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CREDIT BUILDING OR CREDIT CRUMBLING? A CREDIT BUILDER LOAN'S EFFECTS ON CONSUMER BEHAVIOR, CREDIT SCORES AND THEIR PREDICTIVE POWER

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The credit bureau that provided data to us had the right to: (a) review the paper to ensure that the analysis using credit scores was depersonalized, aggregated, and that the scores received the correct trademark attribution; (b) offer comment about the paper, which the authors agreed exante to consider in good faith. We thank: the St. Louis Community Credit Union, and especially Paul Woodruff, for cooperation; the Consumer Financial Protection Bureau (CFPB), in particular Sarah Bainton Kahn and Daniel Dodd-Ramirez for their assistance; participants at many conferences and seminars for comments; Innovations for Poverty Action, in particular Anna Cash, Lucia Goin, Nora Gregory, and Kayla Wilding, for research support. We gratefully acknowledge research funding provided by the Consumer Financial Protection Bureau (under competitive award CFP-12-Z-00020/0002). The views expressed are those of the authors alone and are not necessarily shared by the CFPB or any other arm of the U.S. government. Institutional Review Board approval for human subjects protocols from Innovations for Poverty Action (no. 14January-001) and RAND Human Subjects Protection Committee (no. 2013-0660). This study was registered with the AEA RCT Registry with the ID number AEARCTR-0000441. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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ABSTRACT

There is little evidence on how the large market for credit score improvement products affects consumers or credit market efficiency. A randomized encouragement design on a standard credit builder loan (CBL) identifies null average effects on whether consumers have a credit score and the score itself, with important heterogeneity: those with loans outstanding at baseline fare worse, those without fare better. Selection, treatment effect, and prediction models indicate the CBL reveals valuable information to markets, inducing positive selection and making credit histories more precise, while keeping credit scores' predictive power intact. With modest targeting changes, CBLs could work as intended.

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A randomized controlled trials registry entry is available at AEARCTR-0000441

1. Introduction

Consumer credit histories are important inputs to various markets. Lenders use them in determining willingness to ration or lend, and at what terms.¹ Landlords, insurers, and employers also increasingly use credit report information when evaluating potential customers or employees.² Yet about 20% of the U.S. population lack a credit score due to a thin or non-existent credit file. For these "credit invisibles", and many more, there is much information beyond standard credit histories that credit risk modelers could use, as evidenced by recent investments in alternative credit bureaus and data sources such as utility and rent payments, and social media.³

Many programs and products seek to help consumers signal or improve creditworthiness, including financial education, financial coaching and credit counseling programs, and credit repair and/or monitoring services. Whether these efforts actually help consumers is an open question.⁴ So is the question of whether these interventions enhance market efficiency by revealing unobservable information to the market or worsen market efficiency by providing misleading signals that distort credit scores.

Credit builder loans ("CBLs") are a prevalent option for signaling creditworthiness outside of a standard credit history, with hundreds of U.S. deposit-taking institutions now offering them. CBLs are short-term installment contracts on small amounts (typically \$500 to \$1,000, repaid monthly over 6-24 months) in which the "lender" eliminates its credit risk by inverting the sequence of origination and repayment: loan proceeds are held in an escrow account and only released after the contracted payments are made (which include principal and an administrative fee).⁵ The CBL thus operates less like a loan and more like either a costly commitment savings device (if individuals do not withdraw the funds from the restricted account) or a costly sequence of deposits and withdrawals (if individuals choose to withdraw the funds immediately after making each payment). Nevertheless, and critically, credit reporting treats CBLs as standard installment loans, per industry agreements between CBL providers and the three major credit bureaus. And as with standard loans,

¹ A majority of credit users in the USA have below-prime credit scores (Brooks et al. 2015), and belowprime credit usage typically increases borrowing costs by several percentage points and hundreds or thousands of dollars per year (Pulliam Weston 2010; Zinman 2015).

² See, e.g., Consumer Financial Protection Bureau (2012), Bartik and Nelson (2018), Bos et al (2018), Clifford and Shoag (2017), Dobbie et al (2017).

³ See, e.g., Brevoort et al (2015) and Brevoort et al (2017).

