes in credit card debts should be unpredictable (see Deaton (1992) for an introduction and Blundell, Pistaferri, and Preston (2008) for a recent application). For revolvers, on the other hand, credit card debt carries over from month to month by definition. Shocks to debt will therefore persist for revolvers.

Using the different models of debts for convenience users and revolvers to separate between them in the data using a Finite Mixture of Regressions framework, we show that the fraction of revolvers slowly declines over the life-cycle, matching similar observations from cross-sections in the SCF and the SCPC. As one would expect, shocks to credit utilization for revolvers decline much more slowly than the average: on average 83% of a increase in utilization is left after a quarter. The utilization of revolvers is remarkably constant over the life-cycle: revolvers in their 20s use just under 60% of available credit, those in their 60s use just under 50% on average. Moreover, the pass-through of credit into debt for revolvers is nearly complete: following a 10% increase in credit limits the debts of revolvers eventually increase by 9.99%. While for revolvers the pass-through is nearly complete at all ages and current levels of credit utilization, it occurs particularly rapidly for the young and those using much of their current credit.

How consumers respond to changes in credit is rarely studied, despite the centrality of credit and debt in the economic lives of consumers and households. It is particularly hard to study changes in credit because credit—unlike debts, assets, or income—is only occasionally reported in surveys. Indeed, Zinman (forthcoming) argues that household debts are understudied even within the field of household finance, itself understudied compared to other areas of finance. Other than some work on mortgages (Iacoviello and Pavan, 2013), this paper appears to be the first to study the life-cycle of credit limits. As such, we view one of our major contributions as documenting the life-cycle of credit and debts.

A small literature has examined changes in credit, but has only considered changes in limits for singly credit card accounts and has not considered the difference between convenience users and revolvers. The pioneering work is Gross and Souleles (2002) who use a panel from a single credit provider to look at how households respond to changes in interest rates and changes in available credit. Limit increases were followed by increases in debts, particularly for consumers close to their credit limit already. Their work also noted the “credit card puzzle:” that some households pay high interest on credit card debts while at the same time earning low interest on liquid savings. Agarwal et al. (2015) use limit increases that are discontinuous with credit score to examine how exogenous changes in credit limits matter. For those with the lowest scores a dollar increase in limits is followed by 59 cents more debts within a year, while those with higher credit scores had almost no increase in debts. Fulford (2015a) demonstrates that there is substantial credit variability using a the Equifax/CCP. Short-term credit volatility is larger than most measures of income volatility, and long-term credit volatility is much higher than long term measures of income volatility. This volatility can help explain the credit card puzzle. Ludvigson (1999) examines the response of consumption to credit volatility at the aggregate level. Leth-Petersen (2010) studies a Danish reform that allowed home owners to use housing equity for the first time as collateral. The reform increased available credit, but produced relatively moderate consumption responses. The response was strongest for the youngest households. Fulford (2013) examines the short and long term consumption responses of buffer-stock consumers following changes in credit and finds

evidence consistent with the model in India following a massive banking expansion.

While changes in credit over the life-cycle have been largely unstudied, much work examines the decision to save and consume over the life-cycle. In much of this work credit is intentionally pushed to the background. In the standard versions of the life-cycle or permanent income hypotheses, for example, the assumption that young consumers can smooth relies directly on available credit (Deaton, 1992). More recent life-cycle models take seriously that credit constraints may bind, but do not allow credit to vary over the life-cycle. The typical assumption is that either there is no credit available, or a fixed limit and so only net assets need to be studied (see, for example, Gourinchas and Parker (2002)).

Some recent work has attempted to endogenize borrowing constraints, and much of this work has direct life-cycle implications. Cocco, Gomes, and Maenhout (2005) build a model of consumption and portfolio choice over the life-cycle. Their work adds portfolio choice to the approach of Gourinchas and Parker (2002). As an extension, they introduce endogenous borrowing constraints. These constraints are based on the minimum value that income can take since with limited enforcements borrowers have to choose to pay back rather than face the penalty of default. Borrowing greatly affects portfolio choice as young consumers borrow if the endogenous constraint permits, and only start investing in equity late in life. Lopes (2008) introduces a similar life-cycle model with default and bankruptcy. Lawrence (1995) appears to be the first to introducing default in a life-cycle model. Athreya (2008) develops a life-cycle model with credit constraints, default, and social insurance. Relaxing default policy creates severe credit constraints among the young. Eliminating default relaxes credit constraints for the young and reduces consumption inequality, but increases consumption inequality for the old who now can no longer default after sufficiently bad shocks.

This paper also overlaps with a larger literature understanding the ways that individuals use the financial products available to them. Stango and Zinman (2009) examine how much a sample of US consumers pay in fees and interest for their financial products. Credit card interest is the biggest financial expense, although some households also pay significant overdraft fees. More than half

of households could substantially reduce fees by moving among products. Agarwal et al. (2007) note that middle aged adults pay the least in these kinds of avoidable fees with the minimum at age 53. Zinman (2013) examines the question of whether markets over- or under-supply credit and concludes that, while there are models that suggest over-supply, and models that suggest under-supply, there is not strong evidence of either.

We organize our analysis to move from the aggregate to the individual. First, we describe the data. Then in section 3, we provide an overview of debt in the United States since 2000. In section 4, we describe the life-cycle of credit and debts. We start non-parametrically, imposing no assumptions on the relative importance of age, year, cohort, or credit limit. Section 5 examines the evolution of individual credit utilization, while in sections 6 and 5.4 we model and estimate the relationship between debt and credit taking into account the difference between convenience users and revolvers.

## **2 The data**

The Equifax/NY Fed Consumer Credit Panel (CCP) contains a five percent sample of all accounts reported to the credit reporting agency Equifax quarterly from 1999-2014. For much of the analysis we use only a 0.1% for analytical tracability. Once an account is selected, its entire history is available. The data contains a complete picture of the debts for any individual account that are reported to the credit agency: credit card, auto, mortgage, and student loan debts, as well as some other, smaller, categories. Lee and van der Klaauw (2010) provide additional details on the sampling methodology and how closely the overall sample corresponds to the demographics of the overall United States and conclude that the demographics match the overall population very closely—the vast majority of the population over age 18 has a credit bureau account. The CCP also records whether an account is a joint or co-signed account.

Rather than capturing too few people, the main issue is that a sizable fraction of accounts represent either incorrect information reported to Equifax or individuals who are only loosely attached

to the credit system, either by choice or because they lack the documentation. For example, the accounts are based on Social Security numbers and so reporting an incorrect Social Security number can create accounts incorrectly attributed to an individual. For this reason, we limit the sample throughout to accounts with an age listed and who have an open credit card account at some point from 1999-2014 to capture the population that has a potential access to credit. Depending on the analysis, we also limit the sample only to those with current open accounts, debts, or limits.

Much of this paper focuses on credit cards since they have explicit limits not readily observable in most other markets. However, the credit card limits reported to credit reporting agencies are at times incomplete. The Equifax/CCP reports only the aggregate limit for cards that are updated in a given quarter. Cards with current debt are updated, but accounts with no debt and no new charges may not be. To deal with this problem, we follow Fulford (2015a) and create an implied aggregate limit by taking the average limit of reported cards times the total number of open cards. This method is exact if non-updated cards have the same limit as updated cards. Estimating the difference based on changes as new cards are reported and the limit changes, Fulford (2015a) estimates that non-updated cards typically have larger limits, and so the overall limit is an underestimate for some consumers. This issue is mostly a concern for consumers who are using only a small fraction of their available credit, since they are not even using one their cards at all. For the consumers who use more of their credit, and so may actually be bound by the limit, the limit is accurate because all cards are updated.

While the Equifax/CCP give a complete picture of debts, it does not distinguish how the consumer is using those debts. For example, we cannot directly distinguish between those who hold debt from month to month, referred to by the industry as revolvers, and those who accrue debts in a month but pay them back, often referred to as convenience users. We use the Survey of Consumer Payment Choice (Schuh and Stavins, 2014) and the Survey of Consumer Finances to gain more insight into how people are using the debts we see.



### 3 Credit and debt over the business cycle

Since 2000 overall credit and debt have varied tremendously. Figure 1 shows how credit card limits and debts have varied from 2000 through 2014. Although the Equifax data starts in 1999, we exclude the first three quarters since the limits initially are not comparable (see Avery, Calem, and Canner (2004) for a discussion of the initial reporting problems). The scale on the left is in logarithms and so proportional changes in debt have approximately the same importance as proportional changes in credit. Between 2000 and 2008 revolving credit increased by approximately 40% from around \$10,000 on average to a peak of \$14,000. Over 2009, overall limits collapsed rapidly before recovering slightly in 2012. In a slightly more sophisticated analysis that accounts for age and region later, we show that the recovery in 2012 was largely driven by large dollar values at the top end of the credit distribution (see figure 7).

Credit card debts show a similar variation over time. From 2000 to 2008 debts increased from just over \$4,000 to just under \$5,000 on average, before returning to around \$4,000 over 2009 and 2010.

Utilization is much less volatile than credit or debt. The thick line in the middle of the figure shows credit utilization, the average fraction of available credit used. Credit utilization falls slightly from over 35% in 2000 to around 30% in 2006 before increasing again to 2010 and declining slightly since then. Although it is not immediately evident, the scales for the credit and debts are the same as the scale for utilization. A one percentage point change in utilization has exactly the same vertical distance as a one percent change in credit or debt. Larger changes are less exactly comparable, but the distance between \$4,000 and \$5,000 for example, is still almost exactly 20 percentage points on the right axis. The similar scales mean that we can directly compare the relative changes over time in limits, debts, and credit utilization. Credit and debts vary together in ways that produce extremely stable utilization that has no obvious relationship with the overall business cycle. Such a relationship is not just mechanical: when credit was cut in 2009, families could have decided to maintain or increase their debts, and the cut in credit could have translated directly into an increase in utilization rather than a decrease in debt. That utilization did not change

much suggests the importance of credit constraints and a strong behavioral response to credit limits changing.

While other credit markets do not have as clear limits, the aggregate debts in other markets are directly observable. Using the same Equifax/CCP data, the Federal Reserve Bank of New York (2015) examines aggregate trends in households debts. Housing debt predominates, especially after nearly doubling between 2000 and 2008, then falling somewhat more modestly since. Student loan debt increased rapidly after 2008. The other major debt categories are home equity loans which rose and fell with mortgage debt, and auto loans which have been fairly stable over the period.

## **4 Credit and debt over the life-cycle**

Both credit and debt change substantially over the life-cycle. This section provides a non-parametric description of these changes focusing on the both the level and distribution of credit and debt.

### **4.1 The credit score over the life-cycle**

A useful summary of the availability of credit is the credit score. One of the services that a credit reporting agency provides is the score since it allows less sophisticated parties, such as landlords, the ability to quickly understand the likely credit worthiness of a potential borrower. Equifax scores are based on a proprietary scoring model that produces a score ranging from 250-850 and are distinct from scores created by the Fair Isaac Corporation (FICO scores). In the Equifax/CCP data we only observe the proprietary Equifax score.

Figures 2 and 3 show how credit scores change with age. Figure 2 is an entirely non-parametric approach to understanding the effects of age, birth cohort, and year on the mean credit score. Each line represents a single birth cohort over the entire time that they are in the CCP between age 20 and 80. Very young or old cohorts we might observe for only several years. For example, the cohort born in 1990 turns 20 in 2010 and so has a line for when they are 20 through 25. Most cohorts we

observe for the entire 15 years, although which 15 years depends on the age. The information in the figure gives the cell means for every cohort-age-year, and so could be presented with year or cohort on the axis instead of age. For example, if there are large changes that happen at the same place in every cohort line, then this suggests there are large shared year effects. Similarly, if the cohort lines shift, then there are likely to be large cohort effects. As always with age-cohort-year analysis, it is impossible to fully distinguish between age, cohort, and year effects since there can be a trend in any one of them. By putting age on the axis, the figures put visual emphasis on life-cycle changes, but since all of the information is present they makes no assumptions that age matters while cohort or years do not.

The remarkable feature in figure 2 is how uniformly and nearly linearly the average score of a cohort increases with age. While there is some variation by year or cohort, where cohorts overlap they show remarkable uniformity. Each decade scores increase approximately linearly by 25 points. The 20 year olds have an average score of around 625, while 40 year olds score 675, 60 year olds 725, and 80 year olds 775. The change is not entirely linear—scores seem to increase slightly more rapidly between 50 and 60—but the trend increase is extremely consistent across years, cohorts, and ages.

The nearly constant increase of the mean credit score hides substantial heterogeneity in scores at any age. Figure 3 shows the score at the 1st, 10, 25, 50 75, 90 and 99th percentile of the score distribution at each age. Unlike in figure 2, figure 3 averages over all cohorts at a given age, and so averages out any year or cohort effects. The median person at age 20 has a score of 650, while the 1st percentile at the bottom is below 400, and the 99th percentile at the top around 750.

