Sustained Credit Card Borrowing*

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Abstract

Using a large panel of credit card accounts, we examine the dynamics of credit card borrowing and repayment in the United States and what these imply for the expected costs of credit card debt to consumers. Our analysis reveals that: (1) credit cards are predominantly used to borrow, (2) card debt is sustained for long periods and balances frequently rise before being repaid, (3) this debt is potentially more costly than anticipated. Specifically, we document that 82% of outstanding balances are debt and that 70% of this debt accrues to those borrowing continuously for a year or more. The expected annualized cost of an episode of continuous borrowing is 28% of its initial balance, or 13 p.p. higher than the average APR. Moreover, credit scores decline during episodes, further raising the expected cost of borrowing on a card.

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1 Introduction

Financial institutions, and their respective regulators, dedicate substantial resources to tracking how much the American public spends on their credit card.[1] According to the 2016 Survey of Consumer Finances, eight in ten U.S. households have a card. Moreover, aggregate outstanding credit card balances exceed \$800 billion, or 30 percent of personal non-durable goods expenditures.[2] Given the wide-spread use of credit cards, these institutions rely on knowledge of how consumers use their card to assess the health of the consumer credit market, and the stability of the U.S. economy more generally.[3]

A credit card can be used to purchase goods and services. However, when users carry over, or revolve, any portion of their balance across the billing cycle, they begin to borrow on it. Since it is open ended, credit card debt can be revolved for short periods or for many months or years. Widely available aggregate trends do not clearly disentangle balances that are transacted, or which are paid-off at the end of each month, from those that are revolved, or carried over as debt. Moreover, they mask the underlying age profile of balances that are debt. An understanding of the age profile of credit card debt is important because persistent debt can be unexpectedly costly, eroding financial opportunities, distorting consumption choices, and amplifying the exposure to fluctuations in income and asset values (Dynan and Kohn, 2007).

In this article, we assess the extent to which credit cards are used to borrow and the age profile of credit card debt. For this purpose, we introduce the idea of a revolving episode, or a sequence of months with continuous borrowing on a card. We use this notion of an episode to document that a majority of outstanding credit card balances are debt, that this debt is long lived, and that most borrowers do not regularly pay down what they owe on their card. We then evaluate what these patterns imply for the costs associated with holding credit card debt.

First, we propose a new cost measure based on a revolving episode and which we call the Expected Episode Cost of Credit (EECC). The EECC captures the expected annualized cost of a revolving episode as a fraction of the initially borrowed amount. We argue that many revolvers likely underestimate their future borrowing needs. As a result, they may benefit from information about the expected cost of an entire episode of revolving, or cycle

[1]The Federal Reserve Board (FRB) has been tracking credit card spending since the 1960's using its G.19 series, which has been redistributed by the Federal Reserve Bank of St. Louis' *FRED* database. Further, the FRB publishes the triennial Survey of Consumer Finances, as well as the Flow of Funds (Z.1), in small part as additional benchmarks for credit card borrowing in the U.S. Prompted by the Great Recession, the Federal Reserve Bank of New York (FRBNY) began producing quarterly reports on credit card borrowing using its newly developed Consumer Credit Panel. In the wake of the Credit Card Accountability, Responsibility, and Disclosure (CARD) Act of 2009, the Consumer Financial Protection Bureau (CFPB) began publishing in 2013 a detailed and comprehensive biennial outlook of the U.S. credit card market. Lenders also compile, and often publish, data on credit card borrowing. One particular initiative by JP Morgan Chase & Co. started in 2014, the JP Morgan Institute, has begun producing extensive reports on credit card borrowing, as well as on household financial decision making more generally.

[2]For details on aggregate balances see (https://www.newyorkfed.org/microeconomics/hhdc). For details on non-durable goods consumption see https://fred.stlouisfed.org/series/PCEND

[3]For more information on the role of credit card debt, and household debt more generally, in assessing the stability of the U.S. economy see the Federal Reserve Board's Financial Stability Reports at https://www.federalreserve.gov/publications.htm.

of card debt. From a policy perspective, when compared to a per dollar cost of credit such as the Annual Percentage Rate (APR), the EECC gives a simple summary of the cost implications of the duration (age profile) and realized repayment of card debt. Second, we provide estimates on the magnitude of potential indirect costs that can stem from card debt via lower credit scores.

Our analysis leverages a large panel of credit card accounts from the Consumer Financial Protection Bureau's (CFPB) Credit Card Database (CCDB). The CCDB is uniquely suited for this study as it allows us to directly measure the extent of credit card borrowing, repayment, and related costs. Specifically, the CCDB contains monthly updates on each account's end of cycle balances, payments, finance charges, and fees in every billing period. From end of cycle balances and subsequent payments we identify instances when balances are carried over, or revolved, and instances in which they are paid off, or transacted. We construct a revolving episode by counting the sequence of months during which balances are continuously revolved, or borrowed, on an account. We then connect revolving episodes to the cost of borrowing by incorporating information on accrued fees and finance charges in the data. As the CCDB comprises a vast majority ($> 85\%$) of all credit card accounts in the U.S., our results can be interpreted as applying to the market as a whole.

Approximately 82 percent of outstanding credit card balances are debt, or are revolved for a month or more. In other words, we find that credit cards are predominantly used for borrowing, as opposed to solely a method of payment. Even among cardholders with credit scores greater than 660, or the prime segment of the market, about 78 percent of balances are debt. Of the balances that are debt, about 70 percent accrues to accounts revolving continuously for a year or more, and 55 percent to those revolving for 2 years or more. This suggests that credit card debt frequently endures for prolonged periods, and that, as a result, borrowing on a card is not best described as short-term for a large fraction of revolvers.

A complete revolving episode lasts for 10 months on average, whereby allowing for balance transfers across cards increases this expected duration by about one month. Further, the proportion of remaining revolvers fully repaying their balance declines sharply as the episode becomes more protracted. As compared to the average borrower, those who do not eliminate the debt on their account in the first six months of an episode are less than half as likely to repay it in any subsequent month.

Only a minority of revolving episodes are characterized by the regular pay down of an initially borrowed amount, as would be the case for a regularly amortizing installment loan. In most episodes, debt remains at its initial level or rises prior to repayment. Among these "surging episodes", the initial balance triggering revolving is markedly higher than subsequent monthly changes in debt, e.g. the amount of debt outstanding grows slowly, or creeps up, until repayment begins in the final months. This suggests that factors governing the decision to enter into card debt may be qualitatively different from those guiding subsequent borrowing and repayment.

These findings on repayment echo results in the literature indicating that many borrowers are not adept at forecasting their future revolving. Three main channels have been highlighted. First, card users can be dynamically inconsistent decision makers, whereby they do not internalize their future desire for consumption (Angeletos et al., 2001). Second, users are perhaps not skilled at assessing the relative costs and benefits of revolving, potentially leading to an overconfidence in the ability to repay (Lusardi, 2008). Third, many users can be inattentive to their debt (Keys and Wang, 2019). Unanticipated revolving is problematic because it can leave borrowers over indebted and financially vulnerable (White, 2007).

Using data from Strategic Business Insight's (SBI) Macro Monitor (MM), we provide new and direct evidence on these mechanisms and the claim that future revolving is not well anticipated. Moreover, we tie card borrowing to a sense of financial vulnerability. In particular, we show that individuals who typically revolve a balance are nearly twice as likely to report poor self control in their spending and 20 percent more likely to report a lack confidence in their financial decision-making. Moreover, we show that individuals who revolve, or borrow, on their card are over twice as likely to be very concerned about excessive borrowing overall, e.g. not just on their card.

As is shown previously, providing prospective borrowers with information about the entire cycle of debt can help them make better choices of when, if, and how to borrow on their card (Navarro-Martinez et al., 2011; Bertrand and Morse, 2011). Combined with our direct survey evidence, this helps motivate our EECC, which is a measure based on a revolving episode, or an entire cycle of debt. To construct the EECC, we combine patterns of revolving with information on finance charges and fees incurred during an episode. Specifically, we measure the expected annualized cost of a revolving episode per dollar of initial debt. First, we sum all charges incurred during each of the 5.5 million episodes in our sample. Then, we formulate an expected annualized cost using the empirical distribution of charges during episodes. Unlike the APR, which is the contractual price of a dollar of debt, the EECC incorporates information on the duration of indebtedness and the likelihood of rising debt from the population of borrowers.

We calculate that the expected annual cost of an episode is 28 percent of its initial balance. As a point of comparison, the average APR quoted to borrowers is 15 percent. Given that in a typical month aggregate initial balances from new episodes are $14.1 billion, the EECC suggests an expected annual cost of new episodes that is about $1.6 billion higher than that implied by applying the APR. This difference is driven primarily by the prevalence of rising balances during episodes, and by the fact that this rise is more severe for longer lived periods of indebtedness.

Lastly, we document a substantial and persistent decline in individuals' credit score during a revolving episode. This further indicates that sustained credit card borrowing is associated with a strain on cardholders' finances that goes beyond the direct repayment of this debt. Given that credit scores are ubiquitously used for pricing loans, this decline also introduces a potential for indirect costs of borrowing on a card via worse terms on other credit. Using data on mortgage and auto loan pricing, we calculate that lower scores imply an average increase of $20 in the annual cost of servicing a new auto loan, and $27 for a new mortgage. Though small in value relative to the cost of servicing a mortgage or an auto loan, note that this amount nevertheless constitutes $47/$247 = 19 percent of the dollar difference between the EECC and the APR.

The remainder of the article is organized as follows. In Section 2 we describe the data and in Section 3 we present our findings on the age profile of debt and the dynamics revolving. In section 4 we detail implications of revolving dynamics for cost, introduce and discuss the EECC, and assess the extent to which sustained revolving is associated worsening financial prospects. Section 5 concludes.

2 Data

2.1 Credit Card Data

The credit card data used in this analysis come from the CFPB's Credit Card Database. The CCDB is a de-identified panel of credit card accounts comprising the complete credit card portfolios of all large lenders and a sample of smaller lenders covering approximately 85% - 90% of credit card balances in the United States.[4] While the CCDB is not strictly representative, participating lenders' overwhelming share of industry balances makes it likely that our findings would not materially change if the entire universe of issuers were available.[5]

Information on each account in the panel is updated monthly, i.e. in each billing cycle, and includes the account's end of cycle balances, payments, finance charges, accrued fees, and the credit score of the associated cardholder. Given its size, it is not feasible to analyze the CCDB in its entirety. For this analysis, we use a one percent random sample of the database's general purpose card accounts, which comprise the bulk of issuers' credit card business. Our sample extends from 2008 to January 2016.

We focus on general purpose cards because other popular credit card types, such as small business, student, and private label cards, are markedly different products. Private label, most often store cards, are predominantly used in deferred interest promotions, while borrowing decisions by small businesses can differ from those of individuals. Student card portfolios are small. Moreover, purchase and, especially, repayment decisions on these accounts may not always be independently managed by the primary account holder, e.g. the students themselves. A limiting feature of the CCDB is that multiple accounts in the database belonging to a single consumer or household cannot be linked. As a result, the unit of analysis in the data is an account, rather than individual and/or household.

Table 1 shows summary statistics from the CCDB. The top panel of the table, labeled *Full Sample*, shows statistics for the complete account-month level data in our one percent sample. As shown in the panel, there are 7.8 million accounts in the sample, for a total of 328,448,682 account-month observations. About 76 percent are in the prime segment, with credit score > 660. On average, subprime revolving accounts have a lower cycle ending balance and pay less in finance charges as compared prime revolving accounts.[6] The average subprime revolving account pays \$10 in fees per month, while the average prime revolving account pays \$5.

[4]The CCDB includes data collected by the Office of the Comptroller of the Currency and shared with the CFPB pursuant to a Memorandum of Understanding and data collected by the CFPB. In 2016 these data collections ended. Since 2017 the Bureau has receives similar data from the Board of Governors of the Federal Reserve System. For details see CFPB, Sources and Uses of Data pp. 57-58 (2018).

[5]According to the CFPB's CARD Act report of 2013: "The Bureau recognizes that the issuers who supply data to the CCDB constitute a non-random sample in that they are the largest issuers. The practices and experiences of these issuers are not necessarily representative of the practices and experiences of many small credit card issuers. Thus, we do not attempt in this report to extrapolate from the CCDB data to make projections for the entire market. However, because the participating issuers represent 85%-90% of credit card industry balances, the Bureau is confident that the findings reported here would not materially change if data from the entire universe of card issuers were available". (pp. 14) (Consumer Financial Protection Bureau, 2013)

[6]Unconditionally, subprime accounts have a higher cycle ending balance. This is largely driven by the lower proportion of unused accounts in this cardholder segment. See Figure A.1 in Appendix A for details.