⁴ The overall effectiveness of programmatic interventions on credit scores and other outcomes is mixed in an intent-to-treat sense, and plagued by low take-up (e.g., Hastings, Madrian, and Skimmyhorn 2013; Fernandes, Lynch, and Netemeyer 2014; Miller et al. 2015).

⁵ Operationally, the lender typically first disburses loan proceeds in whole to a locked savings account it controls, and then releases proceeds to the borrower, either in parts after each of the borrower's payments or in whole after the borrower makes all of the payments. In our setting the lender releases proceeds after each payment. This setup imposes modest liquidity demands on the CBL user, who need only come up with \$54 on the payment due date and can get \$50 of the \$54 back within minutes of making the payment.

CBL providers report all CBL payment performance to the bureaus, both positive (<30 days late) and negative (>=30 days late).

Like all credit building interventions, CBLs could have impacts on consumers, lenders, and markets alike. For consumers, CBLs could help them become credit visible, or shift their credit scores up or down. Our descriptive evidence suggests that both shifts likely occur; e.g., 40% of CBL users in our sample pay >=30 days late at some point. For lenders, CBLs provide marginal customers a point of entry or re-entry into the mainstream financial system, opening the possibility of cross-sells. For the market as a whole, via lenders reporting to credit bureaus, CBLs could help or harm market efficiency. If take-up predicts downstream behavior in ways that are not fully captured by other observables, market efficiency could improve. Or CBLs could worsen market efficiency if the post-CBL credit score is a less accurate measure of creditworthiness than the pre-CBL credit score.

We estimate CBL treatment effects using an encouragement design that randomizes take-up requirements. St. Louis Community Credit Union (SLCCU) has offered CBLs since 2009 and worked with the research team from September 2014 through February 2015 to identify a sample of over 1,500 SLCCU members who expressed interest in a CBL. Our sample is well-suited for studying CBLs in the sense that nearly 20% lack a score at baseline, while those with scores have mostly (very) low ones, with a mean of about 560 (sd 65 points) compared to the national average of a bit below 700 during our study enrollment period.⁶

We then randomly assigned these individuals to one of two arms: a "CBL Arm" that followed SLCCU's standard enrollment process for a CBL, and an "Extra Step Arm" facing an additional requirement to complete five modules of online financial education, taking about 50-60 minutes in total, either onsite or offsite.^{7,8} The CBL Arm had a take-up rate of 30% within 18 months of entering the study, while only the take-up rate in the Extra Step Arm was only 12%. The financial education requirement thus strongly deterred CBL adoption (this has its own policy implications, as we discuss below).

We measured FICO[®] Scores (a credit score developed by Fair Isaac Corporation)⁹ and other aspects of credit market behavior using four data pulls obtained from one of the three major credit bureaus: one at baseline, and three more at endlines of roughly 6 months, 12 months, and 18 months post-random assignment. Our two main outcomes are whether the consumer has a FICO[®]

September 9, 2014 and accessed May 20, 2019.

⁶ See, e.g., <u>https://blog.credit.com/2014/09/americas-fico-scores-hit-all-time-high-95420/</u>, dated

⁷ The financial education content did not include anything specifically about credit builder loans, and participants were not informed about the content of the financial education modules at the time of randomization: they were simply told they needed to "complete five online lessons" that would take about an hour or less.

⁸ Only six individuals in the Extra Step Arm even started a financial education module, and thus the financial education itself should have no treatment effect.

⁹ FICO is a registered trademark of Fair Isaac Corporation.

Score and their score conditional on having one at baseline. Having a credit score is an important step for consumers in becoming credit "visible" and potentially signaling a positive credit history, and an important step for lenders and the market in the sense that the scoring companies only report a consumer's score when it has sufficient confidence in its predictive power. The numerical credit score itself is important, as discussed above, because of its widespread use in credit and other markets.

Averaging across the three endlines, we find a null average intent-to-treat effect of the CBL on the likelihood of having a credit score (2pp, se=2pp, Extra Step Arm baseline mean=0.84). We also find a null average treatment effect on the credit score (-2 points, se=3 points, Extra Step Arm baseline mean=561), among the subsample of individuals with a credit score at baseline.