The steady increase in the average credit score in figure 2 comes from different parts of the distribution over the life-cycle. Early on the average growth of scores occurs as those individuals with already good credit increase their scores. The median score actually falls slightly between ages 20 and 25. This effect may be from changing composition: new individuals without any credit history may first establish credit relationships after age 20. These new accounts will typically have lower scores since they are new, and so will bring down the median. Even after the fall in the early

20s, the median or lower scores increase relatively slowly until age 40. After age 40, the 75th, 90th, and 99th percentiles grow more slowly, having hit the upper bound, while the median and lower scores start to increase more rapidly, particularly after age 40.

The combination of increases first at the top of the distribution and only later at the bottom of the distribution leads to a continuing increase in the dispersion of scores up until age 40, and then a slow decrease. Figure 3, for example, shows the standard deviation of the credit score for each cohort as they age. The standard deviation pulls in changes in the extremes, and so there is more variation across cohorts and time, but nonetheless the overall life-cycle pattern of the standard deviation is evident.

While there is a life-cycle component to the heterogeneity of credit-scores, one surprising characteristic of the credit score distribution is how large it is already by age 20. One way to interpret this heterogeneity is that the credit score partially reflects the total life-cycle income, or at least the best market prediction of it, and so captures the heterogeneity of life-cycle income which is much higher than the heterogeneity of incomes at age 20. Put a different way, college students have low income, but high potential life-cycle income, and so receive much more credit and higher credit scores than their current incomes would suggest. Credit is a potentially important source of consumption inequality since it may allow some individuals to consume closer to their life-cycle income than others.

## **4.2 Credit card debt and credit over the life-cycle**

The increase in credit scores with age allows for a potential increase in available credit, which increases opportunities to take on debt. This section examines the interplay between changing credit and debt over the life-cycle in the credit card market where both limits and debt are observable. Figure 4 shows the fraction of each cohort at each age that has a positive limit on a credit card and positive credit card debt. Having a positive limit in any given quarter is not a requirement for having debt, since the debt could have been accumulated previously when the consumer could borrow. Having a positive limit is increasing with age at least until 60, and after that appears to fall

on average. Interestingly, there appears to be a downward trend within cohort after approximately age 30.

A large fraction of account holders have positive debt at any given point in time. This large fraction is slightly misleading, however, since the Equifax/CCP does not allow us to distinguish new charges from debts acquired previously. Some credit card 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 debts at any given point in time and so they are indistinguishable in the data, but other work makes clear that the usage patterns of convenience users and revolvers are distinct. Using the 2008-2014 Survey of Consumer Payment Choice, we examine the fraction of credit card users who do not revolve debt from month-to-month out of all of those who either used a credit card in the past month, or rolled over debt from a previous month. Figure 5 shows the fraction in different age groups who report that they do not revolve credit card debts from month to month, but do use their cards. Between age 25 and 50, only around 35% of the credit card using population—those who would show up in figure 4 with positive debt in the Equifax/CCP data—are not revolving at least some of those debts from month to month. Starting at age 55, the fraction of non-revolvers slowly increases to 55% by age 70. Put a different way, even at age 70, 45% of those who used a credit card in the last month will not pay off their debts in full that month, and so are actively borrowing.

Credit card limits are not quite the same as a credit line since the card issuing bank can reduce the credit limit without notice. With enough lead time, a consumer may be able to increase her credit line by applying for additional credit or asking for a limit increase, and so the limits existing at any given time may not represent the full amount of credit card credit a consumer could obtain. Nonetheless, the limit is the maximum amount a consumer could borrow at a given instant, and so represents at least a short term constraint. The costs of reaching or exceeding the limit are potentially large since alternative sources of credit, such as pay day loans, are likely to be even more expensive and may not be available.

Figure 6 shows the log credit limit and the log debt, both amounts conditional on being positive,

and credit utilization in the bottom panel. Credit limits increase very rapidly early in life, increasing by around 400% between age 20 to 30. They continue to increase, although less rapidly, after age 40. There appears to be common trends within each cohort, suggesting that there are common factors that affect all cohorts equally.

Early in the life-cycle, credit card debts increase with credit limits and continue increasing until age 50. After age 60, credit card debt starts falling. On average, however, 70 and 80 year olds have more credit card debts than 20 year olds. Some of that debt is convenience use, but it illustrates the extent to which credit is an integral part of the finances of everyone across all ages, as well as the importance of credit limits.

Credit limits and debts combine to give the fraction of credit used in the bottom panel of figure 6. Those with zero debts have zero credit utilization, and so are included in utilization while they are excluded from the mean credit which only includes the positive values. Credit utilization falls continuously from age 20 to age 80. On average, 20 year olds are using more than 50 percent of their available credit, and 50 year olds are still using 40 percent of their credit. Credit utilization only falls to below 20 percent around age 70.

The slow fall in credit utilization comes from two different sources over the life-cycle. Early in life, credit utilization is high as a substantial portion of the population uses much or all of their available credit. Credit increases somewhat more rapidly than debt, however, and so credit utilization falls slowly. In mid-life debts stabilize, but credit limits continue to increase. Finally, only starting around age 60 does average debt, conditional on having any, decline, and so credit utilization declines. While the credit and debt cohorts show only those with positive credit or debt, figure 4 shows the fraction in each cohort that have positive credit and debt. Averaging in the zeros would lower the average credit limit and debt, but actually makes the life-cycle variation larger.

Estimating a simple model that divides the variation between age and year allows us to make the importance of life-cycle variation even more clear. Figure 7 shows the age and year effects

from estimating a simple regression of the form:

$$\ln D_{it} = \theta + \theta_t + \theta_a + \epsilon_{it}, \quad (1)$$

where  $\ln D_{it}$  is either log debts, log credit limits, or utilization and allows these to vary between age effects  $\theta_a$  and year effects  $\theta_t$ . While the previous figures made no assumptions about the relative importance of birth cohort, year, and age, the estimates assume that birth cohort does not matter. The excluded group is age 20 and year 2000, so each panel in figure 7 starts at zero at age 20 and year 2000.

Life-cycle variation dominates everything else in figure 7. The scale of the figures varies so it is easy to miss that the variation of credit card limits and debts over the life-cycle is around 10 times larger than over the time. If all of the figures were on the same scale there would appear to be no variation over time, and the fall in credit utilization with age would not be as obvious, and so we use different scales. Allowing for the log scale, the increase from age 20 to age 30 in credit limits is about 1.5 in log units or approximately 450% ( $e^{1.5}$ ) and the increase is over 300% for debts. The scale of the right hand columns showing limits, debts, and utilization over time are relatively similar. Credit utilization varies only slightly over time, while aggregate credit card limits and debts are quite volatile. A similar conclusion holds for credit utilization with age. Although credit utilization falls steadily with, that stability is masking much larger changes in credit and debts.

While figure 7 shows the average credit and debt for each cohort, the distribution of credit and debt is changing across ages as well. Figure 8 shows the percentiles and standard deviation of the credit card limit (panel A), credit card debt (panel B), and credit card utilization (panel C), including all cohorts at a given age from 1999 to 2014. The median line in panel A for credit card limits, for example, shows that 50% of the population with a positive credit limit at that age has a credit limit below the line. The credit and debt distributions exclude those with zero debts or zero credit limits, but the credit utilization includes those with zero debts and a positive limit.

Over the life-cycle, inequality in credit limits starts out very high, increases somewhat to ap-

proximately age 40, and then decreases slightly as shown in figure 8 (A). The credit limit and debt percentiles are largely parallel with age from the 50th to 99th percentile. The distance in logs between the 99th percentile and the 50th is almost the same at age 20 as it age age 50. The lower percentiles grow much less fast, and so inequality is increasing up to age 50. After age 50 there is some compression of the distribution of credit limits as the median draws closer to the 99, and the 10th and 25th percentiles continue to grow.

Inequality in credit card debt is large initially, and then increases slightly over the life-cycle as shown in panel B of figure 8. Conditional on having any, debt increases rapidly in the 20s for all percentiles, reaching a peak around age 50 before declining. The same evolution occurs for every percentile of the distribution, and so the spread of debt is relatively constant.

The distribution of credit utilization has a somewhat different evolution as shown in the bottom panel of figure 8. Up through age 60, at least 10 percent of the population with a current positive limit has debts that exceed that limit. The median utilization looks much like the mean utilization in figure 6. Median credit utilization is close to 50 percent at age 20 and falls very slowly. At least 10 percent of the population at any age is not using any of their available credit. The standard deviation of credit utilization is largely stable over the life-cycle, declining only slightly from age 20 to 60, but somewhat faster after.

### **4.3 Other debts over the life-cycle**

Since credit scores and credit cards interact with other forms of credit and debt, it is useful to understand the life-cycle variation in other debts. Figure 9 shows the cohort-age profiles for mortgage debts, student loan debts, and auto loans. The first column shows the fraction of each birth cohort who have that particular debt, the second the mean log debt, conditional on having any. Unsurprisingly, there are strong life-cycle components to all three. Few people at age 20 have a mortgage, and the mortgages they do have are typically much smaller. By age 40 approximately 40 percent of individuals have mortgage debt. The number of households with mortgage debt is likely higher, since not everyone over age 20 in a household is on the mortgage. The average size of mortgages



appears to decline with age, although there is a strong trend towards larger mortgages over time as well, even with the fall after 2007, so the cohort age graphs make it difficult to disentangle life-cycle, age, and cohort effects.

Student loans are mostly taken out by the youngest ages, and so display a distinct life-cycle pattern. Between ages 40 and 60 over this period around 20 percent of the population has positive student loan debt, whose size seems to diminish only very slowly. One reason may be that parents are taking on debts for their children, which may explain the surprising upward trend of the size of the debts for some cohorts in middle age. Student loans also display clear cohort differences. For the youngest cohorts in our data—those aged approximately 20-25 between 2010 and 2015—nearly half have student loan debts.

Following a rapid increase in the 20s, about 35 percent of individuals have an auto loan. The size of auto loans increases slightly until age 40, then decreases slightly, but auto debt is relatively constant in size over the life-cycle compared to other markets.

The only other major debt held by US households are revolving loans, usually based on home equity. Home equity loans are large in total dollar value (see Federal Reserve Bank of New York (2015)), but are not as widely held as credit card debts. The amount of revolving debt increases rapidly until age 50, and then declines, following the same pattern as credit card debt in figure 6, and so we do not separately show the cohort figures for revolving debt.

## **5 Individual credit, debt, and credit utilization**

The previous two sections show that despite very large changes in credit and debt over the life-cycle and business cycle, credit utilization is remarkably stable. The aggregate data could be hiding substantial individual volatility in utilization, however. We begin by describing the distribution of utilization and how the distribution varies over the life-cycle. Next, we examine non-parametrically how utilization changes at the individual level, and finally estimate a series of regressions on how individual credit utilization evolves. The basic conclusion is that utilization for an individual is

extremely stable; while individuals have different credit utilization ratios that represent their individual steady state, and these ratios may change slowly as they age, individuals return rapidly to their own ratio. Credit utilization is best characterized by fixed heterogeneity across individuals, and relatively small deviations for an individual over time.

Since credit utilization is a ratio, there are two things that can change it: credit (the denominator) and debt (the numerator). In the final section we examine how credit and past debts influence future debts. Credit utilization changes both as individuals change their consumption and savings behavior, thereby increasing or decreasing their debts, and as card-issuing banks increase and decrease credit limits depending on age and credit management. Debts seem to be highly related to credit, with around 90% of credit passing through into higher debt eventually, consistent with findings for utilization.

This section does not divide between revolvers and convenience users and so, while it estimates population average effects, may miss important heterogeneity. Section

## **5.1 The distribution of credit utilization**

Figure 10 shows histograms of credit utilization for broad age groups. Credit use predominates until very late in life. The median person is always borrowing, although at the end of life she is not borrowing much and so may be a “convenience” user who pays her balance in full at every month. Among users in their 20s, a large portion are close to or exactly at their credit limit. More than 10% are actually over their limit, since a previously higher limit has since been reduced. As people age, the distribution slowly shifts left, putting more and more mass at low or zero credit use. Over age 60 around three quarters of the population is using less than 25% of available credit. Conditional on using more than a small amount of available credit, the spread is fairly even, with about the same fraction using 30% of their credit, as 60% or 90%.

A useful way to read the histograms in figure 10 is that there are broadly speaking two populations mixed together: a population that uses almost none of its credit, and a population that can use anywhere from 20 to 100% of its available credit about evenly. As people age, more and more fall

into the first group, using little of their credit. But conditional on using more than 20% of credit, the distributions from age 20-30 to age 60-80 are very similar: mostly flat with a peak around 80%. While we cannot cleanly distinguish between them, it seems likely that most of the group using less than 20% of its credit are “convenience” users, while those using more are mostly revolving debt. Of course, the histograms do not show dynamics. It may be that an individual uses little of her credit in one quarter, then 50%, then little credit, and the frequency of the transitions decreases with age. Instead, we show in the next two subsections that individuals have extremely persistent credit utilization.