Table 1: CCDB Summary Statistics

	Mean (1)	5^{th} Pctl. (2)	25^{th} Pctl. (3)	75^{th} Pctl. (4)	95^{th} Pctl. (5)
			Full Sample		
Subprime Accounts (Credit Score$_m$ $\leq$ 660)					
Cycle Ending Balance ($)	1,778	0	0	1,950	8,326
Cycle Ending Balance for Revolvers	3,038	200	551	3,825	11,000
Monthly Finance Charge for Revolvers	37	0	5	44	146
Monthly Accrued Fees for Revolvers	10	0	0	18	49
Number of Observations	79,001,457				
Prime Accounts (Credit Score$_m$ > 660)					
Cycle Ending Balance ($)	1,577	0	0	1,392	8,387
Cycle Ending Balance for Revolvers	4,530	164	987	6,054	15,108
Monthly Finance Charge for Revolvers	47	0	6	62	174
Monthly Accrued Fees for Revolvers	5	0	0	0	36
Number of Observations	249,447,225				
Proportion Prime	76				
Number of Accounts	7,827,993				
			Episode Sample		
Subprime Episodes (Credit Score$_{m=0}$ $\leq$ 660)					
Original Balance ($)	1,399	47	228	1,213	6,002
Number of Episodes	956,467				
Prime Episodes (Credit Score$_{m=0}$ > 660)					
Original Balance ($)	2,322	59	332	2,647	9,248
Number of Episodes	4,498,429				
Proportion of Episodes that are Prime	82				

The bottom panel of Table 1 shows statistics for our constructed sample of revolving episodes, the *Episode Sample*. Using the panel dimension of the data, we define a revolving episode as a sequence of months during which a cardholder continuously revolves a balance, or borrows, on their account. The start of an episode is the month in which the cardholder begins revolving a balance on that account, transitioning from transacting or inactive into revolving. The end of an episode is the month (billing cycle) in which she repays the entire balance on that account. Cardholder accounts that do not revolve debt across the billing cycle, either because they transact or go unused, are assigned an episode length of zero.[7] We categorize episodes as prime and subprime using the associated cardholders' credit score in the first month of the episode ($m = 0$).

[7] For details on definitions of inactive, transacting, revolving, and transitioning see Appendix A.

Our primary objective using our episode sample is to analyze the duration of debt and the dynamics of repayment. As a result, for our episode level analysis we restrict our attention to episodes that resolve through repayment. In particular, we exclude episodes in which the cardholder is ever more than 90 days delinquent on payment. These are frequently resolved through charge-off. We further exclude those that extend beyond the close of our sample period, January 2016. These restrictions reduce the number of episodes we analyze from 7.8 million to 5.5 million. Finally, As compared to the total, episodes in our final sample have a lower original (starting) balance on average, $2,160 vs. $2,268 overall. Moreover, associated borrowers begin their episodes with a higher credit score. The average (starting) score in our final sample is 732; it is 710 among all episodes in the data. As shown in Table 1, the average original (starting) balance is $2,322 for prime episodes, as compared to $1,399 for subprime.[8] About 82 percent of episodes, or 4,498,429, are classified as prime.

2.2 Macro Monitor Survey

We also use data from Strategic Business Insights' (SBI) Macro Monitor (MM) to provide insight into how various aspects of households' financial attitudes and perspectives correspond to the decision to borrow on a credit card. The MM is a nationally representative biennial survey of approximately 4,300 U.S. households.[9] The survey collects respondent households' demographics, income, financial assets, investment activities, and debt information. In addition, it inquires as to respondents' perspectives on financial matters, such as their attitudes toward credit use and how they value various financial products.

The survey asks respondents about their credit card repayment decisions. In particular, it asks whether the household typically repays its credit cards in full at the end of the month, or whether it revolves debt. Separately, it asks these same respondents to provide details about their time preferences (discounting), their comfort or confidence with financial matters, their assessment of self-control when it comes to spending, and their level of anxiety or distress about their finances. These data serve two purposes. The first is to provide new and direct evidence on the relationship between credit card borrowing decisions, self control, financial ability/confidence, and distress. The second is to complement the lender reported data in the CCDB and give context to documented patterns of credit card borrowing and repayment.

3 The Age Profile of Credit Card Debt

3.1 The Prevalence of Borrowing and Long Lived Debt

We begin our study of sustained borrowing by documenting that (1) the majority of outstanding credit card balances are debt, or that credit cards are most often used for borrowing, and that (2) most credit card debt is long lived in borrowers' balance sheets. This is important because it establishes the prevalence of credit cards as a means of borrowing as opposed to a method of paying for goods and services. Further, it shows that starting to borrow

[8]See Appendix C for further details on the relationship between original balance and episode duration.

[9]Respectively, the 2012, 2014, and 2016 waves have 4,261, 4,405, and 4,320 respondents.

on a card can lead to a substantially long period of indebtedness. Aggregate debt statistics constructed using lender reported data, such as from consumer credit panels, do not disentangle transacted balances from those that are revolved. As a result, statistics compiled from these data sources do not provide an accurate picture of how often credit cards are used for borrowing. Nor do they provide information on the age profile of this debt.

Figure 1 illustrates this using the the Full Sample (Table 1) via decomposition of accounts (Left Panel) and aggregate balances (Right Panel) by duration of revolving. The the

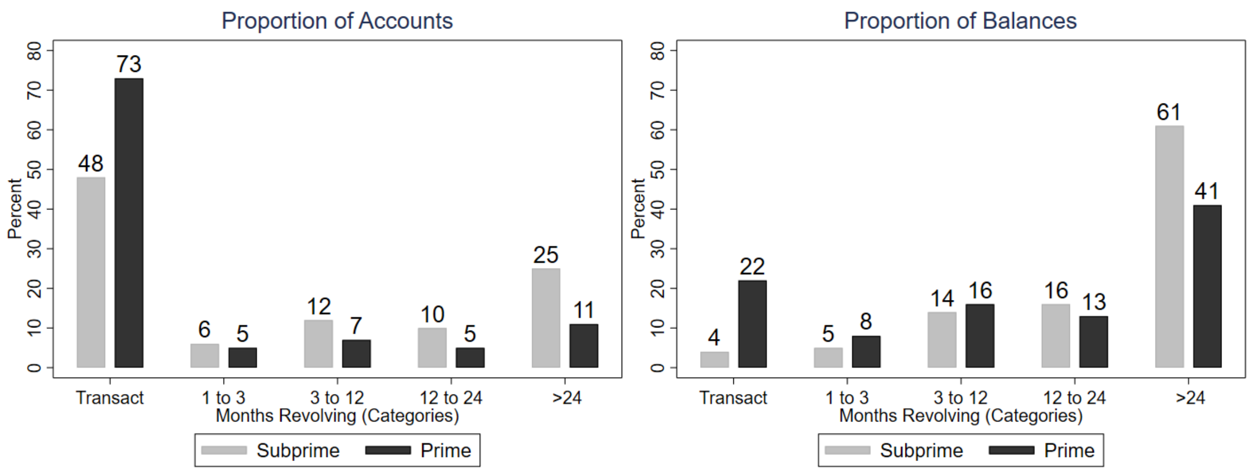

Figure 1: Age Profile of Credit Card Debt

proportion of accounts in an average month (m) that have been revolving for (1) < 1 month (transacting/inactive), (2) 1-3 months (3) 4-12 months, (4) 13-24 months (4) > 25 months. The right panel of Figure 1 shows the proportion of balances revolved by accounts in each of the aforementioned categories. As shown in the figure, about 82 percent of outstanding balances can be categorized as revolving. Among subprime cardholders ($Score_m \leq 660$), 96 percent of balances are revolved, whereas among prime cardholders ($Score_m > 660$) this is a smaller proportion (78 %), though still the vast majority.[10] While these proportions are for the most part stable over time, especially among prime accounts, they vary substantially by account characteristics, borrower type, and usage. In Table A.1 of Appendix A, we detail how the proportion of balances that are revolved vary by credit score, limit, and utilization, information commonly available in credit reporting data.

The figure further shows that a majority of credit card debt is long lived. Specifically, more than 70 percent of outstanding credit card debt accrues to accounts revolving continuously for a year or more, and 45 percent to those revolving for two years or more. As might be expected, subprime revolvers are more likely to be sustaining credit card debt for at least a year ($77/96 = 80\%$) relative to prime cardholders ($54/78 = 69\%$). Nevertheless, long lived debt dominates revolvers even in the prime market.

[10]Alternatively, this can be described as lender reported outstanding balances over stating true credit card revolving by a factor of $1/0.82 = 1.22$. Likewise, this over counting varies by borrower type. Among subprime revolvers, the ratio of reported balances to true debt it is 1.04, and among prime revolvers is ratio is closer to 1.28.

3.2 Revolving Episodes and the Exit Hazard

Having shown the prevalence of credit card debt and the fact that it is often long lived, we turn to our analysis of complete borrowing episodes, or continuous periods of indebtedness. An episode begins when an outstanding credit card balance becomes debt an ends when this debt is repaid. The analysis of episodes is long and therefore allows us to document how long cardholders who begin revolving on their account hold on to this debt prior to repayment.

The left panel of Figure 2 plots the distribution of episode lengths among these revolvers. Revolving episodes for prime and subprime accounts last for 9 and 13 months on average,

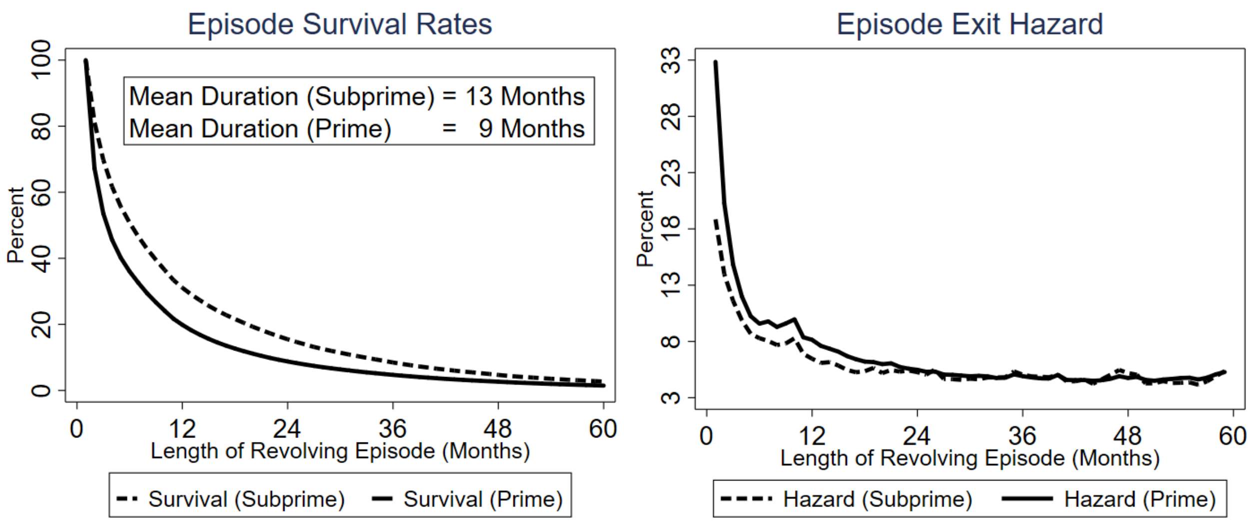

Figure 2: Sustained Debt Episodes

respectively. Moreover, about 12% of prime and 20% of subprime revolvers sustain balances continuously for 2 years or more. Interestingly, while substantial, the difference in revolving duration between prime and subprime cardholders is less stark than differences in the propensity to revolve between these groups (Figure 1 and Figure A.1 in Appendix A).

Recall that the CCDB does not link multiple accounts belonging to a single individual or household, either in the cross section or over time. As a result, given that borrowers often receive offers to transfer balances across cards, the above analysis may substantially underestimate the degree of sustained revolving. To better understand the contribution of balance transfers in sustaining debt, we utilize a feature of the CCDB which helps identify revolving episodes arising from new purchases as distinct from those which begin from a balance transfer. Using this, we provide a statistical assessment of balance transfers on duration, which we detail in Appendix A. Accounting for balance transfers raises the average, or *expected*, episode duration by about one month, or 10 percent.

The right panel of Figure 2 plots percent of surviving episodes that end at each month m, or the *exit hazard*.[11] As shown in the figure, the likelihood of exiting a state of indebtedness drop substantially in the first 6-8 months of revolving then levels out as borrowing becomes

[11] More precisely, the exit hazard $EH = Pr(exit|m)/Pr(duration \geq L)$ where L is the length of an episode in months and m refers to a month in the episode.

more protracted. In other words, the likelihood of a revolver repaying the debt drops by more than half after six months into an episode. After two years of continuous revolving, the hazard rate of repayment is constant: a longer duration of indebtedness ceases to be associated with lower payoff rates. Unsurprisingly, the decline in repayment rates during the early months of is more pronounced among those who began their episode as prime cardholders. However, conditional on revolving for 18 months or more, the exit hazard no longer varies by prime or subprime.