These null average effects obscure important heterogeneity in treatment effects by baseline borrowing status. We were motivated to examine this heterogeneity by both theory and practice. In theory, those with existing loans may benefit less from CBLs since they already have a recent credit history (we examine the inputs to credit scoring models below). Those with existing loans may also struggle to manage their existing loan obligation(s) in tandem with a CBL— with installment loans being perhaps particularly challenging to juggle in tandem, given that they allow for less repayment flexibility than revolving credit— if learning and/or behavioral considerations are important. On the other hand, those with existing loans may have experience and/or better access to liquidity that helps them successfully manage the CBL. In practice, baseline borrowing is prevalent (73% in our sample), and readily observable; should it drive treatment effects, any CBL provider could target on baseline borrowing status.

We find that those without a loan in the credit report at baseline tend to have more positive treatment effects, while those with a loan at baseline tend to have more negative treatment effects. Some examples: the CBL effect on the likelihood of being scored is 10pp (se=5pp) for those without a loan at baseline but -2pp (se=1pp) for those with a loan at baseline. The CBL effect on the credit score, conditional on having one at baseline, is 8 points (se=6 points) for those without an installment loan at baseline, and -5 points (se=3 points) for those with an installment loan at baseline. The four differences between treatment effects for no-loan vs. loan groups, in our main specifications, have p-values ranging from 0.01 to 0.10. We find no evidence that this is driven by installment loans in particular; rather any debt of any sort at baseline drives the result.

These treatment effects imply economically significant magnitudes, whether one considers differences between the baseline borrowing groups or the level point estimates for each group. In interpreting economic magnitudes, it is important to keep in mind that treatment-on-the-treated estimates scale up by the reciprocal of the differential take-rate between the two experimental arms: i.e., by roughly a factor of five in our case. For example, the implied credit score difference between CBL users with and without an installment loan at baseline is roughly (8-(-5))*5=65

points, which enough to move someone across credit score bins that affect market access and terms.¹⁰

Examining mechanisms underlying our heterogeneous treatment effect results, we find no evidence that baseline borrowing status merely proxies for other consumer characteristics that mediate treatment effects. Specifically: our baseline survey, together with baseline credit report and credit union administrative data, helps us construct a powerful test of the hypothesis that baseline borrowing status *per se* matters – by conditioning on a rich set of additional baseline consumer characteristics – and we fail to reject that hypothesis.

We also examine whether treatment effect heterogeneity reflects heterogeneous treatment effects on behavior—in how consumers with versus without a loan at baseline respond to the CBL—and/or heterogeneity in how FICO weights the same behaviors. We cannot reject the latter hypothesis; since the FICO model is proprietary, we do not know exactly how FICO weights the behaviors (and treatment effects thereon) that we observe. But we do find evidence supporting the former hypothesis: heterogeneity in downstream responses to the CBL is important within several behaviors that FICO uses as score inputs. Perhaps most interesting, we find evidence that CBL increases *non*-CBL delinquency for those with a (installment) loan at baseline. This suggests that, even though the CBL studied here imposes minimal liquidity constraints in principle,¹¹ adding a CBL to one or more existing credit obligations is too much for many borrowers to manage. We lack the additional data required to identify *why* this is, but offer some speculation and guidance for future work testing models of consumer decision making in the Conclusion.

Turning to treatment effects on other SLCCU products (cross-sells), there is some evidence that the CBL increases non-CBL borrowing for those without baseline debt while increasing savings account balances for those with baseline debt; e.g., the estimated treatment effect on savings for those with a loan at baseline is \$347 (se=\$161). This is consistent with some consumers using the CBL for what it is, functionally, aside from the credit reporting: a costly commitment to save. Having said that, this inference is not robust to alternative functional forms of savings balances, and treatment effects on total deposit account balances (e.g, \$183 with a se=\$223 for those with a loan at baseline) do not rule out balance-shifting from checking to savings.

¹⁰ E.g., consider someone with the baseline mean credit score in our sample, 560. Moving them up 65 points, or even 40 points per the point estimate on the no installment loan at baseline group, moves them from being clearly "sub-prime" (a "very poor" score, 579 and below), to "near-prime" (a "fair" score, 580-669). See, e.g., one of the big three credit bureau's description of credit score bins here, <u>https://www.experian.com/blogs/ask-experian/infographic-what-are-the-different-scoring-ranges/</u> (January 7, 2019, accessed May 20, 2019).