## **5.2 Changes in credit utilization: non-parametric evidence**

Figure 11 shows conditional mean scatter plots of credit utilization in one quarter against credit utilization in the next quarter, in the next year, and in two years. The top row shows the mean conditional only on having the utilization on the x-axis in that quarter. The bottom row instead takes the within transformation and allows for age and year effects. It therefore shows how far from the individual’s average credit utilization she is in the next quarter conditional on differing from her average utilization by the amount on the x-axis this quarter. In other words, on if an individual is 10 percentage points above her typical utilization in one quarter, how much will she be on average in the next quarter, next year, and in two years. Each dot contains an equal portion of the sample whose overall distribution is shown in figure 10. Figure 11 thus captures the relationship between utilization today and in the future without imposing any parametric assumptions. Each panel also shows the best fit line for the conditional means and the estimated coefficients.

The top panels show that credit utilization is highly persistent and does not tend to zero on average. Credit utilization this quarter is typically very close to credit utilization next quarter since the conditional means are typically very close to the 45 degree line. Put a different way, on average if a person is using 40% of her credit this quarter, she will be using about 40% percent of her credit next quarter. Looking closely, however, average credit utilization is higher next quarter for those using less than 20% of their credit, and lower for those using more than 80% of their credit. The

best fit line through the conditional means suggests that credit utilization is not trending to zero. Instead, the long-term steady-state utilization is 0.39.<sup>3</sup> The same conclusion is evident from the conditional changes from changes comparing utilization this quarter to a year from now and to two years from now. Those using less than approximately 40% of their utilization this quarter are using more of their credit in one year and in two years, Those with more than 40% of their credit are using less of their credit on average within one year and two years. The steady state credit utilization is around 40% (evident by finding where the conditional expectation function cross the 45% degree line), although the movement towards the steady state is fairly slow.

It is important to notice that on average individuals do not trend to zero utilization, nor to using all of their credit. Conditional on using zero credit this quarter, credit utilization is nearly 5% within one quarter and nearly 8% in a year. On the other hand, the average person using all of her credit in one quarter is using less than 90% of it in a year.

The second row of figure 11 allows individuals to return to their own mean and adds substantial nuance. The reason credit utilization is so persistent in the top row is that it appears that individuals have their own mean to which they actually return quite rapidly. The speed of the return is evident from the slopes of the lines. Only 2/3 of a shock to utilization is left within one quarter and 13% in two years.

Even if individuals return very rapidly to their own means, it is important to note that those means are not zero. Credit utilization is persistent in the top row of figure 11 because individuals are typically quite close to their own mean credit utilization. Since credit utilization is the ratio of debts and credit, the stability of credit utilization implies that an individual with an increase in credit has increased her debts by 33% of the increase credit within one quarter and 87% of the increase in credit in two years.

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<sup>3</sup>Since the conditional expectation of utilization next quarter given this quarter is  $u_{t+1} = 0.041 + 0.896u_t$  the steady state utilization is  $0.39=0.041/(1-0.896)$ .

### 5.3 Changes in utilization: parametric estimates

In this section we examine how credit utilization changes from quarter to quarter parametrically. In Figure 11, the conditional expectation functions are surprisingly linear, although at longer horizons there appears to be an inflection at the steady state. The effect of being 20 percentage points above the mean is nearly the same as being 20 percentage points below. The linearity suggests we can summarize the changing utilization relationship extremely parsimoniously. Table 1 shows how utilization this period is related to utilization in the previous period. We estimate regressions of the form:

$$v_{it} = \theta_t + \theta_a + \alpha_i + \beta v_{it-1} + \epsilon_{it} \quad (2)$$

where  $v_{it} = D_{it}/B_{it}$  is the credit utilization given the credit limit  $B_{it}$  and the current debts  $D_{it}$ , conditional on the credit limit  $B_{it} > 0$ , and age ( $\theta_a$ ) and quarter ( $\theta_t$ ) effects that allow utilization to vary systematically by age and year.<sup>4</sup> Column 1 does not include fixed effects and so assumes a common intercept as in the top row of figure 11, column 2 includes year and age effects, while the other columns include fixed effects and so are the equivalent of the bottom row of the figure.

Without fixed effects credit utilization is very persistent and returns to a non-zero steady state  $\alpha/(1 - \beta) = 0.38$ . Note that this utilization is close to the average in figure 1, as it should be since they are estimated from the same data and the conditional expectation function in figure 1 is nearly linear. In the other columns since the age, year, and fixed effects change the steady state, we do not report it, but it is important to realize that the steady state credit utilization is not zero.

Given the heterogeneity of utilization shown in the distributions in figure 10, we next allow individuals to return to their own utilization rather than a single common steady state. The next two columns report how credit utilization varies around an individual specific  $\alpha_i$  by estimating using the within transformation. Nearly half of the overall variance in utilization comes from these fixed effects. In other words, we can think of the distribution of utilization as coming about half from factors that are fixed for an individual, allowing for common age and year trends, and half

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<sup>4</sup>The combined age, year, and individual fixed effects are not identified. We drop one of each and use the normalization on the age effects discussed in section 5.4.

from relatively short term deviations from the mean. The distribution of these fixed effects matches the distribution of credit utilization in figure 10 closely since deviations from a individual's steady state disappear rapidly. A deviation from the mean diminishes at a rate of about  $0.353=1-0.647$  per quarter. And so after a 10 percentage point increase in utilization, 6.47 percentage points remain in one quarter, 1.7 percentage points in a year, and less than 0.3 percentage points after two years.

The last column suggests that the speed of return to individual utilization depends on age. For a 20-year-old, only a fraction 0.58 of the shock is left after one quarter, for a 60-year-old 0.70 of a shock remains. It is not obvious why the speed of return should increase with age. One possibility is that credit represents a much more important factor in the overall portfolio of young people, who typically have acquired few assets. A 60 year old may have some other assets, and is more likely to be a convenience user, and so may not target credit utilization as closely.

The estimates in Table 1 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. Both the parametric and non-parametric evidence suggests that individuals have a strong tendency to return to their own credit utilization following shocks. Since the credit utilization is not zero for most people, the results suggest a strong tendency to hold credit card debt for the long term. Since the parametric estimates include age effects, these deviations are around a life-cycle average which the previous sections have shown is declining slowly, but persistently, with age. Both the slow decline of utilization with age and the quick return to individual credit utilization suggest that the pass-through from the credit card limit to credit card debts is large and occurs relatively rapidly. We explore these implications in the next two sections.

## **5.4 Individual changes in credit and debt**

This section examines how debts change for an individual and how these changes are related to changes in credit and debt in the past. We begin with a series of regressions that do not distinguish between convenience users and revolvers to understand the average effects from the data. Later, we will use the insights from section 6 to divide between convenience users and revolvers. However,

all of the estimates are very precisely estimated conditional expectations and so do not require the model to illuminate how debt and credit are related.

The basic specification we employ is:

$$\ln D_{it} = \theta_i + \theta_t + \theta_a + \alpha \ln D_{it-1} + \beta \ln B_{i,t-1} + \epsilon_{it}, \quad (3)$$

where  $D_{it}$  is credit card debts,  $B_{i,t-1}$  is the credit card borrowing limit observed at the end of the quarter, and we allow for individual specific levels of log credit card debt, common time shocks ( $\theta_t$ ), and common age shocks ( $\theta_a$ ), and for past accumulated debt. Since we observe the credit limit and debt only once a quarter, it is necessary to make a decision about timing. The relevant constraint for the debts accumulated at time  $t$  is the credit limit that existed between  $t-1$  and  $t$ . Since consumption and credit limits can change continuously, the relevant binding constraint on additional debts is the last one to hold. An increase in limits just before the end of a quarter still allows an increase in debts. We therefore measure  $D_{i,t}$  and  $B_{i,t-1}$  in the same quarter, even though their subscripts are different.

The coefficient  $\beta$  then determines how quickly a shock to credit card debt dissipates back to individual long term effect which is given by:  $\theta_i + \theta_t + \theta_a + \beta \ln B_{it}$ . 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 will 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.

Equation 3 is not identified since it contains individual, time, and age effects. Like the age-cohort-period problem, it is impossible to fully identify all effects since there can be a trend in any one of age, time, or cohort or split between all three, and any division is observationally equivalent since birth cohort equals the year minus age. Put a different way, if we estimate all individual effects it is not possible to fully separate between getting older and a time shock. The size of the data set means that rather than estimating individual coefficients—sometimes referred to as nuisance parameters—we instead perform the standard within transformation by removing the mean from all variables in equation 3. The within transformation means that any additional

restriction for identification must be on either the time or age effects. Rather than imposing the questionable assumption that two of the age or year effects are exactly equal—the implication of dropping more than one of the age or year dummies—we instead impose the restriction that there is no trend in the age effects. This restriction is innocuous in the sense that there can still be a trend with age as individual effects that are older when we observe them can have larger  $\theta_i$ , but that trend will appear in the individual effects rather than the age effects. Moreover, the age effects can still allow life-cycle variation, but that variation must average out to zero.<sup>5</sup>

The functional form in equation 3 with logs necessarily excludes both those who have zero credit limits, and those with zero debts this period or the previous period since the log of zero is undefined. Equation 3 therefore estimates the response of those with debts to changes of limits conditional on having debts and a positive credit limit. The fraction of accounts with a positive credit limit and positive debts changes with age in figure 4. A standard approach to understanding the implications of excluding zeros is to use a slightly different transformation by giving everyone a small amount. In some specifications, we explore the implications of this conditionality by giving everyone \$10 in both credit and debt so that rather than being undefined these individuals are included as having nearly zero debts and credit. We estimate similar specification in levels as well.

Table 2 shows the results of estimating several variations of equation 3. Column 1 shows the base specification, column 2 excludes individual fixed effects but still includes overall cohort effects, column 3 gives everyone \$10 in credit and debt and so includes those with no credit or no debts. Columns 4 and 5 estimate the same specification on levels rather than logs, with column 4 including those with zero debts and zero credit and column 5 excluding them and so estimating on the same sample as columns 1 and 2. At the bottom of the table we calculate the long-term effect of a permanent increase in credit  $\beta/(1 - \alpha)$ .

The pass through of credit into debt, adjusting for age, occurs rapidly and is nearly 90% in the long term. Using column 1, a 10% increase in credit is associated with a 4% increase in debt

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<sup>5</sup>We implement this restriction following Deaton (1997, pp. 123-126) by recasting the age dummies such that  $\hat{I}_a = I_a - [(a - 1)I_{21} - (a - 2)I_{20}]$  where  $I_a$  is 1 if the age of person  $i$  is  $a$  and zero otherwise.



within one quarter and 8.6% in the long term. Not including fixed effects in column 2 changes the persistence of debt, but not the ultimate pass-through of credit, shown at the bottom of the table. Including those with zero debts and limits in column 3, seems to reduce the immediate effect slightly—perhaps because credit limit changes for those using none of their credit do not matter as much—but the long-term change in debts is still close to 90% of the change in credit.

The results are similar in dollar rather than percentage terms shown in columns 4 and 5. A dollar increase in credit limits results in 0.27 dollar increase in debts within one quarter and 0.63 dollars in the long term. The effects are remarkably similar including or excluding those with zero debts or credit limits.

Finally, we briefly examine whether there is an important feedback mechanism from debt to credit. Columns 7 and 8 in table 2 show the impact of past credit and debt on current credit. Allowing for fixed effects, deviations from the long-term are fairly persistent with between 80 and 85 percent of a deviation still existing within a quarter. Debt has small positive impact on credit. A permanent 10% increase in debt results in a 0.08% in credit in one quarter using the estimates in column 7, and a 0.5% increase in the long term. Including those with zero debts and credit results in slightly smaller estimate in column 8. It seems likely that this small positive is hiding substantial heterogeneity: card issuers may be happy to raise the limit for those they think are a good risk when they acquire more debts, but may actually reduce the limit for more risky types acquiring more credit. Either way, the average effect is very small, and so focusing primarily on the impact of credit on debt does not miss much.

## **6 Credit, debt, and consumption**

The stability of credit utilization over the short and long term indicates that debt and credit evolve together. This section derives the implications of changing debt and credit for debt in the future for two different groups: those who use credit to borrow from period to period or credit “revolvers;” and those who use credit cards primarily as a convenient payment mechanism or “convenience”

users. The debts of revolvers and convenience users evolve in distinct ways we use to separate them in the data in the next section.

## 6.1 Debts for credit revolvers

We begin by building a model of a “Revolver” who is using credit cards for debt rather than as a payment mechanism. By definition, debts change from period to period according to the standard accounting accumulation equation:

$$D_{t+1} = (1 + r)(D_t - Y_t + C_t) \quad (4)$$

where  $Y_t$  is income and  $C_t$  is consumption and  $t$  is either age or time which are indistinguishable for an individual. Equation 4 does not make any behavioral assumptions about how consumption is decided. A revolver pays off debt if her income is greater than her consumption, and accumulates debt if consumption is greater than consumption.