The shape of the exit hazard indicates that revolvers who do not eliminate the debt on their account in the first six months of an episode are much more likely to sustain that debt for long periods. This could be due to a selection of consumers into revolving ex-ante. However, it also raises the possibility that, upon borrowing on a card, individuals find it increasingly difficult to eliminate their credit card debt the longer they hold it. As the figure shows, conditioning on revolvers' creditworthiness at the outset does little to alter this seeming bifurcation: most revolving episodes end relatively quickly, but a substantial share become sustained, or long term, episodes.[12]

3.3 The Evolution of Balances and Repayment

Next, we turn to the evolution of balances within an episode. Unlike traditional installment loans, such as auto loans or mortgages, credit cards do not provide any preset repayment schedule. This means that, while installment loan balances as a rule only decline over time, this is not necessarily the case for credit card borrowing. Revolved balances can be paid down, maintained at the initial level, or even grow throughout the episode. We assess the relative importance of each in Figure 3.

The top panels of the figure illustrate how borrowed balances on a card evolve over the course of an episode. More specifically, the left and right panels plot the distribution of net pay-down in each month for moderate (1 year) and long (3 year) episodes, respectively.[13] As shown in the figure, the lowest quartile of revolving accounts show clear signs of cardholders regularly paying down their balances. At the median, net repayment is enough to sustain the initial balance throughout the length of an episode, with rapid payment in the final months. At the top quartile, revolving balances creep upward throughout an episode before pay down begins in the final months of the episode. [14]

Broadly, these patterns lend themselves to characterizing episodes according to three types: (1) *repaying episodes*, (2) *sustaining episodes*, and (3) *surging episodes*. Revolvers of

[12]This is consistent with the analysis in Stavins (2018), which uses matched survey and credit panel data to show that traditional socioeconomic variables. such as income or credit score, are often poor predictors of revolving behavior.

[13]For ease of exposition we show only 12 and 36 month episode, though we have completed this exercise for numerous other lengths as well. The patterns shown here are robust across episode lengths.

[14]Rapid pay-down could be indicative of a balance transfer. However, as shown in the Figure 3, this is the case for more than half of episodes. In contrast, about one in ten episodes begin via a balance transfer (Figure B.1). Consequently, it is unlikely that what we observe here is driven by direct card-to-card balance transfer. Still, there may also be some movement of debt out of cards without repayment, such as via debt consolidation using an unsecured personal loan or by extracting home equity. While we cannot directly assess the importance of these for the patterns that we observe, we note that the unsecured debt consolidation market is targeted towards subprime revolvers, and we document these patterns across all cardholders.

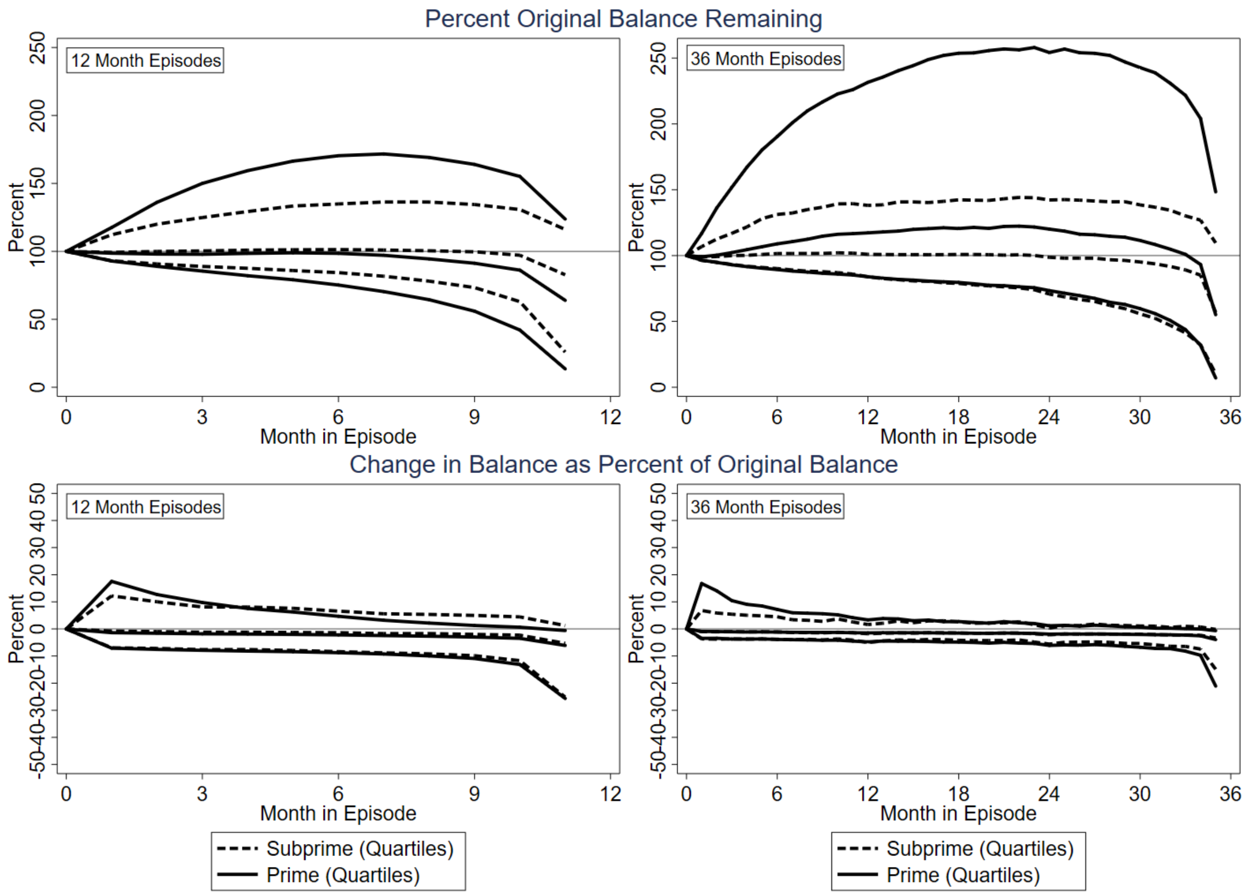

Figure 3: Episode Repayment

repaying episodes, make an initial purchase and then repay this loan gradually over time, as they would a regularly amortizing installment loan. In contrast, revolvers of sustaining and surging episodes maintain or grow an initial balance for a long period of time with zero or negative net pay-down prior to a repayment in the final months of the episode. Sustaining and surging episodes abound among both prime and subprime cardholders, as well as for varying duration of episode. Factors driving these borrowing and repayment patterns are not exclusive to any one group.

In the bottom panels of Figure 3, we plot changes in balances during an episode as a percent of the initial purchase amount. We do this to assess the relative contribution of subsequent months to the balance revolved. As shown in the figure, average monthly changes in balances are small relative to the original purchase. For year long episodes (left), following a small spike in the second month, the 75^{th} percentile change is roughly 10 percent of the original balance. For episodes lasting three years (right), we observe a similar spike in the second month for the 75^{th} percentile followed by an average increase of closer to 5 percent of the original balance. In other words, the initial expenditure triggering an episode is substantially larger than subsequent additions to balances, or that what we observe are "balance creeps".[15] This indicates that the rise in revolving balance subsequent to the initially revolved amount is spurred on a sequence of smaller purchases. Over time, these balance creeps can become substantial, at times larger than the initial purchase. This is especially the case for longer episodes, during which revolvers have more time to generate debt, and among prime revolvers, who have more slack in their available credit.

4 Cost

4.1 Expectations, Open Ended Credit, & Per Dollar Cost of Debt

Since enactment of the Truth in Lending Act (TILA) in 1968, the APR, a per dollar cost of credit, has been the most common method of reporting the price of borrowing. However, a perennial challenge in the design of effective cost measures for revolving, or open ended, credit products is the uncertainty about future borrowing at the point when such a cost needs to be disclosed.[16] This is especially important to consider when prospective borrowers form incorrect beliefs about their future revolving. In this case, individuals may not be able to apply a simple per dollar cost of debt like the APR to forecast the expected costs of becoming indebted. This can lead to over borrowing.

Existing work on credit card borrowing has highlighted three main reasons why prospective borrowers may have difficulty forecasting the extent of their revolving. First, credit card borrowers lack self control in their spending. In other words, they do not fully internalize their preference for future consumption when deciding how much to borrow, or repay, today (Meier and Sprenger, 2010; Angeletos et al., 2001). This triggers a conflict between an intention to pay down debt and actual repayment, a fact documented both among U.S. and U.K. borrowers (Kuchler and Pagel, 2018; Adams et al., 2018*b*).[17] Second, revolvers may possess a

[15] The median (75^{th} percentile) original balance is approximately $2,000 ($5,000) for prime and $500 ($1000) for subprime revolvers. It is very similar for episodes lasting one year as compared to those lasting 3 years. This means a 10 percent rise in balances constitutes about $200 ($500) among prime and $50 ($1000) among subprime episodes. For details see Figure C.1 in Appendix C.

[16] TILA was fundamental not only to the way cost of credit was disclosed, which is its stated objective, but to the way the cost of credit is conceived. Revolving credit, nascent at the time of TILA's passing, was a point of great debate about the efficacy of the APR in properly conveying the cost of borrowing to consumers. This is in no small part because of the flexibility in repayment, the "revolving" feature of the product. In a retrospective of the laws' passing, Fleming (2018) discusses that, though the initial purpose of TILA was to help consumer better understand the cost of borrowing, in its final version the bill moved away from this endeavor and instead emphasized the fostering of competition among lenders via a standard disclosure of cost. Fleming (2018) quotes one scholar in particular as arguing this was in contrast to existing state laws which were not meant to "provide buyers with a uniformly applied yardstick of credit costs." but rather "to limit and watch overcharges" (pp. 248). As discussed in Durkin (2008), dissatisfaction with how TILA treated credit card borrowing led to numerous revisions and updates in the subsequent decades following the bill's passing. More recently, studies of sustained use in other "short term" loan markets, such as payday or deposit advance, have shown that rolling over balances, or short loans, for extended periods can dramatically (and unexpectedly) increase the cost of borrowing what may initially be a modest amount (Burke et al., 2014). The argument is that the likelihood of rolling over loans constitutes an important element in determining the cost of these products to consumers.

[17] Interestingly, consumers' inability to stick to a repayment plan following a purchase prompting revolving has not been lost on the industry. Issuers have in fact developed commercial products specifically geared

low level of financial literacy. As a result, they are not well equipped to evaluate the relative costs and benefits of revolving on their card. These individuals can underestimate the costs of credit card debt, or alternatively be overconfident in their ability to repay it (Lusardi, 2008, 2015). Third, revolvers can be inattentive to their debt (Ausubel, 1991; Calem and Mester, 1995), forming rules of thumb or heuristics in their repayment of this debt (Keys and Wang, 2019; Gathergood et al., 2019). Mis-perceptions regarding the likelihood and/or persistence of future shocks to income or expenses, brought on by inattention, may force them to become more indebted than they initially intended to be.

Using survey data from SBI's MM, we provide new and direct evidence on these mechanisms and the view the revolvers are often biased when forecasting their future indebtedness. For this we use two modules in the survey. The first is a module on borrowing choices that features a question about whether a respondent pays their credit card balances in full "in a typical month". This helps us identify revolvers in the data. The second is a module on respondents' financial attitudes and perspectives. This part of the survey features questions designed to lend insight into what drives respondents' financial decisions.[18] It is important to note that the module on financial attitudes is framed generally and makes no reference to questions about card borrowing. Moreover, it precedes that on credit card use.[19]

We tie respondents' action of revolving to potential mechanisms underlying it by measuring the extent to which a respondent's agreement with a particular statement is indicative of whether she revolves.[20] Attitudes may be highly correlated with respondents' other financial characteristics, namely their income and the size of their household. To account for the role of these we use a regression analysis in which we control for these household variables. In the regression, we also control for secular changes in revolving over time via survey wave fixed effects. More formally, we estimate

$$\mathbb{1}[\text{Revolve}]_{i,t} = \alpha_t^k + \gamma^k X_{i,t} + \beta^k \cdot \mathbb{1}[\text{Agree}]_{i,t}^k + \epsilon_{i,t}^k \tag{1}$$

separately for each statement k. α_t is a survey wave (time) fixed effect, and $X_{i,t}$ is a vector of controls that includes household size and income. Table 2 displays estimates of the parameter β for each regression k. Among the respondents in our data, approximately 48 percent report revolving a balance.