¹¹ Footnote 5 and Section 2-A elaborate on liquidity requirements. We attempted to engage participants in qualitative follow-up discussions to better understand participants' experiences with the CBL, particularly regarding cash flow management, but we were stymied by a low response rate.

Last, we examine the impact of the CBL on market information, specifically on whether the applicant reveals information about their type by applying for a CBL (selection), and on whether the CBL improves or worsens the predictive power of the credit score (prediction).

On selection, we find that CBL takers, relative to non-takers in the CBL Arm, show estimated credit score improvements of 14 or 15 points (se=4 points) over the post-treatment months, depending on specification. This upward trend is in theory a combination of selection and the CBL average treatment effect. In practice, since the average treatment effect is a precisely estimated zero, the upward trend reveals strong positive (advantageous) selection: those who choose to open a CBL are improving irrespective of the CBL itself. This suggests that CBL take-up provides a valuable signal to lenders, and that credit providers should consider reporting CBLs as a distinct category rather than lumping them together with standard installment loans.

On prediction, we examine whether CBL-influenced credit scores (e.g., 12-month endline scores for those without a loan at baseline in our CBL Arm) are better or worse predictors of default than credit scores less-influenced by the CBL (e.g., 12-month endline scores for those without a loan at baseline in our Extra Step Arm). Although these tests are "young" in that, once we allow time for the CBL to causally affect scores (12 months), we only have 6 months of endline data remaining, the results are reassuring: we find no evidence that the CBL weakens the predictive power of the credit score.

All told we add to extant literatures in several respects. First, we use random variation to help separately identify CBL selection and treatment effects.¹² Our experimental findings deliver some surprising results and implications, principally that CBL providers should consider screening out consumers with existing loan obligations.¹³ Second, and closely related to the first, our findings that a CBL with modest liquidity requirements causes delinquency on non-CBL loans, at least for those with pre-existing debt, adds to work on consumer liquidity constraints, cash flow management, and financial distress (e.g., Gelman et al. 2018; Olafsson and Pagel 2018; Dobbie and Song 2019). Third, we replicate and expand on the key finding from prior CBL studies-CBL usage is advantageously selected (Chenven 2014; Wolff 2016)—and infer that the credit bureaus could better harness this information revelation by reporting CBLs as a distinct product category. We thereby build a bridge to work on whether and how credit bureaus reduce asymmetric information (e.g., de Janvry, McIntosh, and Sadoulet 2010; Hertzberg, Liberti, and Paravisini 2011; Manso 2013; Garmaise and Natividad 2017; Kovbasyuk, Larinsky, and Spagnolo 2018). Fourth, our findings suggest that "product-linked" financial education requirements may be counterproductive, despite strong policy and programmatic interest in that approach (Askari 2009; Sledge, Gordon, and Kinsley 2011; Reves et al. 2013).

¹² See also Liberman et al (2018) on signaling and treatment effects in the U.K. payday loan market.

¹³ We discuss other approaches to CBL-seeking consumers with existing loan obligations in the Conclusion.

2. Study setting and design

A. Implementing partner and credit building product

We partnered with St. Louis Community Credit Union (SLCCU) to design and implement our study. SLCCU, a certified Community Development Financial Institution (CDFI), serves approximately 51,000 members who live or work in the greater St. Louis area. SLCCU has 11 branches (including three located within social service agencies), provides access to online financial education and phone-based credit counseling and education, and offers numerous financial products designed to improve members' financial stability. SLCCU has offered the "Credit Builder Loan" ("CBL") since 2009 and had originated approximately 4,400 CBLs at the onset of the study.

SLCCU markets and structures the CBL per credit union and CDFI industry standards. It markets the CBL as an opportunity to build credit history and improve credit scores (Figure 1 shows the marketing materials used by SLCCU, both in our study and routinely). The terms are such that no money changes hands at origination. Instead, the credit union places \$600 in a restricted access savings account (an escrow account, basically). Borrowers then make 12 monthly payments of approximately \$54 and the credit union releases \$50 from the restricted savings account back to the consumer's regular savings account immediately upon receipt of payment each month. As such, the payments portion of the CBL functions like a costly commitment savings account, yielding a certain and negative pecuniary return on saving; e.g., if the consumer makes all 12 CBL payments and does not make any withdrawals, they will have invested \$648 over the course of the year and yielded \$600 at year's end.