Even without putting additional structure on the evolution of income and consumption, the accumulation equation directly implies that that past debts must impact future debts for revolvers. Dividing by the credit limit, the accumulation equation implies a relationship for credit utilization like 2 in which the past credit limit predicts current credit limits.

How consumption changes with previously accumulated debts  $D_t$ , the current credit limit  $B_t$  and the current income  $Y_t$  is a central question in economics. The standard assumption is that consumption is a function of available resources or cash-at-hand  $W_t$  and varies with age as expectations of future income change (Carroll, 2001) and so

$$C_t = C_t(W_t) = C_t(Y_t + B_t - D_t).$$

Appendix A.1 shows that taking a log linear approximation of the the accumulation equation:

$$d_{i,t+1} = \mu_i + \mu_t + g(\text{age}_{i,t}) + \alpha d_{i,t} + \beta \frac{b_{i,t}}{\nu(\text{age}_{i,t})} + \epsilon_{i,t} \quad (5)$$

where the lower case indicates logs, and where where  $\alpha = (1 + r)(1 - m)$ ,  $\beta = (1 + r)m$  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.  $\nu(\text{age}_{i,t})$  is the age specific average credit utilization. Under somewhat stronger assumptions about the income process, a similar relationship holds for the dollar value of debts:

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

where  $\alpha = (1 + r)(1 - M)$  and  $\beta = (1 + r)M$  and  $M$  is the marginal propensity to consume out of cash-at-hand at its steady state.

For revolvers, a regression of debt on previous debts and the active credit limit provides a test that credit limits are important and recovers the marginal propensity to consume  $M$  out of liquid wealth or its elasticity. While the model assumes that credit limits matter, it is possible that 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, and so it may not represent a true constraint. Similarly, the model assumes away alternative assets since if the consumer is borrowing she must not be saving. In reality, consumers do keep a small amount of liquid assets (Gross and Souleles, 2002), and some have substantial illiquid assets. If these assets are easily substitutable for consumer credit, then the credit limit will not matter as much. Then a simple test for whether the credit limit matters for consumption and debt is  $\beta > 0$ .

Moreover, the accumulation equation approximations make the prediction that the effect of changing credit is closely related to the impact of past debts and so  $\alpha + \beta = (1 + r)$ . This prediction is useful for understanding both the economic content of the model and its empirical

implications. While it is possible that credit limits do not matter, debts certainly do since they directly affect the intertemporal budget constraint whether or not credit limits ever bind. Put a different way, 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, the creditors will insist and can enforce a change in behavior following an increase in debt. While  $\beta > 0$  implies that credit constraints matter, if  $\beta = (1 + r - \alpha)$ , then changes in debts have the same impact as changes in assets or income.

Why might credit be less salient than assets? Perhaps it is less well reported or remembered. Perhaps its volatility means it is less valuable than a savings or checking account Fulford (2015a). Then a change in credit will have a smaller impact than a similar increase in assets, for example, from a positive income shock. We can back out a value for salience by assuming that in the accumulation equation 4 only a fraction  $\sigma B_t$  of credit matters for consumption decisions. Then given estimates of  $\alpha$  and  $\beta$ , and an appropriate interest rate  $r$ , the salience of credit compared to assets is  $\sigma = \beta / (1 + r - \alpha)$ .

Finally, we can allow some important forms of non-linearity to matter. Individuals whose cash-at-hand is low may have a much higher marginal propensity to consume. We can capture such non-linear effects by allowing the marginal propensity to consume to vary with the individual credit utilization  $v_{it} = D_{it} / B_{it}$  so that consumers whose budget constraints bind tightly this period may have a different response than those whose constraints are less binding. Similarly, the marginal propensity to consume may change with age. Both the effect of credit utilization and age can be flexibly captured by allowing for functions of age and utilization to alter the MPC through interactions:

$$d_{i,t+1} = \mu_i + \mu_t + g(\text{age}_{i,t}) + \alpha(\text{age}_{i,t}, v_{i,t})d_{i,t} + \beta(\text{age}_{i,t}, v_{i,t}) \frac{b_{i,t}}{\nu(\text{age}_{i,t})} + \epsilon_{i,t} \quad (6)$$

where the prediction is still for any given age and utilization  $\alpha(\text{age}_{i,t}, v_{i,t}) + \beta(\text{age}_{i,t}, v_{i,t}) = (1 + r)$ .

## 6.2 Debts for convenience users

Many of those with credit card debts in our data 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. They still show up as having debts but are not well described by equation 4 since the debts are not representative of their asset positions. Instead we assume that convenience users charge some stochastic fraction  $\omega_{i,t}$  of their consumption to their credit card each month:

$$D_{i,t} = \omega_{i,t}C_{i,t}.$$

Since by definition a convenience users has access to credit but is not borrowing in the revolving sense, she is not directly credit constrained in a given month. Standard intertemporal theory suggests that in changes in consumption should follow a martingale with age and time specific drift terms that capture changes in tastes or the decision environment.<sup>6</sup> Then:

$$\ln C_{i,t} = \eta_i + \eta(\text{age}_{it}) + \eta_t + \epsilon_{it}^C$$

where by intertemporal optimization the consumption shock  $E_{t-1}[\epsilon_{i,t}^C] = 0$ . Further, if the ability to consume with a credit card is stochastic around an individual specific mean so that:

$$\omega_{i,t} = \omega(\text{age}_{i,t}) + \omega_i + \omega_t + \epsilon_{i,t}^\omega$$

then changes in log credit card debt for a convenience user can be written as:

$$d_{i,t} = \tilde{\eta}_i + \tilde{\eta}(\text{age}_{i,t}) + \tilde{\eta}_t + \epsilon_{i,t} \tag{7}$$

where  $\epsilon_{i,t} = \epsilon_{i,t}^C + \epsilon_{i,t}^\omega$ . The key difference between equation 7 and the difference in credit card debt for revolvers in equation 5 is that neither credit limits nor past debts matter. Credit limits do not

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<sup>6</sup>See Hall (1978) for the original formulation, Deaton (1992) for an extended discussion, and Blundell, Pistaferri, and Preston (2008) for a more recent version that incorporates the life-cycle and uncertainty.

matter because, by assumption, since the convenience user is not accumulating debts from period to period, the convenience user has enough credit to charge whatever fraction of consumption is convenient. Past debts do not matter because debts are not kept from the previous period, and for someone who is smoothing marginal utility from period to period shocks to consumption in the past should not predict shocks to consumption in the future.

Alternatively, dividing by the credit limit  $B_{i,t}$ :

$$\text{Credit utilization}_{i,t} = \nu_{i,t} = D_{it}/B_{it} = \omega_{i,t}C_{i,t}/B_{i,t}, \quad (8)$$

should not predict future utilization beyond individual and age drift terms.

## 7 Dividing between convenience and revolvers

In this section we take the modeling insights from the previous section and it to help divide the estimates from section 5 into the effects for revolvers and convenience users. There is a slow shift of the population from revolver to convenience user of the life-cycle, consistent with the estimates shown in figure 5 from the SCPC. For revolvers utilization and debts take longer to return to steady state, and the pass-through of credit into debt is nearly 100% at all ages and credit utilizations.

We begin by examining utilization for revolvers and convenience users. The basic idea is to use the data to divide the population statistically into who at a given period is more likely to be a convenience user and who is more likely to be a revolver. 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.

The basic idea is to let the data help divide between convenience users and revolvers. Since we cannot observe who is who, the observed data is a combination of revolvers and convenience users, where each observation is one or the other, but we cannot observe this latent class. We take

the model as :

$$\begin{aligned} \text{Convenience users:} \quad & \nu_{i,t} = \theta_a^C + \theta_t^C + \theta_i^C + \epsilon_{i,t}^C && \text{with density } f_C(\nu_{i,t}|X_{i,t}; \theta^C, \sigma^C) \\ \text{Revolvers:} \quad & \nu_{i,t} = \theta_a^R + \theta_t^R + \theta_i^R + \beta\nu_{i,t-1} + \epsilon_{i,t}^R && \text{with density } f_R(\nu_{i,t}|\nu_{i,t-1}, X_{i,t}; \theta^R, \sigma^R) \end{aligned}$$

which implies the joint density of the observed data:

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

where  $p^C$  is the unconditional probability that any observation is from a convenience user. Since the mixing probabilities are unobserved, maximizing the sum over all  $i$  and  $t$  of  $\ln H$  requires also finding the unobserved probabilities. We use the EM algorithm which proceeds in two steps: (1) with a set weights use Weighted Least Squares to estimate each of the models for convenience users and revolvers independently, (2) then update the weights and  $p^C$  using Bayes rule based on the new estimates from each model so that for iteration  $j$ :

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

and  $p^{C,j+1}$  is the average of the the new posterior weights for each observation. The two steps alternate until the overall likelihood converges. We assume that the densities are normal, but impose the additional structure that the probability we see that observation from a convenience user follows the same distribution as in the SCF for age and credit utilization.<sup>7</sup> We first remove the fixed effects by removing the mean from all variables, which substantially speeds estimation, but implies that for a given individual  $\theta_i^C = \theta_i^R$ . The problem of the colinearity of age, year, and fixed effects remains. We allow a trend in the fixed effects, and unrestricted time effects, but estimate only a square and cubes of age. The results below then remove the age trend from the fixed effects and places it back with the estimated age effects, maintaining the assumption that

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<sup>7</sup>The density for a convenience user, for example, is:  $f_C(\nu_{i,t}|X_{i,t}; \theta^C, \sigma^C) = p^{SCF}(\text{age}_{it}) p^{SCF}(\nu_{it}) \phi(\nu_{it}|X_{it}; \theta^C, \sigma^C)$  where  $\phi(\cdot)$  denotes the density of the normal distribution with mean  $\theta_a^C + \theta_t^C + \theta_i^C$  and variance  $(\sigma^C)^2$ .

there are life-cycle effects but not systematically trending cohort effects.

Figure 12 shows the fraction of convenience users at different ages that come from the EM estimates for utilization (using the posterior weights for each observation). The fraction of convenience users is increasing with age and decreasing with utilization, closely matching the SCF, which is not a surprise since we used the unconditional probabilities in the SCF in forming the individual densities. The SCF estimates may understate the number of convenience users in early age, however, as suggested by the SCPC in figure 5.

Figure 13 then shows the average utilization of revolvers and convenience users with age. The slow decline of utilization observed in the raw data is mainly coming from the switch to convenience use with age. Conditional on still being a revolver, the average utilization declines slowly from around 60% in the 20s to 50% in the 60s. The average utilization of convenience users also declines. The main factor explaining the overall decline in utilization is the decline in the fraction revolvers as the population slowly shifts from the top line of revolvers to the bottom line of convenience users. The last column of table 1 then shows the relationship of past utilization to current utilization for revolvers. Since convenience users return immediately, in expectation, to their long-term mean, when excluding convenience users the persistence of shocks to credit utilization is longer.

Finally, using the same mixture model approach we estimate the relationship between credit and debt under the assumption that shocks to debt for convenience users do not accumulate. Column 4 of table 2 shows the estimated effects of debt and credit changes for revolvers. Debts return to steady state more slowly than when estimated over all credit users, as one would expect. The immediate impact of credit is lower, but because of the persistence of debt, the long-term impact of a change in credit for revolvers is nearly 100%.

We can also allow the debt response to past debt and current limits to vary flexibly with credit



utilization and age.<sup>8</sup> Since the coefficients from such a regression are difficult to interpret on their own, we show the marginal effect evaluated over ages 20 to 70 and utilization 0.1 to 1 in figure 14 for revolvers. Several important changes with age and credit utilization for revolvers are clear from figure 14. First, at all utilization levels, the effect of the credit limit is decreasing with age, while the effect of the past debt is increasing. Put a different way, older people are less sensitive to credit limit changes, but are more sensitive to having debts. At any age or utilization the sum of the estimated credit effect and estimated debt effect is nearly constant. As a direct consequence the long-term effect of credit on debt is nearly constant across all ages and levels of utilization. Young people reach that long-term faster, but for everyone the long-term effect of credit on debt is large and relatively constant. Consistent with the estimate in table 2 of complete pass-through from credit into debt, the long-term impact of changes in credit is nearly 100% at all ages and utilizations. For example, for a 20 year old using nearly all of her credit the impact is approximately  $0.6/(1-0.4) = 1$ , while for a 20 year old using only 10% of her credit the long-term impact is approximately  $0.25/(1-0.7)=0.83$ . Second, at any age the effect of utilization is extremely non-linear. The effects of credit and past debt are nearly identical for those using between 0.1 and 0.7 of their credit, but then rapidly change as individuals get closer to using all of their credit. Credit utilization only matters much when the the consumer is close to her credit limit. Third, except for the 60 and 70 year olds using little of their credit, 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.