As shown in the table, those who consider themselves as lacking in self control, who more generally think of themselves as "spenders", who or not careful with credit, are significantly

toward helping new revolvers make and follow through on plans to pay down debt. A famous example is that of *Chase Blue Print*, the story of which is detailed in Santucci (2015). While the Chase product was eventually pulled from market, others have taken its place, namely the new *Pay-It-Plan-It* by American Express. This effort of helping consumers better manage debt repayment is largely motivated by idea that these efforts raise user confidence and get them to more effectively engage with credit card products.

[18] Note that this the survey is at its core used for the purpose of marketing to consumers. The underlying questions are designed to get a sense of (1) what is consumers' financial situation, (2) what do they know about finances, and (3) how they would respond to certain products and services were they marketed to them.

[19] In the survey, questions on financial attitudes come first after household information, namely in module B. Questions on card use are in module K.

[20] Responses are measured on a four point *Likert* scale of whether respondents agree or disagree with the statement. Specifically, the choices are: (1) agree, (2) somewhat agree, (3) somewhat disagree, and (4) disagree. Unlike most uses of this scale, respondents are not given a "neutral" option.

Table 2: Consumer Financial Perspectives & Reported Repayment

Dep. Var. = $\mathbb{1}[Revolve]$	β (s.e.) (1)	% Agree (2)
Self Control/Discounting		
I'm a spender rather than a saver	31.03	30.45
	(0.990)	
In the past, I spent more than I wanted because credit cards made it so easy	38.98	54.69
	(0.820)	
Respondent is a heavy discounter (Dummy)	15.20	68.08
	(0.94)	
Financial Literacy/Inattention		
Often I'm not sure whether the financial decisions I've made are the right ones	11.57	42.85
	(0.910)	
My household needs help managing its financial affairs	8.720	33.25
	(0.940)	
I do a very good job of keeping my financial affairs in order	-30.45	84.90
	(1.340)	
I am very organized in my approach to financial matters	-19.91	83.35
	(1.250)	
Financial Distress		
I am concerned that we have more debt than we should	52.23	41.02
	(0.840)	
We struggle to make ends meet	45.30	
	(1.220)	
Percent of Respondents Who Report Revolving	47.71	
Number of Observations	12,986	

Notes: *Data are pooled cross sections from the Strategic Business Insight's (SBI) Macro Monitor for waves 2012, 2014, and 2016. All regressions include wave (year) fixed effects. They also control for household income and size, which are provided as categorical variables and thus treated non-parametrically in the regression. About 37% of respondents reported income below \$50,000, 34% reported income between \$50,000 and \$100,000, 16% reported income between \$100,000 and \$150,000, and 13% reported income over \$150,000. Also, 26% of households have one person, 37% have two, 15% have three, and 21% have four or more. Time discounting is inferred from a sequence of responses regarding money equivalents across one year of time. We detail this variable's construction in Appendix D. Standard errors are in parentheses.*

more likely in a typical month to carry over a balance on their card. The same holds for respondents who report a lower degree of financial sophistication, understanding, or inattention. Moreover, these differences are substantial in magnitude. Those who say they a "spender rather than a saver", or who claim to "spend more than [they] wanted because credit cards made it so easy", are twice as likely to typically rollover credit card debt. Similarly, respondents who claim they are "not sure of whether [their] financial decisions ... are the right ones" are 12 percentage points, $12/48 = 26$ percent, more likely to report carrying balances forward. Importantly, the associations hold even when conditioning on respondents' level of income.

Now, irrespective of the underlying reason, we might care about excessive debt spurred on by an inability to forecast future revolving because it can leave households financially vulnerable. This vulnerability erodes debtors' financial opportunities, distorts their consumption choices, and amplifies their exposure to fluctuations in income and asset values (Dynan and

Kohn, 2007). As a result, they may be less capable of insuring themselves against unforeseen and unfavorable changes in their economic environment, raising the prospect of their reliance on social insurance mechanisms via insolvency (White, 2007).

With the survey, we also provide direct evidence on the link between revolving and financial distress. Existing observational studies on the subject of over borrowing infer what is an excessive amount of debt by appealing to theoretical and/or empirical benchmarks (Angeletos et al., 2001; Dynan and Kohn, 2007). Moreover, they often focus on making the connection between bias and indebtedness. Adding to this, we show that revolving activity is intimately connected to individuals' sense of financial distress. In particular, those who "struggle to make ends meet" are more than twice as likely to regularly keep a balance. Similarly, an expressed concern with the amount of overall debt on one's balance sheet is associated with a 45 percentage point ($45/48 = 94$ percent) higher likelihood of being a revolver.

Though not causal, the findings from the survey strengthen, and are strengthened by, the revolving patterns documented in the CCDB. For example, recall that a typical episode is long and that balances slowly rise well (in some cases years) into it. Some of this rise may be due to household specific circumstances that were known prior to becoming indebted. However, evidence from the survey aides the view that unobserved differences in economic circumstance are likely not wholly responsible.

Further, note that while episode costs rise linearly with duration, the episode exit hazard declines exponentially. This is true for a broad set of revolvers, both prime and subprime. Were this generated solely by differences in information known to prospective borrowers prior to revolving, it would constitute an extreme form of selection based on circumstance. Moreover, this selection would not be well explained by individual's creditworthiness at the outset. Nevertheless, this pattern is consistent with the idea that regular revolvers borrow more than they anticipated, and thus take longer to repay their debt. Providing them with information about the entire cycle of debt may help them make better choices of when, if, and how to borrow on their card.

Finally, a number of studies have shown that disclosing information to cardholders about the future cost of their revolving, in addition to that included in their contract APR, can be effective in altering their borrowing and repayment choices. In a study on the efficacy of recent CARD Act disclosures on the costs of paying the minimum due, Navarro-Martinez et al. (2011) show that, when combined with an alternative plan of action, providing information about the overall costs associated with a minimum payment strategy can induce faster pay down of debt. An important insight of the study is that there may be conflicting effects of the disclosure. While cost information may induce greater paydown, time to repayment information and the anchoring value of the suggestion may counteract this effect, especially for those with poor understanding of interest compounding. A similar set of studies in the United Kingdom further verify this insight in the field (Adams et al., 2018*a*). In addition, other work has shown that providing information to prospective borrowers on the broader cost of debt has been shown to be effective for reducing sustained borrowing in the pay day loan context as well, another case in which short term loans are frequently rolled over for long periods (Bertrand and Morse, 2011).

4.2 The Episode Cost of Credit

With the above evidence in mind, we construct a cost measure based on an entire cycle of debt, or a revolving episode. We do this by combining patterns of revolving with information on finance charges and fees incurred during an episode. For this, we first examine the relationship between the expected sum of finance charges and fees and an episodes' duration, which we plot in the left panel of Figure 4. Note that the APR does not include fees. A

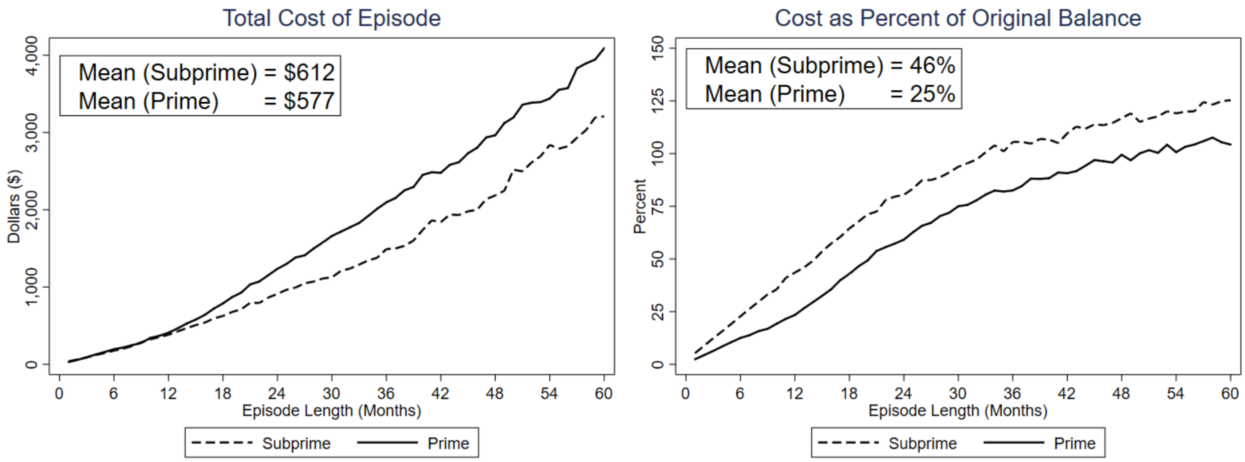

Figure 4: Realized Cost of Revolving Episodes

similar per dollar measure, called the Total Cost of Credit (TCC) is designed to capture the contribution of fees to the cost of borrowing (United States Government Accountability Office, 2006).[21] Our episode based analysis includes fees.

As shown in the panel, the expected dollar costs of an episode can be substantial. Prime borrowers, whose episodes last for 9-10 months on average, can expect to pay the lender $577 in fees and finances charges over the course of an episode. Subprime revolvers, whose episodes last about 13-14 months on average, can expect to pay $612. Naturally, the total dollar cost of revolving rises with duration of indebtedness. However, this increase is more pronounced among prime revolvers, and greater for longer episodes. As aforementioned, this is because prime revolvers are afforded more generous credit lines, whereby they begin episodes with higher balances and, on average, their level of debt rises more throughout. Among prime (subprime) revolvers whose episode lasts 24 months, the expected cost rises to $1,500 ($900) dollars over this time. Total payments within very long episodes can rise to nearly $4,000.

Next, in the right panel of Figure 4 we plot the average cost of an episode per dollar of initial debt, the triggering purchase, as a function of the episode length. A prime (subprime) revolver can expect to pay 25 (46) percent of their initial balance in finance charges and fees over the course of their revolving episode. For very long episodes, this proportion can be

[21] As discussed in Consumer Financial Protection Bureau (2013), pg. 19, this is a variation on an industry metric termed the "gross effective asset yield", which, as its name suggests, is designed to more accurately measure revenues accruing to lenders from their respective portfolios.

well above 100 percent, especially for episodes that last two years or more, about 15 percent of episodes.

Finally, we combine cost information in the right panel of Figure 4 with the distribution of episode duration in the left panel of Figure 2 to calculate an (annualized) expected cost of a new episode. Specifically, for each episode e of length ℓ we calculate the expected annualized sum of fees and finance charges per dollar of initial balance (debt). We then multiply this by the probability an episode lasts for ℓ months to calculated the expected cost of a new episode. We call this the *Expected Episode Cost of Credit* (EECC). More formally,

$$EECC = 100 \times \left(\sum_{\ell=1}^{L} \underbrace{\mathbb{E}_e \left[\left(1 + \frac{[Total\ Episode\ Cost]_e}{[Initial\ Balance]_e} \right)^{\frac{12}{\ell}} - 1 \,\middle|\, \ell \right]}_{\text{Average annualized cost for episode of length } \ell} \times \underbrace{\Big[\Pr(\ell) \Big]}_{\text{\% lasting } \ell \text{ months}} \right). \quad (2)$$

Unlike the APR (TCC), which provide a contractual (expected) annualized price of a dollar of debt, the EECC uses the empirical distributions of realized episodes to calculate the expected cost of a complete period of indebtedness.

For clarity of exposition, the EECC as defined in Equation 2 is unconditional, or for all episodes. However, a natural extension of the EECC formula is one in which we condition on the characteristics of an episode, such as the initial credit score, the initial balance, or the credit limit. This can be done by estimating Equation 2 for individual sub-groups of revolving episodes. In what follows, we compute the EECC separately for prime and subprime episodes.[22] In Section 4.3 we discuss further how to adapt this idea to other context by conditioning on various other episode characteristics.