CBL payments are reported to each of the three major credit bureaus as a standard installment loan, using standard definitions of delinquency (e.g., a loan is first reported delinquent if a payment is more than 30 days late). According to SLCCU policy, if a delinquent CBL borrower does not bring her CBL current within 10 days of the delinquency, the credit union closes out the loan by transferring the restricted portion of the loan amount to pay off the remaining principal balance, "successfully" paying off the loan from a credit bureau perspective.

B. Data

We have three data sources: a baseline survey, SLCCU accounts, and FICO[®] Scores and credit report attributes from one of the three major credit bureaus. Surveyors administer the baseline survey as part of the CBL marketing process, as described below. The survey captures demographics, some aspects of financial status, and attitudes. SLCCU administrative data is pulled monthly for everyone in our sample. These data capture CBL performance and usage of other loan and deposit products. The bureau data capture snapshots of borrowing and repayment activity and one widely-used credit score, the FICO[®] Score.¹⁴ We obtain snapshots at baseline (on a biweekly

¹⁴ Per a research agreement with the bureau, we obtain the data through "soft" credit pulls that do not impact credit scores and do not get access to clients' entire reports (hence the lack of "tradeline"-level data).

rolling basis as participants entered the study), at approximately 6 and 12 months post-random assignment, and at >=18 months post-assignment (with a maximum of 24 months, depending on assignment date). The credit bureau did not share loan-level data, so we only have person-level data; e.g., our measure of 30-day delinquency is the number of loans on which the person is >=30 days late.

C. Sampling and experimental design

Figure 2 illustrates our sampling and experimental design. Our goal for *survey sampling* was to create a sample frame of SLCCU members who are generally interested in improving their credit. Between October 2014 and February 2015, research staff ("surveyors") enrolled participants into the study at seven of the SLCCU branches. Surveyors approached individuals in the branch and first asked if they were generally interested in building their credit. Individuals responding affirmatively were escorted to a private office and asked for consent to participate in a "research study focused on credit markets and products".¹⁵ In total, 2,310 individuals consented and started the short baseline survey. Of these 2,310 we infer that 2,269 were SLCCU members at baseline, as evidenced by a match to SLCCU administrative data.

Our goal for *the experiment* was to engineer variation in CBL take-up within a sample of SLCCU members who are interested in a CBL. After the survey, surveyors described the CBL and elicited participant interest in the CBL specifically (as distinct from credit building generally). We remove the 738 "Uninterested" individuals from the experiment sample: we do not randomly assign these individuals to an experimental arm. The remaining 1,531 expressed interest in the CBL and comprise the "experimental sample".¹⁶ Surveyors randomized these 1,531 participants, in real-time and at the individual level,¹⁷ into one of two arms: a "CBL Arm" that is encouraged to open the CBL on the spot, per standard SLCCU procedures;¹⁸ or an "Extra Step Arm" that is encouraged to

¹⁵ Surveys and treatments were delivered in private spaces within the credit union branches to preserve privacy and minimize the possibility of one applicant hearing about what another applicant receives.

¹⁶ Study participants were compensated for their time (about 15-20 minutes) with a \$5 gift card to a local grocery store. SLCCU preferred paper surveys and surveyors Fedexed them periodically to research team headquarters; unfortunately, one Fedex package containing about 50 surveys was lost (including some who did not receive a random assignment). Thus we have random assignment but no survey data for these 50 individuals (balanced across the two experiment arms, as shown in Table 1).