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<sup>8</sup>We estimate the following functional form for  $\alpha$  and an identical one for  $\beta$ :

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

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

## 8 Conclusion

Available credit appears to be the driving factor of debts in both the short and long-term. Separating between convenience users and revolvers we find that a 10% increase in credit is followed by a 2.3% increase in debt within one quarter and a 9.9% percent increase in debt over the long term. For those revolving debt long-term credit and debt closely related. That debt follows so closely available credit explains the extreme stability of overall credit utilization. Despite very large changes in credit and debt over the life-cycle and in aggregate since 2000, overall credit card utilization varies little. Moreover, we show that individual credit utilization is also remarkably stable, as individuals rapidly return to their steady state credit use. Using credit is not a short term phenomenon for individuals, but is instead a long-term phenomenon.

The large pass-through of credit into debt and the large life-cycle variation of credit have important implications for savings and consumption over the life-cycle. One of the startling facts of consumer finance is how little households save when they are not forced to by Social Security or mortgage payments. Indeed, Gourinchas and Parker (2002) document that the average household only starts acquiring assets for retirement when its head is in her late 40s. We show that credit increases rapidly in the 20s and continues to increase into the 30s. These increases help explain why consumers save so little early in life. For buffer-stock consumers in their 20s many of whom appear credit constrained, it makes little sense to save. The large response to credit changes in our data suggests that early in life almost all are constrained by their credit limits and would prefer to spend more, not save more. Moreover, we show that in expectation, the credit limit for someone in her 20s will be much higher next year. Since credit is a form of wealth, the young are effectively getting wealthier through credit increases, reducing their need to save. In middle age, on the other hand, many households have substantial debts. Saving for these consumers should be mostly about paying down previous debts. Paying off credit card debt has a riskless return which averages 14%, which no other asset class can match. The large life-cycle variation in credit and debts suggests why the average household to has little in positive assets beyond a small emergency fund and illiquid housing until very late in life. Not taking into account this variation leads to a

serious misunderstanding of the financial status of US households.

In future work we expect to introduce models of life-cycle saving that allow for buffer-stock behavior in the short term, planning for retirement in the long-term, the acquisition of illiquid assets such as housing, and the use of credit for payments. Such models have implications for both debt acquisition and the impact of credit. The estimates in figure 14 suggest that the effects of debt and credit change over the life-cycle, and we expect that future work will examine what models are consistent with the observed changes.

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# A Appendix

## A.1 Derivation of debt revolver accumulation equation

From equation 4 we have that

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

Let  $Y_{i,t} = P_{i,t}U_{i,t}$  where  $P_{i,t} = E_{t-1}[Y_{i,t}]$  is the long-term or permanent component of income given age  $t$  and  $B_{i,t}^*$  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:

$$\frac{-rD_{i,t}^*}{1+r} + P_{i,t} = C_{i,t}(P_{i,t} + B_{i,t}^* - D_{i,t}^*).$$

A first order expansion around  $W_{i,t} = D_{i,t}^* + B_{i,t}^* + P_{i,t}$  then gives:

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

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  $M_{i,t}Y_{i,t}$  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  $\alpha = (1+r)(1-M)$  and  $\beta = (1+r)M$  are the average of the  $M_{i,t}$  and  $\epsilon_{i,t}$  captures the approximation error, the unobserved income shocks not explained by age, individual, and time, and the differences from the average  $\alpha$  and  $\beta$ .  $M_{i,t}$  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 debts. A more flexible expansion involves taking logs and expanding around  $D_{i,t}^*$ ,  $B_{i,t}^*$ , and  $P_{i,t}$  and canceling constants using the steady-state equation gives a first order approximation:

$$\frac{D_{i,t}^*}{(1+r)} d_{i,t+1} - D_{i,t}^* d_{i,t} + P_{i,t} \ln U_{i,t} \simeq m_{i,t}(P_{i,t} \ln U_{i,t} + B_{i,t}^* b_{i,t} - D_{i,t}^* d_{i,t})$$

where  $b_{i,t} = \ln B_{i,t}$ ,  $d_{i,t} = \ln D_{i,t}$ , and  $m_{i,t} = C'_t(W_{i,t}^*)/C_{i,t}(W_{i,t}^*)$  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  $m_{i,t} = m + \epsilon_{i,t}^m$ , the ratio of credit-limit-to-debt and assume that the target can be expressed as a function of deviation from the average utilization at each age  $(B_{i,t}^*/D_{i,t}^*) = 1/\nu(\text{age}_{i,t}) + \epsilon_{i,t}^\nu$ ,

then:

$$d_{i,t+1} = (1+r)(1-m)d_{i,t} + (1+r)m \frac{b_{i,t}}{\nu(\text{age}_{i,t})} + \epsilon_{i,t}^s,$$

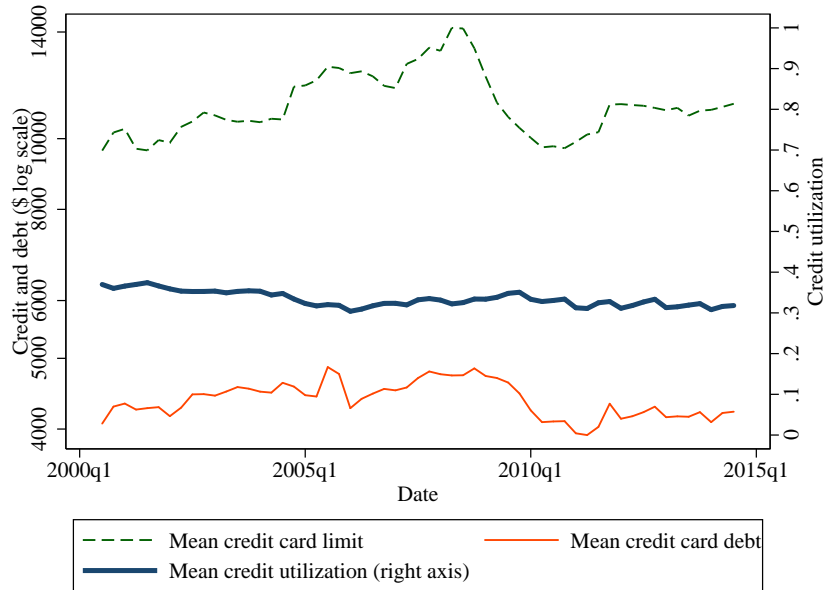
where  $\epsilon_{i,t}^s$  captures the random coefficients and the unpredictable income component. Following Blundell, Pistaferri, and Preston (2008), suppose that idiosyncratic and age specific drift factors are well captured by an individual effect and age effects (or functions) so that the structural and approximation error  $\epsilon_{i,t}^s = \mu_i + \mu_t + g(\text{age}_{i,t}) + \epsilon_{i,t}$  then

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

where  $\alpha = (1+r)(1-m)$ ,  $\beta = (1+r)m$  and  $E[\epsilon_{i,t}] = 0$ .

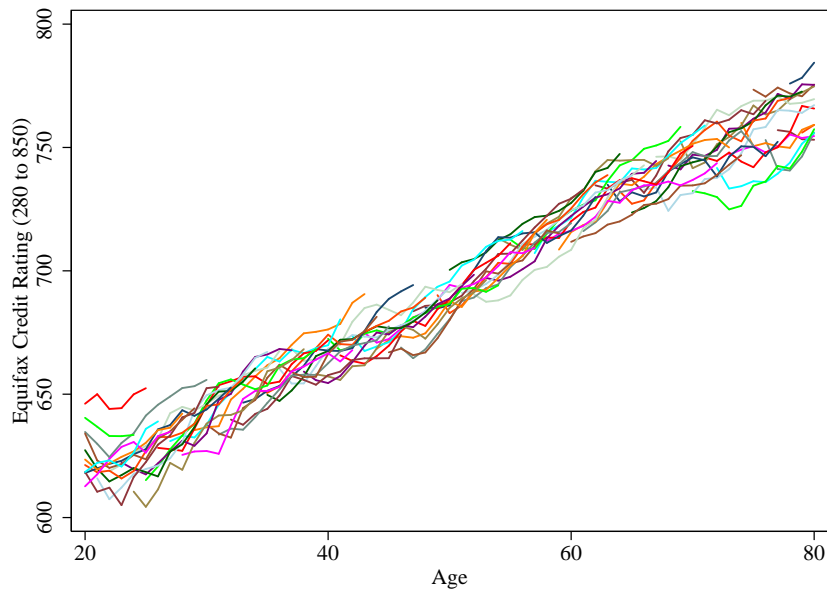


Figure 1: Credit card limits, debts, and utilization: 2000-2014



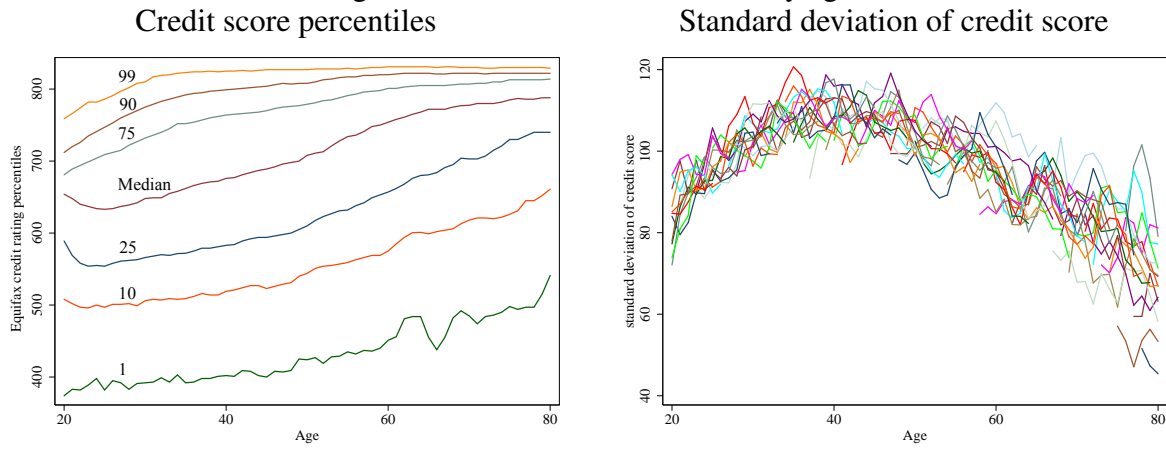
Notes: The left axis shows the average credit card limits (top line) and debts (bottom line) including those with zero limits and or debts. Note the log scale. The right shows mean credit utilization (middle line) defined as the credit card debt/credit card limit if the limit is greater than zero. Source: Author's calculations from Equifax/NY Fed CCP.

Figure 2: Credit score by cohort and age



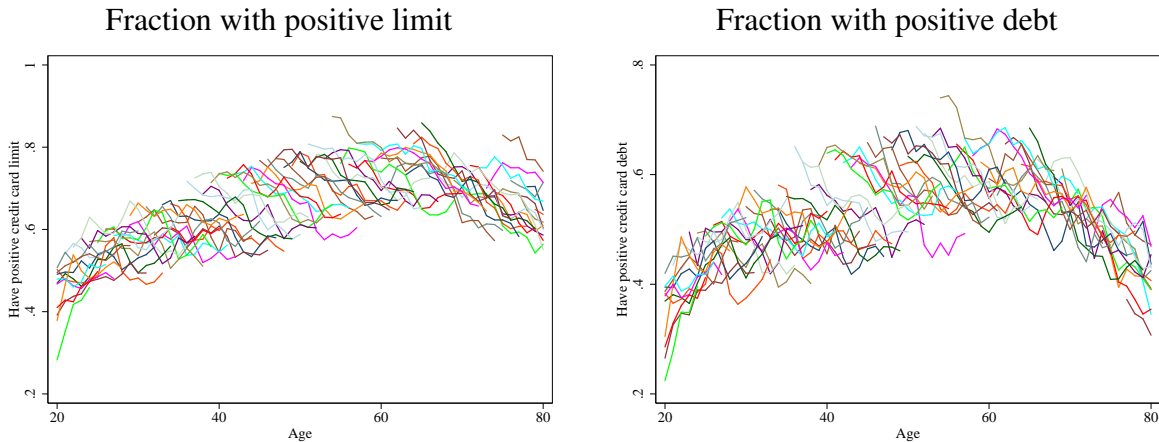
Notes: Each line represents the average credit score of one birth cohort from 1999-2014. Source: Author's calculations from Equifax/NY Fed CCP.