The top panel of Table 3 shows our calculated EECC for all prime and subprime episodes in our episode sample, respectively. Column 1 of the table presents our baseline EECC

Table 3: Comparing Measures of the Cost of Credit

	EECC (1)	APR (2)	TCC (3)	New Debt in a Typical Month ($ Millions) (4)
All Episodes				
Subprime	41.74	17.49	32.67	1,715.52
Prime	23.91	14.66	18.00	12,419.28
Surging Episodes Excluded				
Subprime	26.37	17.14	28.45	
Prime	12.01	14.39	14.23	

Notes: *Data are from the CFPB's CCDB for the period April 2008 to January 2016. Statistics for Columns 1 - 3 are calculated using the Episode sample. Aggregate initial episode debt in a typical month, labeled New Debt in Column 4 of the top panel, is calculated using the Full sample. For details on these samples see Table 1.*

[22] An episode is considered prime (subprime) if the credit score of the associated holder is > (<) 660 as of the beginning of the episode.

measure from Equation 2. We calculate that the expected (annualized) cost of a prime episode is 23.9 percent of its original revolving balance. Among subprime episodes, the EECC is 41.7 percent.[23] As a point of comparison, in Columns 2 and 3 we calculate the average APR and TCC, respectively. Among prime episodes, average APR is 14.66 percent and TCC is 18.00 percent. For subprime episodes these are substantially higher: average APR is 17.49 percent and a TCC is 32.67 percent.[24]

The EECC is not by construction higher than the APR or TCC. If a majority of new episode balances are regularly paid down, such as if most were repaying episodes, the EECC can be lower than TCC. It can even be lower than APR if for example only finance charges are incurred. Further, when the (relative) contribution of fees to cost is more empirically important than the rise in balances, such as if there were many sustaining episodes with occasional fees, then the EECC may fall between APR and TCC.[25] To better understand the contribution of rising balances to the EECC, we repeat our calculations restricting only to episodes whose outstanding balances never exceed 110 percent of the initial balance. This version of the EECC that excludes surging episodes is shown in Column 1 of the bottom panel of Table 3.

Without surging episodes, the calculated EECC drops by about half for both prime and subprime episodes. Among prime episodes in this sample, who are much less likely to incur fees, calculated EECC is lower than both the APR and TCC. In contrast, for subprime episodes, the EECC is higher than the APR but lower than the TCC. This reflects the fact that fees play (relatively) a larger role in determining cost for this group, despite balances remaining stable or falling throughout an episode. The average contract APR is little changed when excluding surging episodes. This suggests that we are not selecting on borrowers' initial credit risk. The TCC falls, likely reflecting a compositional change in revolvers, but by much less than EECC, which is directly altered by this pruning.

To translate the EECC into dollar terms, we multiply by the sum of initial balances, in an average, or typical, month in our sample. This amount is shown in Column 4 of the top panel of Table 3 labeled "New Debt". From the table, the total expected annual cost of new episodes is $(\$1,715.42)(41.74\%) + (\$12,419.2)(23.91\%) = \$3.69$ billion. Of this amount, \$2.97 billion come from prime episodes. As a point of comparison, this is about \$1.56 billion higher than implied by the average APR, and \$890 million more than that implied by the TCC. This underscores the argument that the expected financial burden of debt triggering a new revolving episode can be nearly twice as high as that implied by the APR alone, e.g. holding fixed the amount of initial debt.

[23]As a robustness check, we also calculate a version of the EECC in which we normalize by the episode's third month balance to allow for an initial ramp up in debt, of which there is some evidence (Figure 3). The underlying result does not meaningfully change. Using this normalization we calculate an EECC of 22.28 percent and 40.87 percent for prime and subprime revolvers, respectively.

[24]Higher normalized costs for subprime revolving accounts is driven by two main factors. First, these accounts incur substantially more fees, which drive up cost. Second, they revolve smaller amounts on average. See Figure C.1 for details on initial balances.

[25]See Table E.1 in Appendix E for detailed worked out examples.

4.3 Implications for Policy

Under the view that revolving is not well anticipated at the outset by many, the EECC provides a framework by which to help borrowers better predict the potential cost of indebtedness. In contrast to disclosures used in the above mentioned studies, the information contained in the EECC is not hypothetical, rather it incorporates the experiences of the population of borrowers to ascertain expected costs. As such, it succinctly summarizes both cost and duration in a way that can be easily understood by a consumer, incorporating information on the broader set of repayment choices, not just the minimum payment strategy. Further, as it is annualized, it can be a point of comparison for the contractual price such as the APR, the mechanics of which may not be well understood by consumers. Alternative repayment scenarios that incorporate this comparison might then further help a consumer internalize the impact of their action on overall cost.

The version of the EECC presented here is the most simple. For example, in calculating the expected episode cost we do not condition on any account or episode observable characteristics other than coarse risk categories. Further conditioning can help better define the notion of "consumers like you". Moreover, we also do not balance weight episodes in calculating the EECC, nor do we incorporate discounting other than via the annualization formula. In all, it is not difficult to envision numerous variants on the EECC idea, whereby such modifications can give a more nuanced interpretation of episode costs and provie a firmer basis for applying this idea in a policy context.[26]

A full characterization of how to apply the EECC is beyond the scope of this paper. This is large part because the introduction of disclosures is an exceedingly difficult task with numerous issues to consider.[27] Nevertheless, any variant would still be based on the empirical relationship between duration and the evolution of balances throughout an episode, which is robust across borrower types. Our exposition here has summarized in the simplest way the cost implication of two empirical facts of revolving in America: (1) episodes are often protracted, and (2) balances throughout tend to rise before pay-down begins.

4.4 Potential Indirect Costs of Credit Card Debt

As evidenced in the survey, revolving is strongly associated with financial distress. From Table 2, those who typically leave a balance on their credit card are more likely to "struggle to make ends meet" or to be "concerned about having too much debt". Importantly, the question of distress is not just about credit card debt, but rather the overall leverage of the household. This suggests that, in addition to the direct cost of credit, substantial indirect costs may arise during the course of an episode. The CCDB contains revolvers credit scores in each month, or summaries of their prospective risk of non-repayment. We use this to assess the extent to which credit card debt is associated with worsening financial options.

[26] For example, if the EECC were to be used as a way to disclose cost to borrowers, it may even operate on a rolling basis, conditioning not only on initial episode conditions but rather at each point within it.

[27] A detailed discussion of these issues was provided by Randall Kroszner, then a governor of the Federal Reserve Board, on May 2, 2008 (https://www.federalreserve.gov/newsevents/press/bcreg/kroszner credit20080502.htm).

First, we trace the evolution of revolvers' credit scores during the course of an episode, frequently termed score migration. More precisely, for each episode e of length $\ell = \{1, ..., L\}$ and month in the episode $m = \{1, ..., \ell\}$, we estimate

$$\Delta Score_{e,m} = \sum_{i=1}^{L} \sum_{j=1}^{i} \gamma_{i,j} \mathbb{1}(\ell = i, m = j) + \beta Z_e + \eta_{state,month,year} + \alpha_{Bank} + \epsilon_{e,m}. \quad (3)$$

The dependent variable of Equation 3 ($\Delta Score_{e,m}$) is the change in the associated revolver's score from the start of the episode to month m. The change in score is tracked non-parametrically via a full set of indicators $\gamma_{i,j}$ for each month m in the episode of length ℓ. We further control for fixed characteristics the episode Z_e. These are the initial outstanding balance, credit limit, and the initial utilization rate. In addition, we include bank fixed effects (α_{Bank}) and state by month-year fixed effects as of the start of the episode ($\eta_{state,month,year}$). To allow for auto-correlation in the unobserved determinants of score over the episode, we cluster standard errors at the episode level. We combine all episodes lasting more than two years ($L > 24$ months) into a single category of length $L = 25$.

The top panel of Figure 5 plots the estimated score path for revolvers whose episodes last for 6, 12, 18, and >24 months (labeled $L = 25$ in the figure), respectively.[28] As shown in the panel, for any length of revolving spell, credit scores drop in the early months of the episode, only to rebound just before the debt is eliminated. The decline in score becomes more pronounced and sustained for longer duration spells. For those whose episode lasts 12 months the score drops by as much as 4 points, whereas this drop is twice as large, or 8 points on average, for those revolving two years or more. Further, credit scores remain below their initial level following repayment for more sustained revolvers. In other words, scores of those who hold on to debt for long periods never completely recover.

In the bottom panels of Figure 5, we translate score declines into changes in borrowers' financial prospects by examining the extent to which lower scores imply increases in interest rates on other available loan products. For this purpose, we use aggregated rate sheets on commonly held auto loans (5 year) and mortgages (30 year fixed rate) from the Fair Isaac Corporation's *MyFico* tool. Auto loan and mortgage pricing is tiered by credit score, whereby an individual applying for a loan is matched to an interest rate tier based on their credit score. The *MyFico* tool provides national averages for these tiers.[29]

More specifically, we tie movements in cardholders' credit score to available rates by assigning each revolver a rate at the beginning of her episode and comparing it to the "would be" available rate at each subsequent month of her episode (m_R). Using these imputed "would be" rates, we look at how available interest rates change as revolving becomes more

[28]Though paths for all episode lengths ($1 - 24^{+}$) are estimated in the regression, we exclude them from this panel for visual clarity. Patterns exhibited by episode lengths not shown are strikingly similar to those plotted.

[29]The *MyFico* loan tool shows averages of offer rates from approximately 40-50 large lenders compiled by Informa Research Services Inc. We use interest rates as of 12/25/2018. Whereas the absolute levels of mortgage rates fluctuate daily, differences in rates across FICO categories remain stable. These differences represent a risk premium charged for a less than "perfect" credit score and are rarely revised by lenders. Because our results are based on these differences, rather than absolute levels of interest rates, the use of this one day's worth of data is sufficient for our purposes.

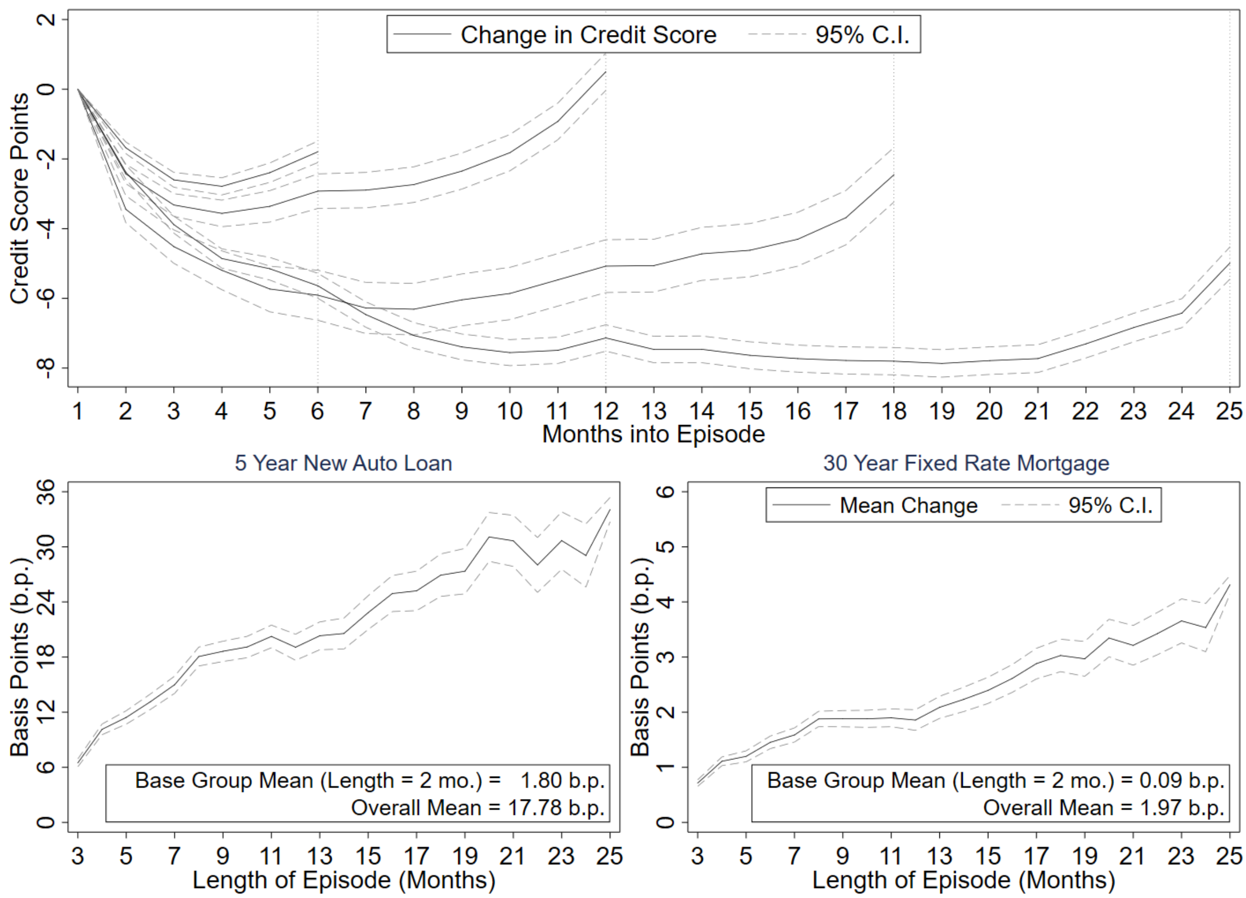

Figure 5: Indirect Costs of Sustained Borrowing

protracted. For revolver in episode (e) of length (ℓ), we estimate

$$\Delta \hat{Rate}_e^k = \sum_{i=3}^{L} \delta_i \mathbb{1}(\ell = i) + \beta Z_e + \eta_{state,month,year} + \alpha_{Bank} + \epsilon_e, \tag{4}$$

for each loan product ($k = \{\text{Auto, Mortgage}\}$). The dependent variable of Equation 4 ($\Delta \hat{Rate}_e^k$) is the difference between the available (imputed) rate between just prior to during an average month in the episode. Controls Z_e, $\eta_{state,month,year}$, and α_{Bank} are as in Equation 3. Also like in Equation 3, standard errors are clustered at the episode level.