¹⁷ Each surveyor used a random number generator on a computer provided, maintained, and monitored by the research team. We also randomly assigned two other treatments. First, an independent crossrandomization provided half the survey sample (unconditional on CBL interest) with information on phonebased credit counseling and financial education. Second, six months after opening the CBL product, half of CBL takers were invited to set up an automatic transfer from checking to savings that would start six months later, after the last CBL payment. Take up of these two treatments was 2% and 0% and thus we exclude them from the analysis

¹⁸ If a CBL Arm member was ready to open a CBL on the spot, our surveyors would escort them to a credit union representative who would further describe the product, establish payment dates, and originate the CBL. CBL Arm members who were not immediately ready to open a CBL received three forms of follow-

open the CBL but told they must first complete approximately 50 minutes of free, online financial education prior to opening.¹⁹ The financial education course is one of SLCCU's standard offerings and clients can complete it from a branch computer or any other web-connected device.

D. Sample Characteristics and Randomization Balance

Table 1 presents baseline summary statistics and randomization balance tests, on our experiment sample, for each variable we use in our analysis.²⁰ Columns 1 and 2 present descriptive statistics, separately for the CBL (N=789) and Extra-Step (N=742) Arms. Column 3 presents an estimate of the difference across the two arms for each variable. The overall pattern is consistent with a valid randomization: only 2 of the 36 variables has a difference with a p-value < 0.05 (although in several cases the confidence intervals do include economically meaningful differences).

Demographically (Table 1 Panel A, Columns 1 and 2), the survey reveals that our experiment sample looks much like the rest of the credit union's membership (based on the credit union's qualitative description): predominantly female, unmarried, African-American, and low-/moderate-income. Only 25% of our sample has a college degree. Other survey variables capture aspects of financial knowledge, attitudes, and condition that we use when estimating heterogeneous treatment effects in Section 3-B.

Table 1 Panel B shows measures of our sample's prior engagement with the CBL provider, from SLCCU's administrative data. Everyone in our experiment sample has at least a savings account by virtue of being an SLCCU member, and 80% have a positive balance in their SLCCU deposit account(s) at baseline, with an imprecisely estimated mean of about \$650. Nearly two-thirds (64%) of the sample holds less than the required CBL monthly payment amount (\$54) in their SLCCU deposit accounts (not shown directly in Table 1 but incorporated into the Lack of Liquidity index in Panel D). Approximately one-third (32%) already have a non-CBL loan with SLCCU (these loans are also counted in the credit bureau variables described next).

Turning to baseline credit report characteristics for our experiment sample (Table 1 Panel C), the overall picture is one of substantial heterogeneity in credit histories, credit scores, and recent credit usage and delinquency, and of almost universally binding liquidity constraints. About 2% of our sample could not be matched to a credit report at baseline, which reduces our main analysis sample from 1531 to 1502.

up: nudges from a teller any time they transacted in a branch; phone calls attempting to set up an appointment to open a CBL; and two emails.

¹⁹ Participants could satisfy the requirement by completing five (or more) modules out of eight available: Savings and Investments, Mortgages, Overdraft Protection, Payment Types and Credit Cards, Credit Scores and Reports, Identity Protection, Insurance and Taxes, and Financing Higher Education

²⁰ Appendix Tables 1a-1d present the same information for our four key sub-groups: those with and without an outstanding loan or installment loan at baseline.

Of our sample, 18% lack a credit *score*: a consumer can have a credit report with information on specific debts, without being scored, if FICO cannot estimate risk with sufficient confidence. Unsurprisingly, lacking a score is far more prevalent among those who do not have a loan or installment loan at baseline; e.g., 63% of those without a loan at baseline also lack a score (from Table 2 Panel B Column 1: 130/(130+78)), while only 1% of those with a loan a baseline lack a score (from Table 2 Panel C Column 1: 7/(7+544)).²¹ Once someone is scored, it is rare for them to become unscored; e.g., only 3% of our sample with a score at baseline is unscored at the 18-month endline (Table 2 Panel A Column 3).

FICO[®] Scores can range from 300 to 850, and the mean credit score among those with a score in our sample is about 560 at baseline (sd=65), indicating that most of our sample is well below the cutoffs for a "prime" borrower (usually 640 or 680). Sub-prime consumers typically face limited credit access and high prices. Binding liquidity constraints are further evident in revolving credit utilization variables (and the components of our Lack of Liquidity index in Table 1 Panel D). 53% of our sample has no open revolving loan, and among those with an open credit line mean utilization is greater than 100%: the average person with a revolving credit line in our sample has exceeded their credit line(s) at baseline (these variables are not shown in Table 1 but included in the Amounts Owed: Utilization Index). Over 70% of our sample already has a loan obligation at baseline, and about 45% had been delinquent on one or more loans in the previous 12 months (delinquency variables not shown in Table 1 but included in the Default Index).