Figure 3: Credit score distribution by age



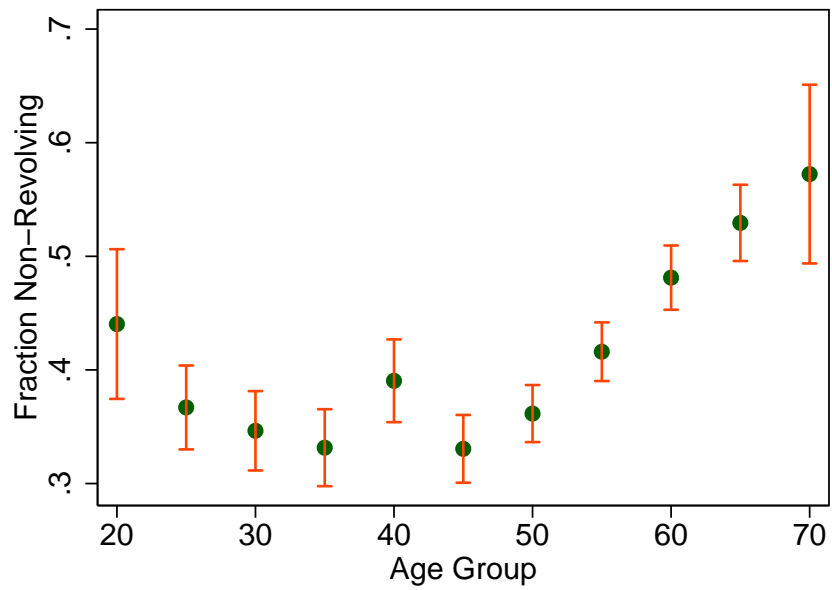
Notes: On left: The lines are the credit scores of the 1, 10, 25, 50, 75, 90, and 99th percentiles of credit score at each age over 1999-2014. The lines are in order from 1 at the bottom to 99 at the top. On right: Each line represents the standard deviation of the credit score of one birth cohort from 1999-2014. Source: Author's calculations from Equifax/NY Fed CCP.

Figure 4: Fraction with positive credit card limit and debt by cohort and age



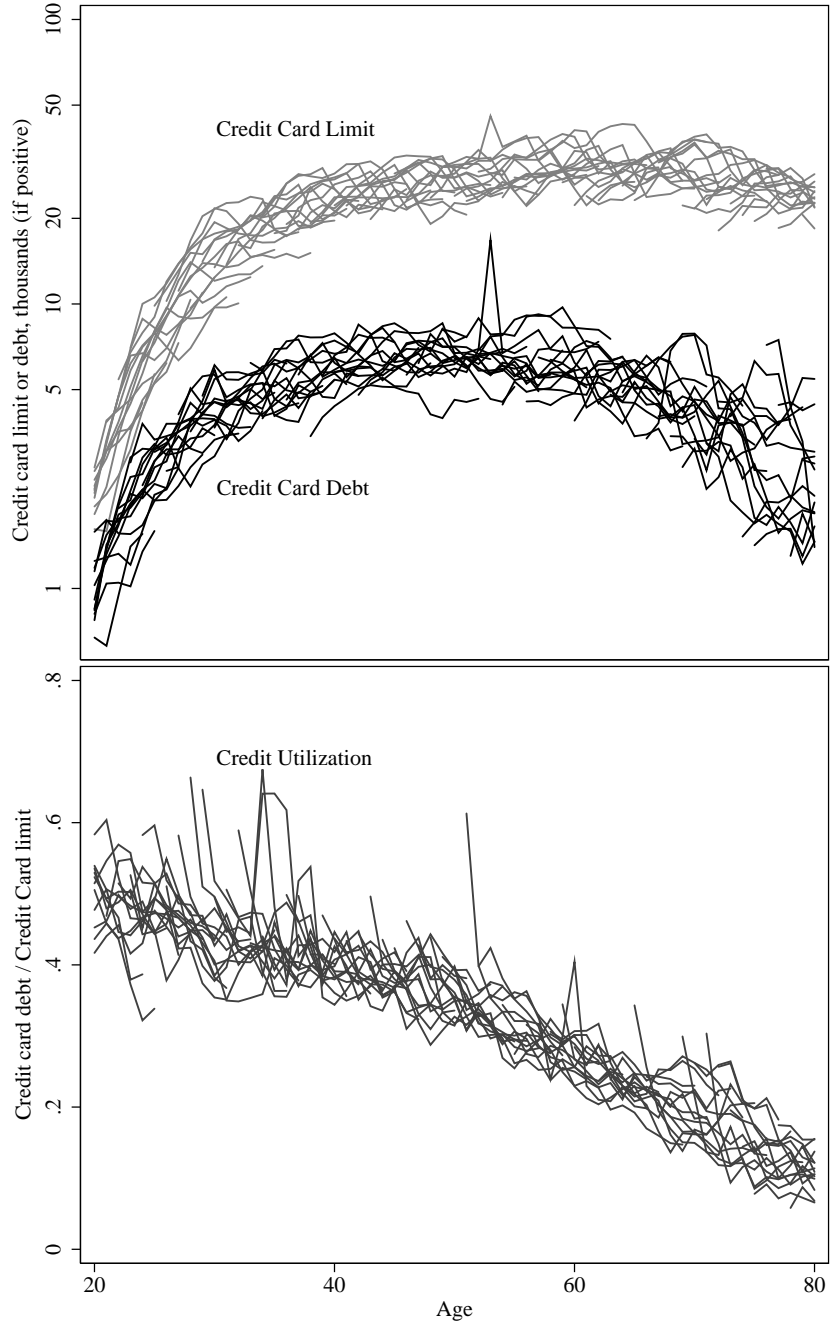
Notes: Each line represents the fraction with positive credit card limits or debts of one birth cohort from 1999-2014. Source: Author's calculations from Equifax/NY Fed CCP.

Figure 5: Fraction not-revolving credit card debt, conditional on use



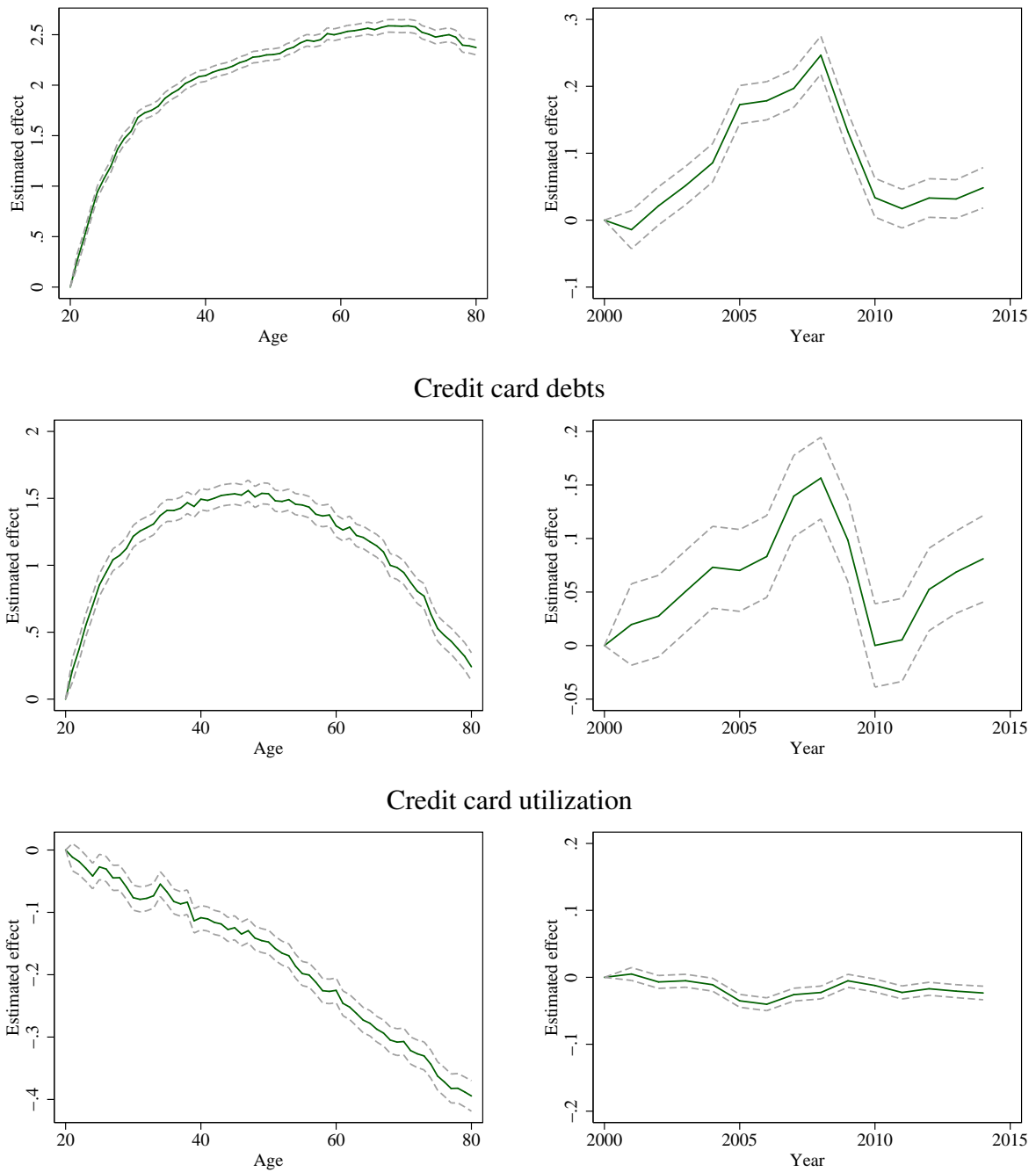
Notes: Each dot shows the fraction in that five year age group (labeled by the youngest member) who did not revolve credit card debt from month to month, 'conditional on using their credit card. 95% confidence intervals in bars. Source: Author's calculations from the 2008-2014 Surveys of Consumer Payment Choice.

Figure 6: Credit card limits, debts, and credit utilization



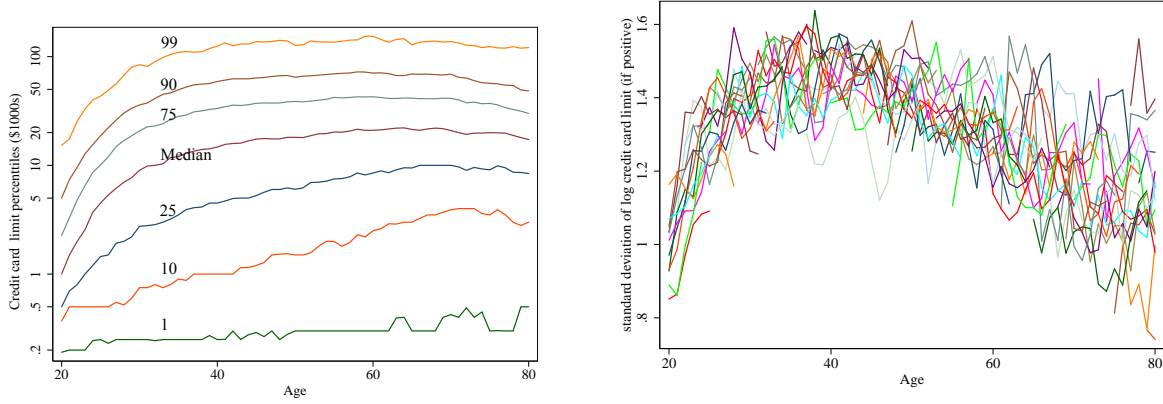
Notes: Each line represents the average credit card limit, debt, and utilization of one birth cohort from 1999-2014.  
Source: Author's calculations from Equifax/NY Fed CCP.

Figure 7: Credit card limits, debts, and utilization: age and year effects

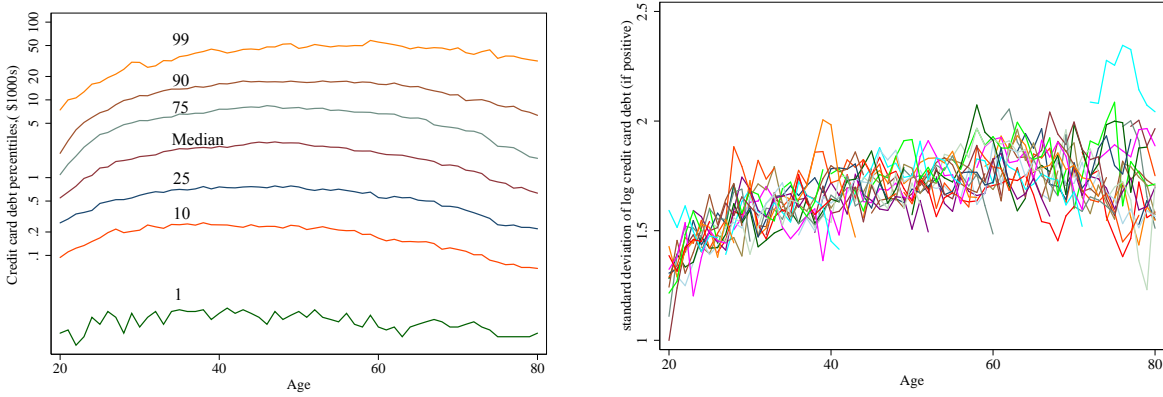


Notes: Each line shows the estimated age or year effects from equation 1. Note the different scales. Source: Author's calculations from Equifax/NY Fed CCP.