As shown in the figure, sustained revolving is associated with higher available rates for standard mortgages and auto loans. As their episode becomes more protracted, revolvers looking for a new auto loan or mortgage may find themselves facing higher rates. Unconditionally, new revolvers can expect rates quoted to them for a new auto loan to rise by 18 basis points (b.p.), or 2 b.p. for a new mortgage. However, among those revolving for two years or more, available auto loan rates are 35.9 b.p. higher during the episode than prior to revolving; mortgage rates are 4.4 b.p. higher.

To put this change into perspective, for a $20,000 loan on a new car, and given a 5 percent base rate, the annual cost of servicing a loan is $20 upon revolving, and $40 higher for those whose episodes last two years or more. For a $200k mortgage, given an underlying rate of 4 percent, expected annual payments on an available loan are $27 higher, unconditionally, and $61 higher among those revolving for two years or more.[30] Admittedly, these amounts are small relative to the annual cost of financing a house or a car. However, the combined indirect cost of $47 constitutes about $47 / $592 = 8 percent of the mean EECC, or $47 / $452 = 10 percent of the mean TCC.[31] In other words, they can add substantially to the cost of borrowing on a card.

Recall that our sample excludes episodes with serious (90+) repayment delinquency. This means that observed credit score declines and implied available rate increases associated with sustained balances are not primarily due to actual non-repayment. Rather, they reflect the *potential* for serious default brought on by this debt.[32] By eliminating the effects of actual non-repayment on scores, our analysis highlights how the debt itself indicates economic distress for revolvers, and what this can imply for the price of borrowing on a card.

Finally, the association between protracted revolving and the erosion of cardholders' creditworthiness, as summarized by their credit score, provides a basis for partially quantifying the potential for indirect costs from revolving, which we find can be substantial. This helps us to tie together how those compelled to borrow on their card, for one reason or another, fare more broadly while indebted. We acknowledge that this analysis is at best suggestive, in part because consumers might adjust on a number of margins when faced with circumstances leading them to revolve. Nevertheless, it uncovers a quantifiable, if narrow, relationship between the notion of financial distress more generally and credit card indebtedness.

5 Conclusion

In this brief article, we establish new facts related to the dynamics of credit card borrowing behavior in the United States. In particular, we highlight the long duration of credit card indebtedness and the fact that balances prompting borrowing rise before being paid down. Combining these elements, we calculate an episode expected cost of credit, or EECC. The idea of the EECC is to consider the cost of revolving in the context of a complete period of indebtedness, incorporating empirically both duration and repayment dynamics. The measure provides a prospective view of the annual cost of a complete episode per initial dollar borrowed. We then look at the association between protracted revolving and the erosion of cardholders' creditworthiness, uncovering the potential for substantial indirect costs of revolving.

To put our results in perspective, it is important to reiterate that the CCDB is a database of accounts. As a result, we are unable to connect various accounts in the data to a single

[30] The loan size and base rate, for auto loans and mortgages, are based on approximate averages during our sample period.

[31] Note that the EECC in levels is calculating as $592 = ($1,399)(42%)(24%) + ($2,322)(24%)(76%). The TCC in levels is calculated as $452 = ($1,399)(33%)(24%) + ($2,322)(18%)(476%). See Tables 1 and 3 for details.

[32] This is precisely the objective of the credit score, which is designed to predict the likely serious derogatory action on any credit line on a prospective two year window.

individual, either in the cross section or over time. This limitation severely hinders any analysis of borrowing (Ponce, Seira and Zamarripa, 2017) or repayment choices (Gathergood et al., 2019) of individuals across cards. The distinction is less relevant when classifying dollar balances in the age profile of credit card debt, though it becomes important when classifying types of borrowers. Still, more than half of cardholders in the U.S. hold over 90 percent of their balances on a single card, despite having over two cards in their wallet on average (Consumer Financial Protection Bureau, 2015). As such, our analysis provides an accurate picture indebtedness for the majority of Americans. Among those for whom it does not, we believe it serves as a conservative estimate on the duration and magnitude of indebtedness. Better accounting for individuals who borrow significantly on more than one credit card may in fact strengthen our message that card debt is most often not short term, that revolving balances frequently rise before being repaid, and that this sustained revolving is very costly.

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Appendix (For Online Publication)

A Trends in Age Profiles and Revolving Propensities

A.1 Revolving Propensities

Figure A.1 shows trends in accounts' revolving propensities over time (top panel) and across credit scores (bottom panel). Using definitions of revolving in Consumer Financial Protection

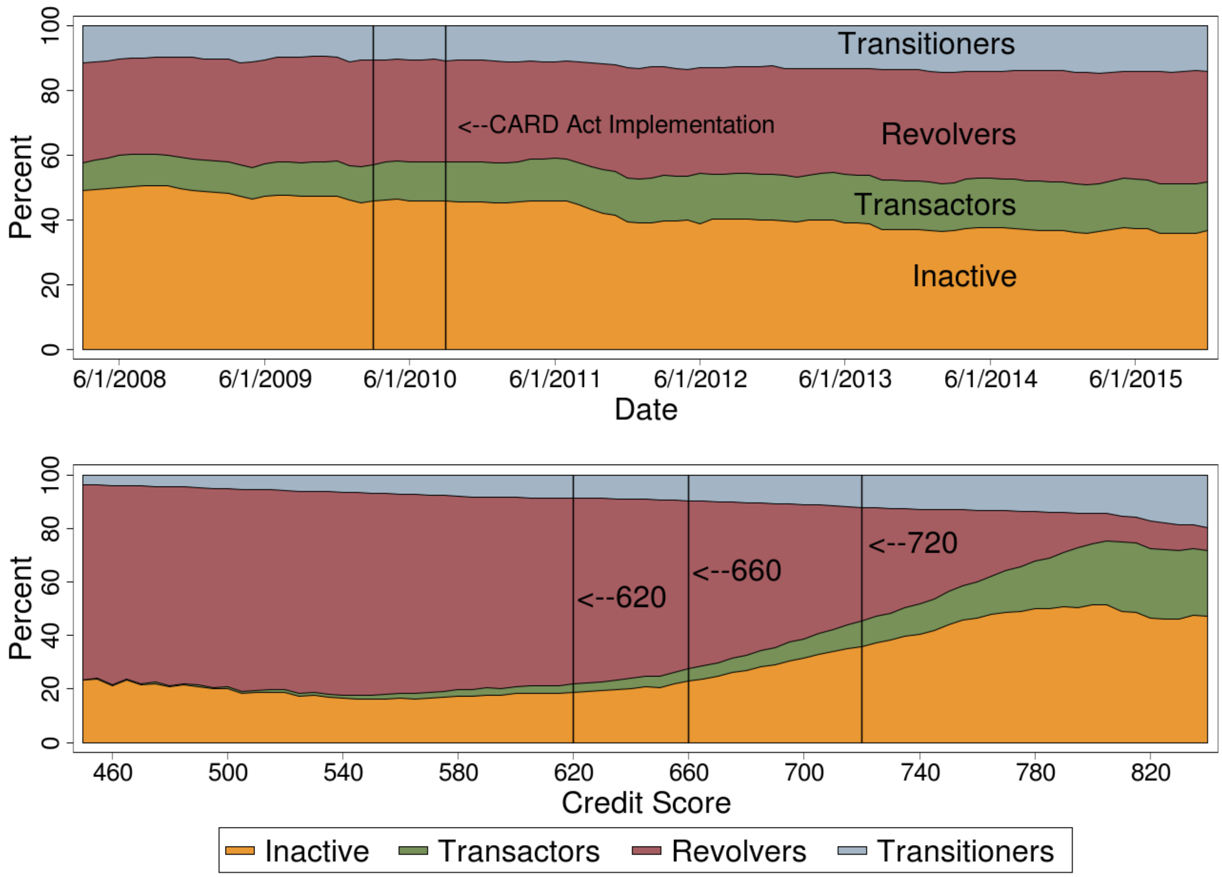

Figure A.1: Revolving Propensities and Transition Dynamics

Bureau (2015), accounts are sorted into four groups. As shown in the figure, these are: (1) Inactive (2) Transactors (3) Revolvers (4) Transitioners. An account is categorized as inactive if there are no purchases, balances, or payments made on it in two consecutive billing cycles. Similarly an account is categorized as transacting if any balance on it is paid in full for two or more consecutive cycles. Revolvers are those who revolve a balance on their card in two or more consecutive cycles. All remaining accounts are categorized as transitioning.[33]

As is shown in the figure, about 40 percent of credit card accounts are inactive. Among active accounts, two of every three carry a revolving balance. Unconditionally, about 36

[33]To be as inclusive as possible, the graph uses total cycle ending balance. Some of these balances may be in promotion. Promotional balances likely are interest free, and thus present no cost to consumers. Although a broader study of promotional rates is outside the scope of this study, the underlying results are largely unchanged if promotional balances are excluded.

percent of accounts carry a revolving balance in a typical month. These findings are somewhat comparable to the proportion of households carrying credit card debt. According to the 2016 Survey of Consumer Finances, just over 40 percent of households report owing on their credit card. The figure further suggests that transitions in an out of credit card debt are somewhat rare, occurring among only 1 in 10 accounts each month. Overall, revolvers are likely to continue borrowing on their card, transactors are unlikely to start revolving, and inactive accounts mostly remain unused.

The years covered by the period of analysis were marked by the Great Recession, the subsequent recovery, and the passing of the Credit Card Accountability Responsibility and Disclosure (CARD) Act, the most comprehensive regulatory effort of this market in decades. Nevertheless, as the top panel of Figure A.1 illustrates, revolving patterns have remained fairly stable. One notable change is a reduction in the proportion of inactive accounts in the middle of 2011, which is likely driven by lenders increased closures of unused lines more stringent underwriting standards during the recession. As evidence of this assertion, note that the decrease in inactive accounts is absorbed proportionally by the three remaining categories. Netting out inactivity, consumers' revolving patterns remain largely unchanged over this tumultuous period.

In contrast to the stability of revolving over time, the bottom panel of Figure A.1 shows substantial variation in revolving patterns across the credit score spectrum. Following definitions in Consumer Financial Protection Bureau (2015), the vertical lines in the panel separate accounts into four default risk categories: (1) Deep Subprime, with credit scores below 620 (2) Core subprime, with credit scores between 620 and 660 (3) Core Prime, with credit scores between 660 and 720 (4) Superprime, with credit scores greater than 720. Credit scores are calculated as of the current month. Among accounts held by Deep Subprime borrowers, the riskiest segment, the vast majority (85 percent) revolve. Nearly no accounts are classified as transactors, and only 1 in 10 are unused. There is also great persistence among these, whereby only 1 in 20 accounts transition in any given month.

The propensity to revolve uniformly decreases for accounts associated with lower risk borrowers. Among the lowest risk accounts, the super-prime segment, the propensity to revolve is substantially less. For example, cardholders with credit scores greater than 800 who are using their cards are 2.7 times less likely to be revolving in any given month relative to the average revolving rate. Accounts belonging to consumers with very high credit scores are also substantially more likely to be unused and to exhibit less persistence. Still, the majority of actively used prime accounts carry a revolving balance and transitions are rare.

A.2 Age Profile of Credit Card Debt

Figure A.2 shows trends in the age profile of credit card balances for subprime (top panel) and prime (bottom panel) accounts. In line with trends of revolving rates (Figure A.1), the age profile of debt was largely stable during our sample period (April 2010 - January 2016).[34] Among subprime cardholders, the proportion of balances that are revolving is quite stable. However, there is some evidence that aggregate debt is "younger" in the latter part of our

[34] Note that we plot the age profile of debt starting in April 2010, whereas trends in revolving start in June 2008. This is because to the age profile includes balances accruing to episodes that are more than two years long, which necessitates a later start.