3. Results

A. CBL Take-up and Performance

Our randomization induced large differences in CBL take-up, defined as opening a CBL within 18 months of entering the study.²² Focusing for now on the first row of Table 3 Panel A, we see an 18pp difference (se=2pp) between the CBL Arm (30% take-up) and Extra Step Arm (12% take-up) in our full experiment sample,²³ and a 20pp (se=2pp) difference in the sample with a credit score at baseline. The next four rows show similar patterns for our four baseline borrowing status groups across the two samples of interest, with one exception out of eight.²⁴

²¹ The traditional credit bureaus have broad but not entirely comprehensive coverage of borrowing, so some people we classify as non-borrowers may in fact have an outstanding loan.

²² Approximately 50 percent of take-up occurred on the same day as the survey and offer, 71 percent occurred within the first 30 days, and 97 percent occurred within the first year. Appendix Table 2 shows that few baseline characteristics are strongly correlated with take-up, with a few noteworthy exceptions: takers have lower credit scores, higher rates of default, and are less likely to have a non-CBL loan at SLCCU than non-takers.

²³ As a point of comparison for level take-up rates, Table 3 Column 7 shows a 4% take-up rate among the Uninterested Group that initially expressed interest in credit building generally, took the baseline survey, but then initially declined information on the CBL.

²⁴ Specifically, the No Loan at Baseline Group in the scored at baseline sub-sample (our smallest subgroup) has a 31pp take-up differential. It is unsurprising to find one outlier among eight estimates (where eight

This strong first stage serves two purposes. The first is methodological: it enables us to estimate the causal effects of CBL access (in Section 3-B). The second is substantive: it sheds light on the deterrent effect of financial education, even when financial education is offered through a convenient delivery channel and at a seemingly opportune moment. The financial education requirement serves as a deterrent even though it was not enforced: only two of the 86 takers in the Extra Step Arm completed the requirement, because credit union staffers had the discretion to waive it.²⁵

All payment behavior on a CBL (both positive and negative) is reported to the three major credit bureaus. Panel B of Table 3 shows that delinquency on our CBL is common: approximately 40 percent of those who opened the product made at least one payment more than 30 days late. This high rate of delinquency (particularly in the CBL Arm that uses standard operating procedures for enrollment) indicates that CBLs could backfire, at least for some borrowers.

B. Treatment Effects and Mechanisms

Recall that the main proximate goal of a CBL is to help consumers improve their credit scores. We examine whether and how CBLs achieve this goal by using the four credit reports we have perperson, and our *random assignment* to either the CBL or Extra-Step Arm, to estimate intent-to-treat (ITT) effects using OLS equations of the following form:

(1)
$$Y_{it} = \alpha + \beta (CBL Arm \times Post_t) + \gamma Post_t + \sum_i \delta_i I_i + \varepsilon$$

Here *Y* is a credit report variable for person *i* at time *t*, where *t* includes the baseline and the three endlines (pulled roughly 6, 12, and 18 months post-random assignment). *CBL Arm*=1 if *i* was randomly assigned to that arm; the Extra-Step Arm is the omitted category. The CBL interaction with *Post* identifies the average effect of CBL access across the three endlines (various Appendix Tables estimate separate effects for each endline). Because we have multiple observations per person we include person fixed effects I_i (thereby absorbing the main effect *CBL Arm_i*) and cluster standard errors at the person level (the unit of randomization).

represents the number of differences estimated in rows (1)-(4) in Table 3 Panel A). The main implication of this outlier, inferentially, is that one might view intention-to-treat-estimates as closer in magnitude to treatment-on-treated estimates for the sub-sample that had no loan but did have a credit score at baseline. ²⁵ As such our estimates of the deterrent effect are likely lower bounds for truly mandatory financial education, with our preferred lower bound estimate using the take-up differential within five days of entering the study (17 pp); after that, the CBL Arm received marketing follow-ups and the Extra Step Arm did not. Also, Table 3 Panel B Column 3 suggests that non-compliance (i.e., take-up) in the Extra Step Arm generates positive selection, in the sense that takers in the Extra Step Arm (Column 2) are more likely to stick to the CBL payment schedule than takers in the CBL Arm (Column 1) and thereby generate positive credit reporting history.