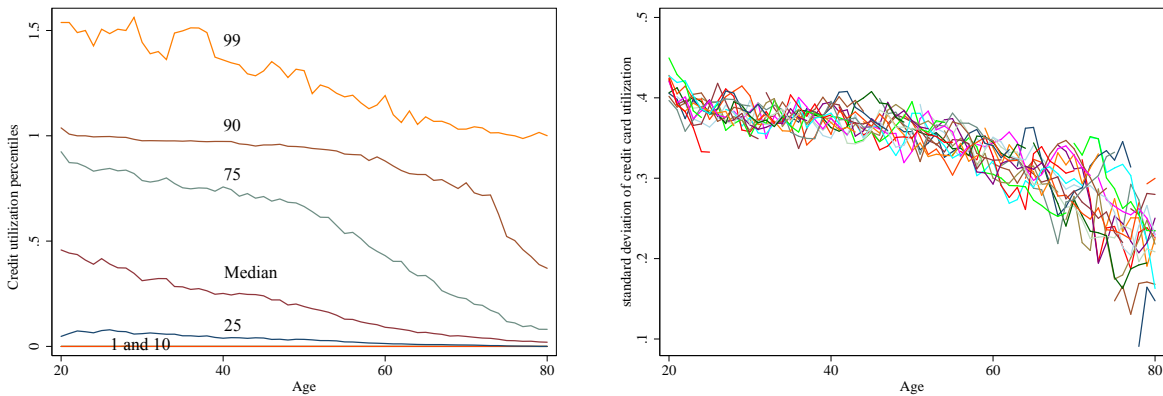
Figure 8: Credit card limit, debt, and credit utilization distributions by age  
 (A) Credit Card Limits



(B) Credit Card Debts

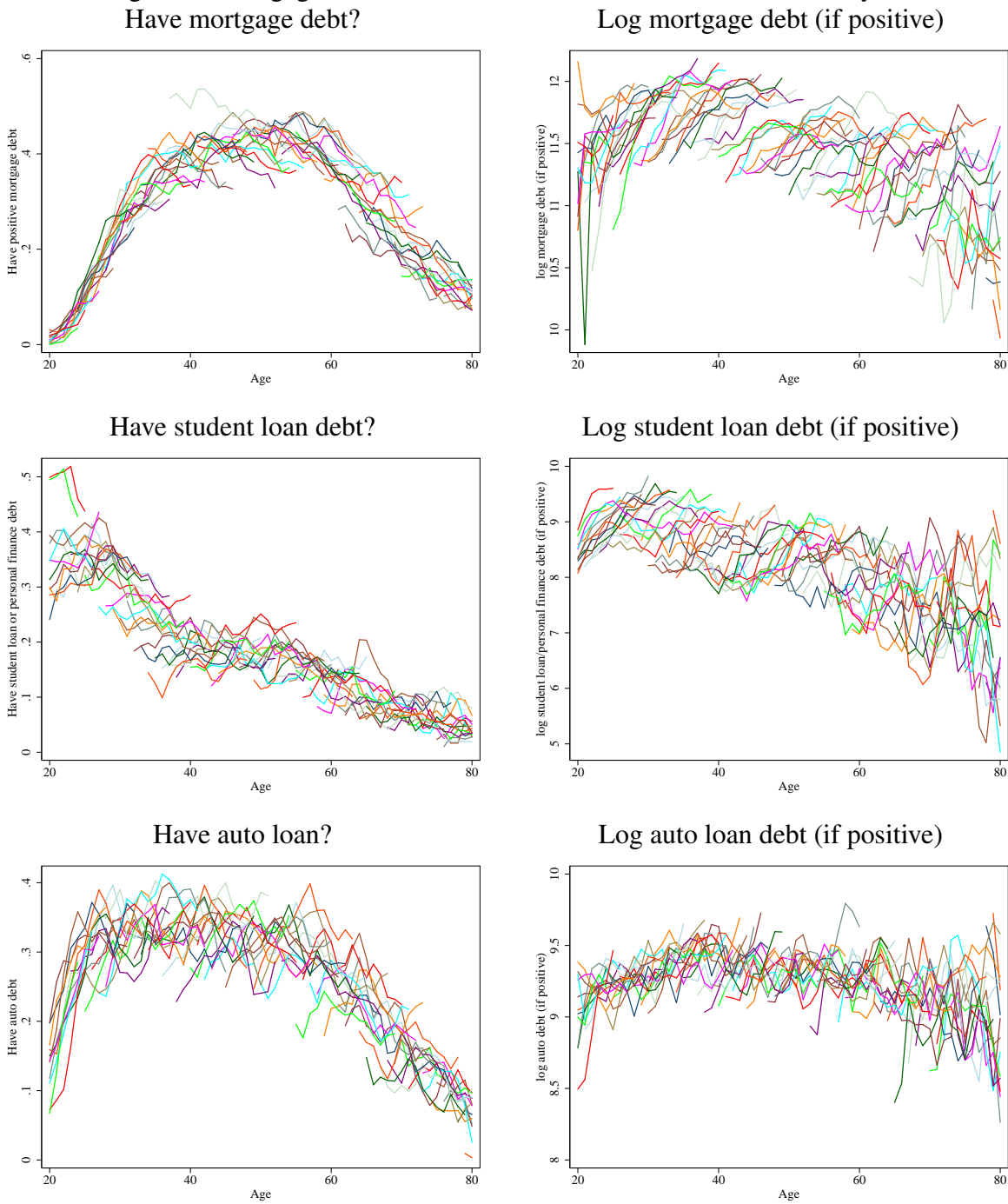


(C) Credit utilization



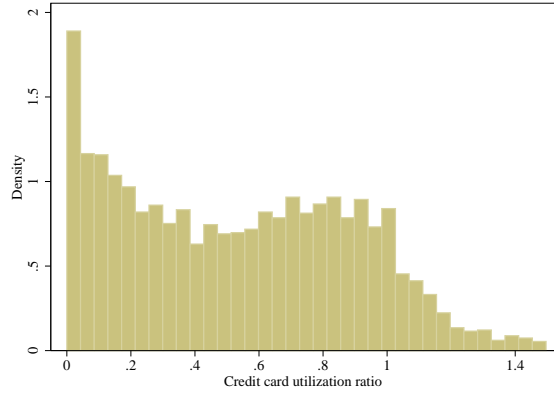
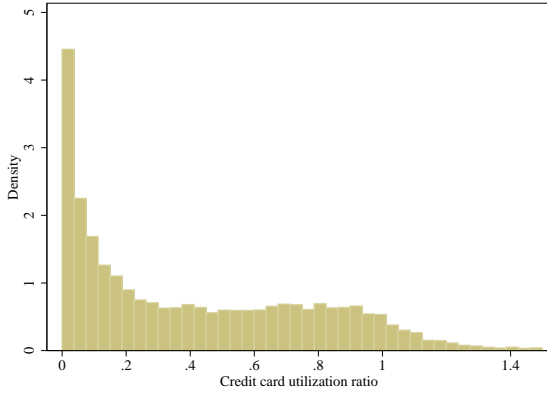
Notes: Each line is the percentile of credit limit at that age, conditional on having a positive credit limit on a log scale. For example, the 90th percentile line shows that 10% of the population (with a positive credit limit) have a limit larger than that line. Source: Author's calculations from Equifax/NY Fed CCP.

Figure 9: Mortgage, student loan, and auto loan debts over the life-cycle

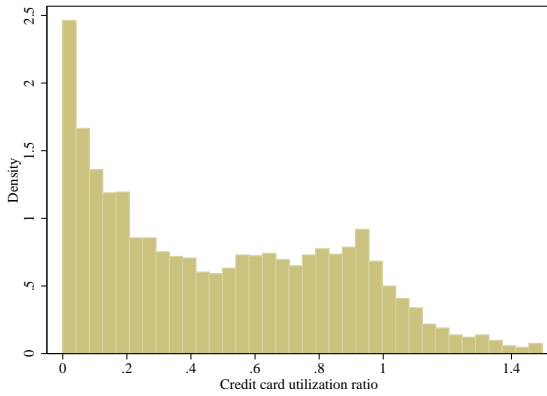


Notes: Each line represents the average for one birth cohort from 1999-2014. Source: Author's calculations from Equifax/NY Fed CCP.

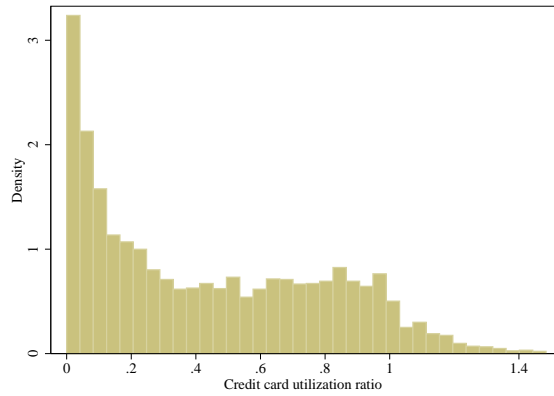
Figure 10: Credit card utilization distribution by age  
 All ages



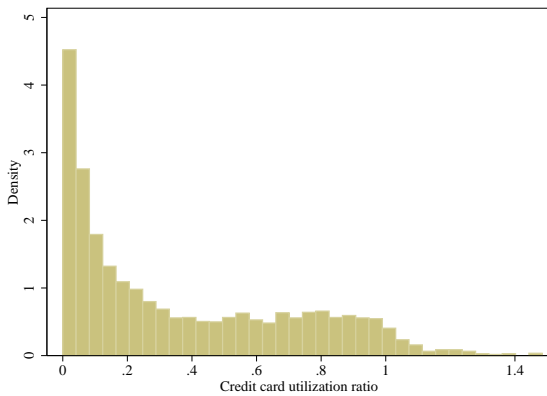
Age 30-40



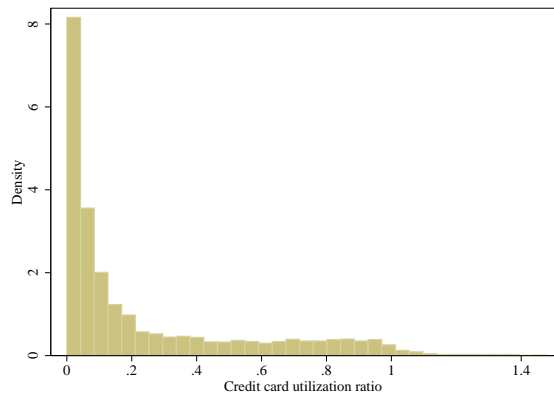
Age 40-50



Age 50-60



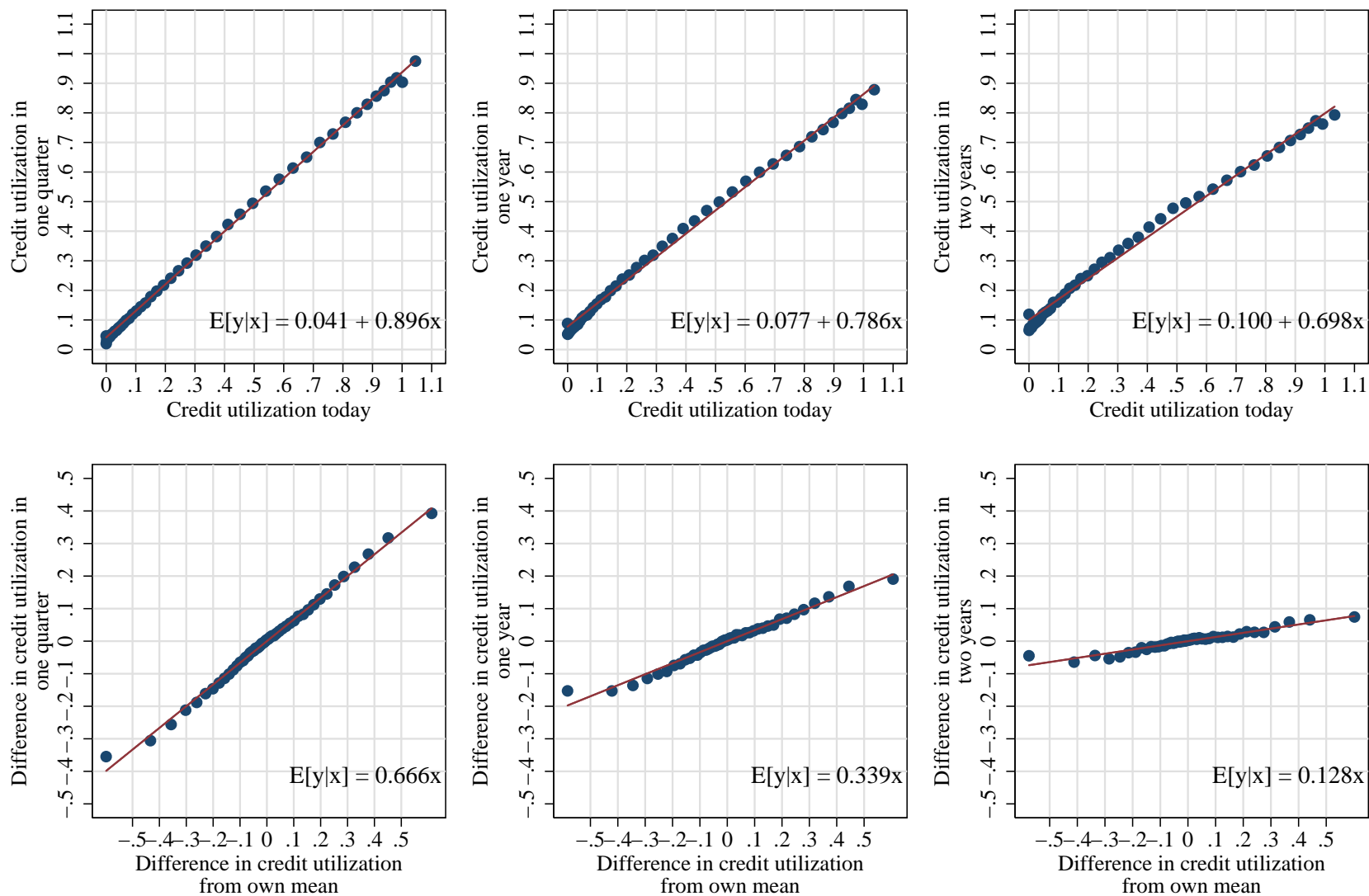
Age 60-80



Notes: Each panel shows the histogram for select age groups of credit utilization (credit card debt/credit card limit if the the limit is positive). The histograms exclude utilizations greater than 1.5 Source: Author's calculations from Equifax/NY Fed CCP.