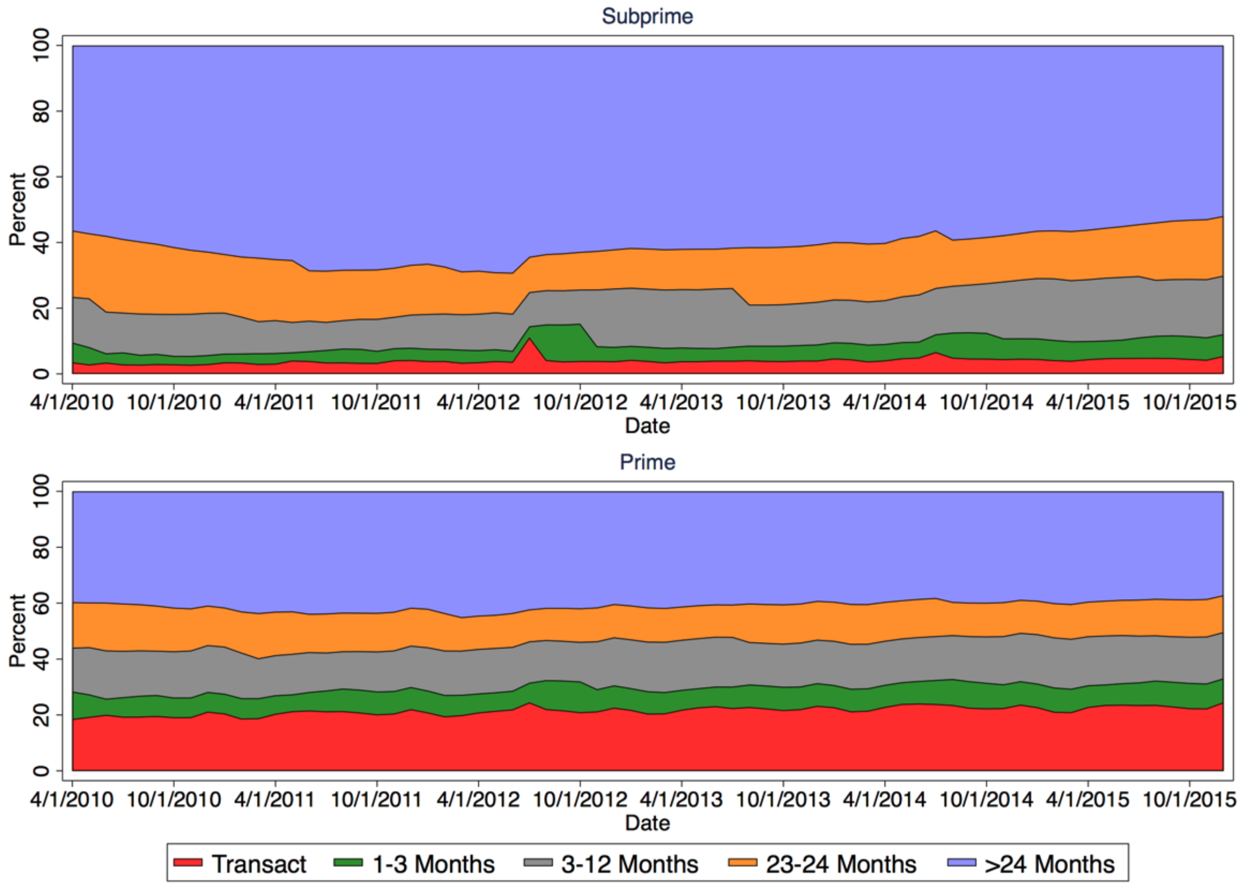

Figure A.2: Trends in Age Profiles of Debt

sample period. This is not surprising given this is a period of economic recovery. For prime cardholders, the entire age distribution varies relatively little over this time.

Table A.1 shows how the proportion of balances forming part of a revolving episode vary across credit limit, utilization rate, and the credit score of the associated borrower. Echoing the results in Figures 1 and A.1, the table shows that the proportion of outstanding balances that are revolved is decreasing in the borrower's credit score. The table also shows that among cards accounts with higher credit limits the proportion of revolving balances is higher, or that these are used more often for borrowing. Unsurprisingly, balances on accounts that are more highly utilized, having a higher ratio of cycle ending balance to the credit limit, are also more likely to form part of a revolving episode, regardless of credit score.

Table A.1: Revolving Balances by Usage, Contract, and Risk Type

Credit Limit ($)	Utilization (%)	Credit Score Band					
		450 - 619	620 - 659	660 - 679	680 - 699	700 - 719	720 - 850
<1,000	0 - 10	3.25	1.63	1.80	1.27	1.38	0.73
<1,000	10 - 20	54.07	43.68	42.44	38.49	33.08	17.06
<1,000	20 - 30	68.03	56.73	62.38	49.50	42.32	20.42
<1,000	30 - 40	75.09	70.53	69.27	61.05	49.38	28.72
<1,000	40 - 50	80.16	78.69	72.95	70.37	63.23	33.49
<1,000	50 - 60	84.92	80.38	77.59	74.00	68.30	40.87
<1,000	60 - 70	88.41	81.99	83.21	80.06	72.10	50.48
<1,000	70 - 80	91.50	86.43	84.89	86.10	80.31	61.92
<1,000	80 - 90	94.42	90.11	88.09	89.06	86.59	73.17
<1,000	90 - 100	95.38	91.21	88.52	88.60	85.20	77.82
1,000 - 4,999	0 - 10	12.96	10.00	8.07	6.43	5.86	3.35
1,000 - 4,999	10 - 20	86.22	73.12	68.72	63.75	55.23	28.90
1,000 - 4,999	20 - 30	90.51	80.40	77.77	72.96	69.20	38.13
1,000 - 4,999	30 - 40	94.37	87.93	85.26	81.74	78.52	47.34
1,000 - 4,999	40 - 50	95.13	91.76	89.02	87.07	84.03	57.92
1,000 - 4,999	50 - 60	97.47	93.50	92.91	89.87	89.55	67.19
1,000 - 4,999	60 - 70	98.42	96.16	94.62	93.18	92.01	75.73
1,000 - 4,999	70 - 80	98.39	96.79	95.13	94.93	93.89	84.13
1,000 - 4,999	80 - 90	98.87	97.36	96.49	96.79	95.73	89.35
1,000 - 4,999	90 - 100	99.25	98.29	97.85	97.21	96.71	92.75
5,000 - 9,999	0 - 10	19.09	15.68	13.68	11.88	11.31	6.57
5,000 - 9,999	10 - 20	91.00	79.67	74.50	71.74	68.75	39.79
5,000 - 9,999	20 - 30	95.82	88.70	84.89	81.63	78.99	51.10
5,000 - 9,999	30 - 40	97.58	92.36	90.52	89.30	86.73	64.11
5,000 - 9,999	40 - 50	98.67	95.81	93.37	93.43	91.92	75.50
5,000 - 9,999	50 - 60	99.02	97.50	96.50	95.56	94.84	83.85
5,000 - 9,999	60 - 70	99.31	97.79	97.52	96.46	95.97	89.18
5,000 - 9,999	70 - 80	99.58	98.47	97.96	97.67	97.24	92.33
5,000 - 9,999	80 - 90	99.54	99.02	98.37	98.41	97.85	95.08
5,000 - 9,999	90 - 100	99.64	99.22	99.02	98.70	98.49	96.42
≥10,000	0 - 10	25.28	21.15	18.95	17.43	15.88	10.90
≥10,000	10 - 20	90.20	82.13	78.76	74.35	73.97	51.53
≥10,000	20 - 30	94.93	89.78	88.16	86.15	85.61	67.16
≥10,000	30 - 40	97.07	95.45	92.82	92.17	91.62	79.38
≥10,000	40 - 50	98.39	97.00	96.01	94.75	95.27	87.30
≥10,000	50 - 60	98.97	97.33	97.74	97.00	97.06	91.77
≥10,000	60 - 70	98.65	98.18	98.16	97.70	97.45	93.76
≥10,000	70 - 80	99.82	98.51	98.60	98.27	98.03	95.86
≥10,000	80 - 90	99.39	99.09	98.80	98.58	98.27	96.87
≥10,000	90 - 100	99.69	99.33	98.84	98.93	98.50	97.49

Notes: *The table shows the proportion of balances in an average month forming part of a revolving episodes (e.g. revolving balances) using the Full Sample of our data (Table 1).*

B Balance Transfers and Duration

The CCDB does not link multiple accounts belonging to a single individual or household, either in the cross section or over time. However, a common feature of the credit card market is the ability to transfer balances across cards, often at promotional rates. Not accounting for balance transfers may lead us to underestimate the average duration of sustained revolving. To provide some empirical assessment of the importance of balance transfers (BT), we utilize a feature of the CCDB which helps identify revolving episodes arising from new purchases as distinct from those which begin from a BT.

We assess the importance of BT episodes using a statistical match. In particular, we match a BT episode to a regular purchase episode according to its observable characteristics. These observable characteristics are

- U.S. State,
- episode balance (starting for BT episodes and final for purchase episodes),
- credit score of the cardholder (starting credit score for BT episodes and last credit score for purchase episode).

We assign each episode types to an observable "bin" using the Cartesian product of this set of observables ($3 \times 3 = 9$ bins). Then, our assignment procedure is as follows:

1. To each purchase episode in an observable bin, we assign a BT episode in a corresponding bin.
2. We then add the length of the BT episode to the purchase episode duration. This gives the BT inclusive episode length.

Because there are far fewer BT episodes (about 10 percent are BT episodes) we do not have a one to one match. Absent any additional information, we apply a "common prior". This means that we assign each BT episode to all corresponding purchase episodes with equal likelihood. Consequently, we extend the purchase episode duration by the probability weighted length of the assigned BT episode.

For example, if 1 BT episode corresponds to 5 purchase episodes, we assign that BT episode with equal probability (1/5) to each of the corresponding purchase episodes. The duration of each of these 5 purchase episodes is extended by one fifth the length of the associated BT episode, e.g. the probability adjusted length. More generally, if there are M purchase episodes and N BT episodes in a bin, where M > N, the same idea applies. The only difference is that now the probability weighted duration increased is based on N BT episodes, each of which is assigned with probability 1/M to a purchase episode. Conversely, if no BT episodes correspond to a particular purchase episode, we assign a probability weighted BT length of zero. Importantly, note that we do not match on origination date. This assumes that BT flows are stable throughout the period of analysis.

The results of the match are illustrated in Figure B.1. The left panel of the figure plots the incidence of balance transfers by credit score. As shown in the figure, though only about 10 percent of episodes start with BT, these form a disproportionately ($> 20\%$) large share of starting balances.

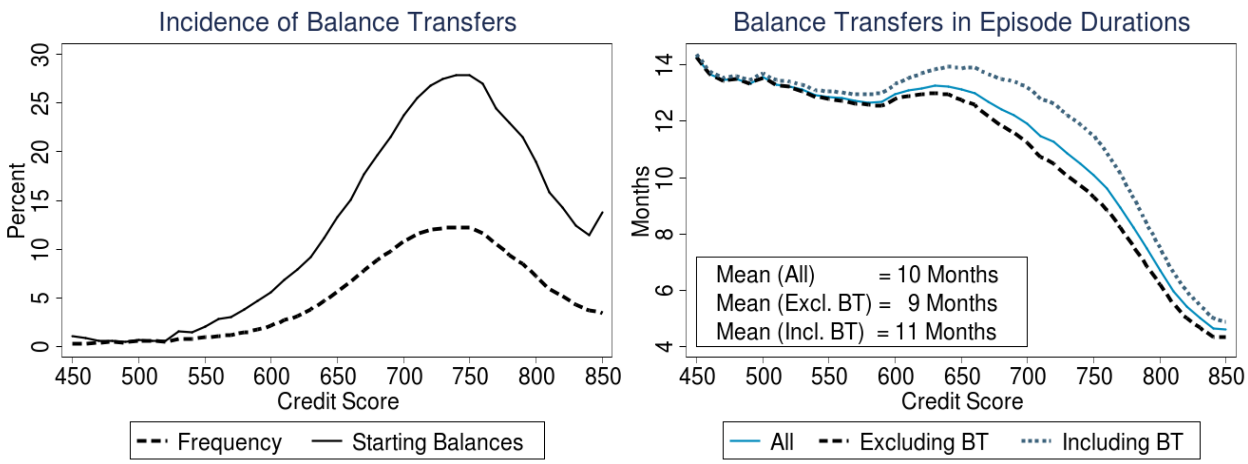

Figure B.1: Balance Transfers in Sustained Debt Episodes

Next, the right panel of Figure B.1, shows the contribution of BT to the average duration of borrowing (vertical axis) against associated users' credit scores (horizontal axis). As shown in the right panel of the figure, accounting for BT has a modest influence on the *expected* episode duration, raising the average duration of indebtedness by 10 percent, or one month.