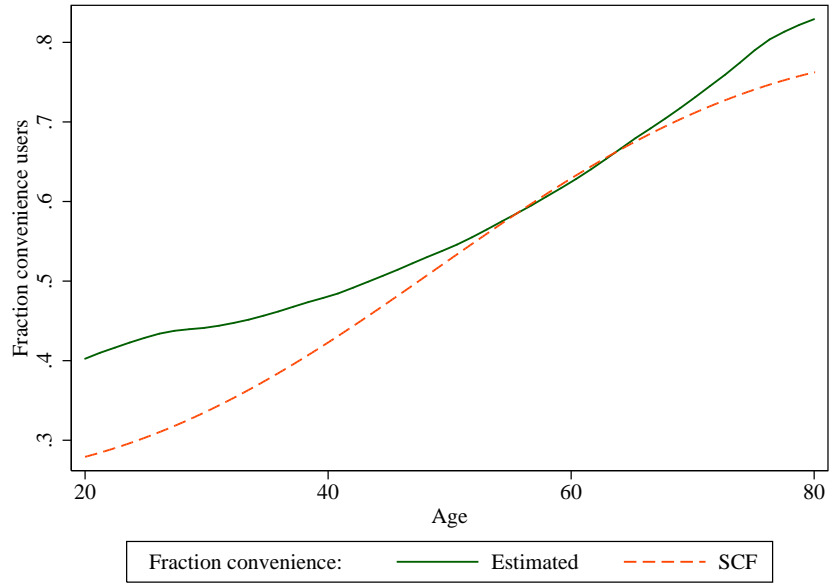


Figure 11: Changes in credit utilization in one quarter, one year, and two years

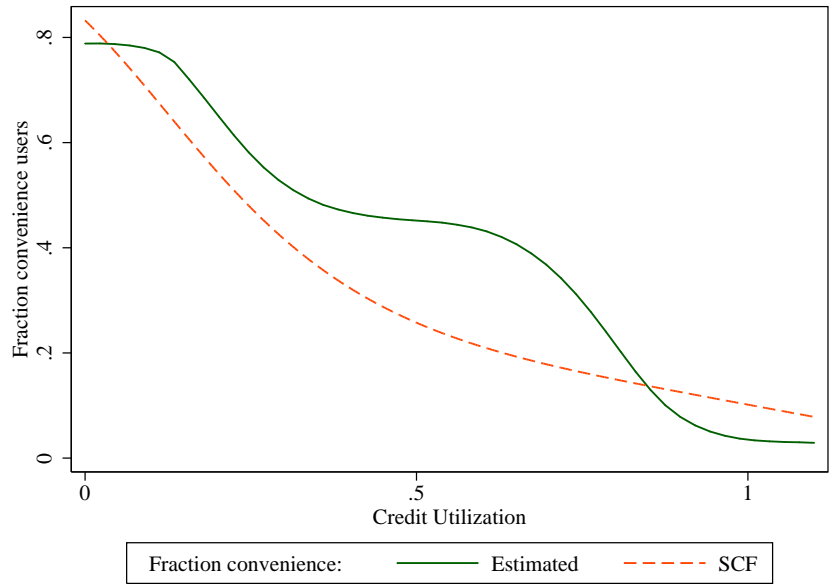


Notes: Each point in the top row shows the credit utilization in the future conditional on having a credit utilization on shown on the x-axis today. The points represent an even distribution of the sample (see figure 10). The bottom row shows the conditional relationship between deviations from the individual mean utilization over the entire sample, adjusting for age and year. Source: Author's calculations from Equifax/NY Fed CCP using the program binscatter (Stepner, 2013).

Figure 12: Fraction convenience from estimates and SCF  
(A) Fraction convenience over age

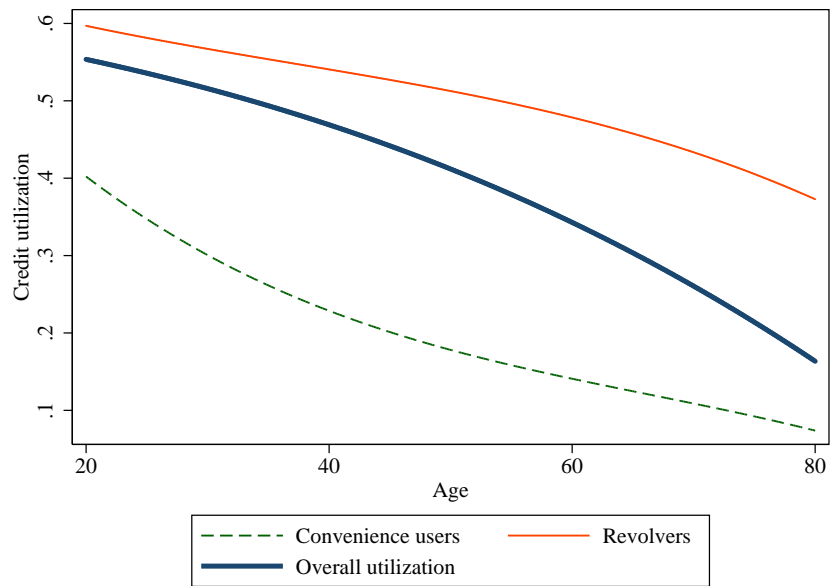


(B) Fraction convenience over utilization



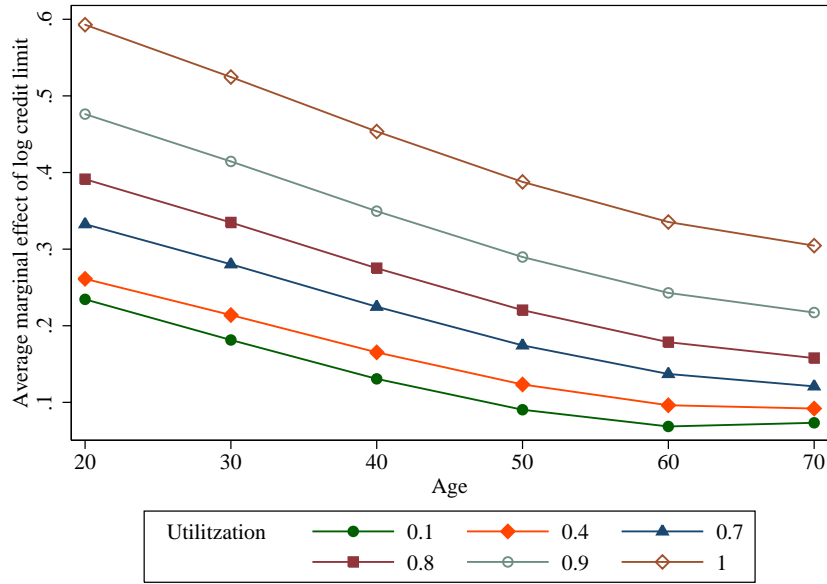
Notes: Source: Author's calculations from Equifax/NY Fed CCP and SCF. The SCF estimates are based on a cubic logistic regression for age or utilization.

Figure 13: Credit utilization of revolvers and convenience users over the life-cycle

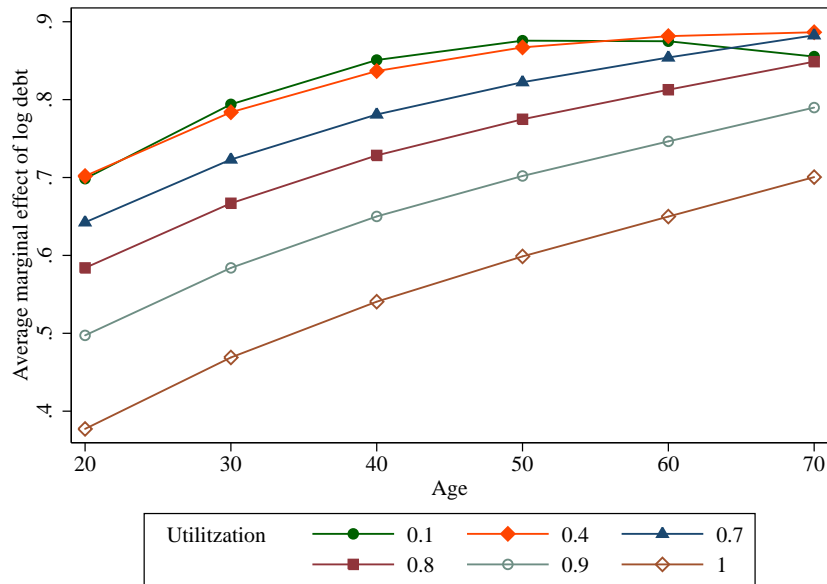


Notes: Authors' calculations from the Equifax/NY Fed CCP based on Finite Mixture Model.

Figure 14: 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



Notes: Source: Author's calculations from Equifax/NY Fed CCP based on a finite mixture model separating between convenience users and revolvers.

Table 1: Credit utilization

	Credit utilization <sub>t</sub>					
	All	All	All	All	All	Revolver
Credit utilization <sub>t-1</sub>	0.874*** (0.000876)	0.868*** (0.000892)	0.647*** (0.00131)	0.647*** (0.00139)	0.514*** (0.00441)	0.826*** (0.00134)
Credit utilization <sub>t-2</sub>				0.0156*** (0.000643)		
Credit util <sub>t-1</sub> × Age					0.00314*** (9.93e-05)	
Constant	0.0479*** (0.000461)					
Observations	347,642	347,642	347,642	332,696	347,642	238,111
R-squared	0.741	0.743	0.429	0.444	0.431	0.616
Fixed effects	No	No	Yes	Yes	Yes	Yes
Age and year effects	No	Yes	Yes	Yes	Yes	Yes
Number of accounts			10,451	10,103	10,451	
Frac. Variance from FE			0.477	0.467	0.498	

Notes: The sample always includes 0 credit utilization but excludes individual-quarters where the utilization is undefined since the limit is zero or utilizations greater than 5 (a very small fraction, see figure 10). All columns include age and year effects, with age effects normalized to have zero trend when fixed effects are included. Source: Author's calculations from Equifax/NY Fed CCP.

Table 2: Debt and credit changes

	Log Debt <sub>t</sub>				Debt <sub>t</sub>		Log Limit <sub>t</sub>	
	All [1]	All [2]	All [3]	Revolvers [4]	All [5]	All [6]	All [7]	All [8]
Log Debt <sub>t-1</sub>	0.505*** (0.00157)	0.758*** (0.00119)	0.604*** (0.00132)	0.774*** (0.000809)			0.00765*** (0.000598)	0.0421*** (0.00108)
Log Credit Limit <sub>t-1</sub>	0.414*** (0.00262)	0.134*** (0.00148)	0.313*** (0.00243)	0.225*** (0.00115)			0.848*** (0.00101)	0.802*** (0.00192)
Debt <sub>t-1</sub>					0.462*** (0.00122)	0.443*** (0.00132)		
Credit Limit <sub>t-1</sub>					0.268*** (0.000740)	0.293*** (0.000830)		
Observations	296,369	296,369	361,280	361,280	351,852	297,818	307,805	361,280
R-squared	0.432	0.667	0.610	0.610	0.576	0.583	0.778	0.412
Accounts	10,028		10,718	10,718	10,481	10,038	10,149	10,718
Fixed effects	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Zero included	No	No	Yes	No	Yes	No	No	Yes
Age effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Long term credit impact	0.862	0.875	0.879	0.999	0.631	0.627		
Credit salience $\sigma$	0.443	0.665	0.530	0.679	0.531	0.524		

Notes: The columns with the Zero included include zeros in the level regressions and give all individuals in all quarters \$10 in credit and debt before taking the log in the log regressions and so includes individuals with either zero in credit or debt instead of dropping them when zeros not included. Source: Author's calculations from Equifax/NY Fed CCP.