C Distribution of Original Balances

Figure C.1 plots the distribution of original (starting) balances for episodes lasting from 1 month to three years, separately for subprime and prime episodes respectively. The figure is

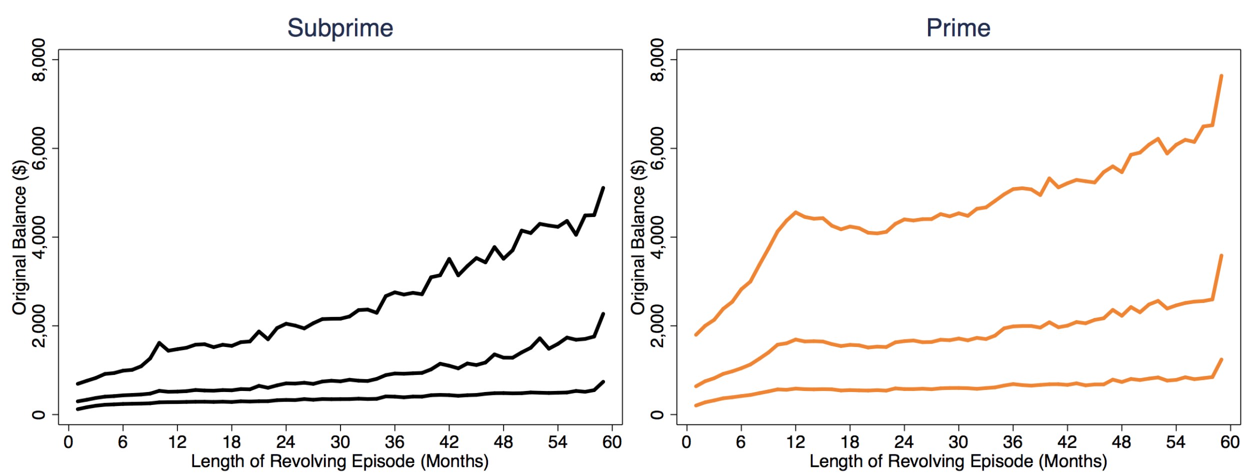

Figure C.1: Distribution of Episode starting (Original) Balances

shown here to put perspective on the relationship between the purchase triggering revolving and duration. As is clear in the figure, longer duration is associated with a larger original balance. Among subprime episodes, there is a steady increasing relationship. However, for prime episodes, the data reveal a plateau after one year and up to three years, especially at the top quartile.[35] What is most apparent, for both prime and subprime episodes, is that much of the rising relationship between duration and the original balance is driven by a sharp rise in the top quartile. Indeed when looking at the mean (not reported here) we see a sharp divergence from the median for longer lasting episodes.

D Detailed Survey Findings: SBI Macro Monitor

D.1 Complete Set of SBI Questions

In Table D.1 we provide a broader list of questions used to tie revolving to respondents' financial attitudes and percpetions. The estimates in Column 1 are from Equation 1 in Section 2. Column 2 shows the proportion of respondents who agree or somewhat agree with the statement.

D.2 Construction of Discounting Measure in SBI

In our analysis of the role of discounting, we create a linear index on the first instance in which a respondent preferred the higher amount one year from today over receiving $100 today. This is based on the following question: Respondents that always preferred $100 today

Suppose you did some work for pay. When it came time to be paid, you were given the following choice: You can either get $100 today or, if you are willing to wait one year, you would be guaranteed to get more.
For each of the following choices, please record which choice you prefer.
Please answer for every row.

1.	(71)	1 – ☐ $100 today	— or —	2 – ☐	$110 in 12 months
2.	(72)	1 – ☐ $100 today	— or —	2 – ☐	$125 in 12 months
3.	(73)	1 – ☐ $100 today	— or —	2 – ☐	$150 in 12 months
4.	(74)	1 – ☐ $100 today	— or —	2 – ☐	$175 in 12 months
5.	(75)	1 – ☐ $100 today	— or —	2 – ☐	$200 in 12 months
6.	(76)	1 – ☐ $100 today	— or —	2 – ☐	$225 in 12 months

Figure D.1: Discount Question in SBI Survey

are given a code of 7 (225+). Our interpretation of the linear index is that individuals must be compensated more for receiving money later discount their future earnings/consumption at a higher rate.

Figure D.2 plots non-parametrically the relationship between the propensity to revolve and reported preferences on discounting using the same regression in Equation 1 of Section 4.1. As shown in the figure, those who required more compensation for their (hypothetical)

[35]For episodes lasting longer than three years, there is an increase in the original balance, especially at the top quartile of the distribution.

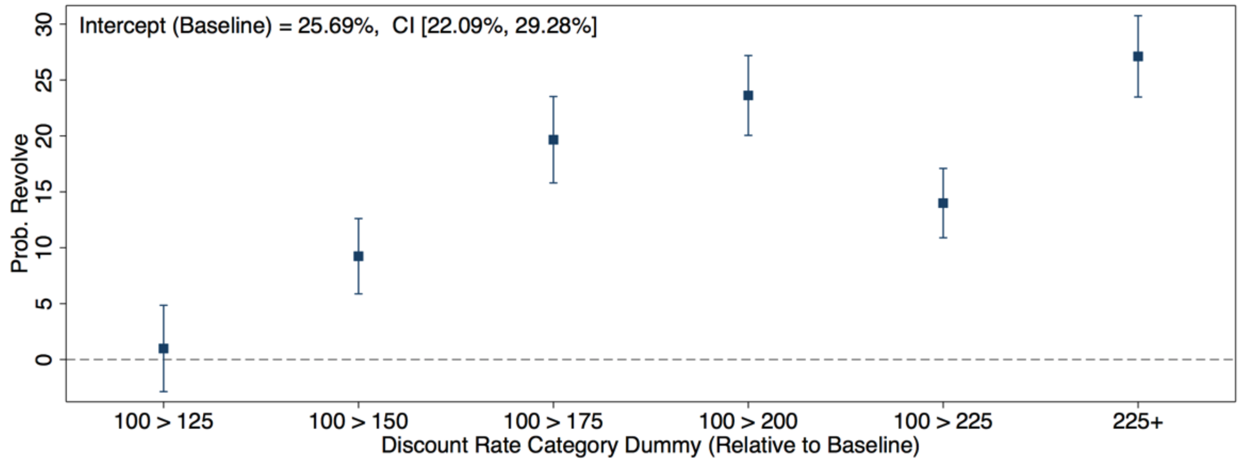

Figure D.2: Expressed Discounting Preference and the Likelihood of Revolving

patience, or heavier discounters, are also significantly more likely to report revolving balances. This intuitive result provides verification with regards to the consistency of respondents preferences and reported actions. In Table D.1 of the main text, we provide summarized version of this result using a dummy variable for those in category 4 and above, as well as a linear index directly in the regression.

Table D.1: Consumer Financial Perspectives & Reported Repayment

Dep. Var. = $\mathbb{1}[Revolve]$	β (s.e.) (1)	% Agree (2)
Financial Sophistication		
I do a very good job of keeping my financial affairs in order	-30.45	84.90
	(1.340)	
I am very organized in my approach to financial matters	-19.91	83.35
	(1.250)	
Often I'm not sure whether the financial decisions I've made are the right ones	11.57	42.85
	(0.910)	
My household needs help managing its financial affairs	8.720	33.25
	(0.940)	
I am always looking for the lowest cost financial services	2.980	56.92
	(0.890)	
Self Control/Discounting		
I am very disciplined in savings and spending decisions	-30.86	68.39
	(0.960)	
To buy anything other than a house or car on credit is unwise	-7.970	58.47
	(0.910)	
I am careful not to use credit more than I should	-26.47	82.16
	(1.210)	
I'm a spender rather than a saver	31.03	30.45
	(0.990)	
I prefer to buy something on credit rather than save up	16.96	22.81
	(1.090)	
I prefer using a debit card rather than a credit card to help control my spending	42.17	53.22
	(0.830)	
In the past, I spent more than I wanted because credit cards made it so easy	38.98	54.69
	(0.820)	
Linear Index on reported rate of time discounting	3.82	
	(0.24)	
Respondent is a heavy discounter (Dummy)	15.20	68.08
	(0.94)	
Financial Distress		
We plan to make a special effort to spend less money in the coming year	22.94	64.68
	(0.880)	
I am concerned that we have more debt than we should	52.23	41.02
	(0.840)	
We struggle to make ends meet	45.30	
	(1.220)	
Percent of Respondents Who Report Revolving	47.71	
Number of Observations	12,986	

Notes: *Data are pooled cross sections from the Strategic Business Insight's (SBI) Macro Monitor for waves 2012, 2014, and 2016. All regressions include wave (year) fixed effects. They also control for household income and size, which are provided as categorical variables and thus treated non-parametrically in the regression. About 37% of respondents reported income below \$50,000, 34% reported income between \$50,000 and \$100,000, 16% reported income between \$100,000 and \$150,000, and 13% reported income over \$150,000. Also, 26% of households have one person, 37% have two, 15% have three, and 21% have four or more. Time discounting is inferred from a sequence of responses regarding money equivalents across one year of time. We detail this variable's construction in Appendix D. Standard errors are in parentheses.*

E Examples of Expected Episode Cost of Credit

Table E.1 shows three worked out examples of how the arch of repayment influences the cost of credit for each of the three measures calculated in the paper, namely APR, TCC, and EECC. We calculate finance charges based on a 15 percent APR, compounded monthly. In order to highlight the role of repayment, the example holds constant the duration of an episode (1 year) and the original balance prompting revolving ($1,000). The table shows how these different cost measures might compare for each of the three categories of episodes discussed in the main text: (1) repaying episodes (top panel), (2) sustaining episodes (middle panel), and (3) surging episodes (bottom panel). It then gives a comparison of costs for each of these types.

From the table, among repaying episodes, for whom balances consistently decline, the EECC predicts a lower cost than both the APR. This is because the APR assumes that the initial amount financed ($1,000) remains fixed for the year. This is despite the fact that this revolver in our example incurs a (late) fee during the eighth month of the episode. Among sustaining episodes, in which revolvers pay the minimum due each month until the final month, the EECC becomes more expensive relative to APR, but not TCC. This is because the relative importance of the late fee in the eighth month of revolving is more important than the finance charges incurred by sustaining the balance. Finally, for surging episodes, greater finance charges due to the rising balance out weighs the importance of the cost of paying the incidental fee.

Table E.1: EECC Examples

Month in Episode	New Purchases	Cycle Ending Balance	Fees Incurred	Payment Amount	Revolved Amount	Accrued Interest
			Repayng Episode			
1	1000	1000.00	0	85.00	927.40	12.40
2	0	927.40	0	85.00	853.90	11.50
3	0	853.90	0	85.00	779.50	10.59
4	0	779.50	0	85.00	704.16	9.67
5	0	704.16	0	85.00	627.90	8.73
6	0	627.90	0	85.00	550.68	7.79
7	0	550.68	0	85.00	472.51	6.83
8	0	472.51	26	111.00	393.37	5.86
9	0	393.37	0	85.00	313.25	4.88
10	0	313.25	0	85.00	232.14	3.89
11	0	232.14	0	85.00	150.02	2.88
12	0	150.02	0	151.88	0.00	1.86
			Sustaining Episode			
1	1000	1000	0	25.00	987.40	12.40
2	0	987.40	0	25.00	974.65	12.25
3	0	974.65	0	25.00	961.74	12.09
4	0	961.74	0	25.00	948.66	11.93
5	0	948.66	0	25.00	935.43	11.77
6	0	935.43	0	25.00	922.03	11.60
7	0	922.03	0	25.00	908.47	11.44
8	0	908.47	26	51.00	894.74	11.27
9	0	894.74	0	25.00	880.83	11.10
10	0	880.83	0	25.00	866.76	10.92
11	0	866.76	0	25.00	852.51	10.75
12	0	852.51	0	863.08	0.00	10.57
			Surging Episode			
1	1000	1000	0	25.00	987.40	12.40
2	100	1087.40	0	25.00	1075.89	13.49
3	100	1175.89	0	25.00	1165.47	14.58
4	100	1265.47	0	25.00	1256.17	15.70
5	100	1356.17	0	25.00	1347.99	16.82
6	100	1447.99	0	25.00	1440.95	17.96
7	100	1540.95	0	25.00	1535.06	19.11
8	100	1635.06	26	51.00	1630.34	20.28
9	100	1730.34	0	25.00	1726.80	21.46
10	100	1826.80	0	25.00	1824.45	22.66
11	100	1924.45	0	25.00	1923.32	23.87
12	0	1923.32	0	1947.18	0.00	23.85
Cost Measure				APR	TCC	EECC
Repaying Episode				15.00	24.51	11.29
Sustaining Episode				15.00	19.78	16.41
Surging Episode				15.00	17.93	24.82