Table 4 Column 1 reports our estimates from (1), where *Y* is an indicator for having a credit score. The point estimate of the CBL treatment effect β is positive, but small (1.8 pp; compare to the baseline mean of 84%) and not statistically distinguishable from zero (se=1.5 pp).²⁶ Column 4 limits the sample to those with a score at baseline and estimates (1) with the credit score itself as the dependent variable. The implied treatment effect is essentially zero, as the confidence intervals rule out effects of more than eight points in either direction. Even eight points would be a minor change, whether relative to baseline scores (about 560), or relative to the increase one would need to obtain improved credit access or terms. Having said that, treatment on the treated (TOT) estimates would be roughly five times as large and hence more economically meaningful.²⁷

However, the lack of average effects in Columns 1 and 4 obscures important heterogeneity by whether the consumer had an existing (installment) loan visible in the credit bureau at baseline. We were motivated to examine this margin of heterogeneity by both theory and practice. In theory, those with existing loans may benefit less from CBLs since they already have a recent credit history (we examine the inputs to credit scoring models below). Those with existing loans may also struggle more to manage their existing loan obligation(s) in tandem with a CBL (Table 3 Panel B; Table 6 Columns 2 and 3), if learning and/or behavioral considerations are important. Practically, baseline borrowing is prevalent (recall from Table 1 that 73% of the sample has a loan), and something any CBL provider could screen on using credit report data.

Columns 2, 3, 5 and 6 estimate heterogeneous treatment effects (HTEs) by splitting the interaction term in equation (1) into two, exhaustive components. E.g., the specifications in Columns 2 and 5 split *CBL Arm*Post* into two variables: *No Loan at Baseline*CBL Arm*Post* and *Any Loan at Baseline*CBL Arm*Post*. We also include the second-level interaction term that is not absorbed by person fixed effects; e.g., *No Loan at Baseline*Post*.

Column 2 shows a stark HTE on the likelihood of being scored. The estimated CBL effect on those without a loan at baseline is 10.2pp (se=4.5pp), while for those with a loan at baseline it is -1.6pp (se=1.0pp). The estimated 11.8pp difference between these two treatment effects has a p-value of 0.011. Column 5 shows a qualitatively similar but less precisely estimated pattern on credit scores, among those who had a score at baseline: the estimated CBL effect on those without a loan at baseline is 9 points (se=7 points), while for those with a loan at baseline it is -3 points (se=3 points). The estimated 12.5-point difference between these two treatment effects has a p-value of 0.098.

Columns 3 and 6 estimate HTEs based on *installment* loan status at baseline, motivated by the hypothesis that any deleterious effects of the CBL would be relatively pronounced for users with inflexible installment loan repayment schedules to juggle with the CBL. We find no support for

²⁶ Appendix Table 3 reports separate treatment effect estimates for each endline.

²⁷ The TOT estimate is in line with the non-experimental difference in mean credit score between those with versus without any loan at baseline (Table 1 Panel C).

this hypothesis: the results here are statistically indistinguishable from those for the any loan vs. no loan split in Columns 2 and 5.

Overall, Table 4 suggests that CBLs work as intended for consumers without pre-existing debt, but not for consumers who already have debt, at least relatively speaking.

Table 5 explores whether the HTEs in Table 4 are due to baseline borrower status *per se*, or to other baseline characteristics and behaviors that are correlated with both baseline borrowing and treatment effects. We detail our measures of these additional covariates in the Data Appendix; these variables come from credit union and credit bureau administrative data as well as our baseline survey that measures financial stability, discounting and self-control, risk attitudes, attention to credit scores, credit knowledge, and liquidity constraints (including age). Many of these additional covariates are collinear, and so we use post double selection Lasso (Belloni, Chernozhukov, and Hansen 2014) to select *Post*covariate* terms from the complete set of baseline covariates in Table 1 (the covariate main effects are subsumed by person fixed effects).²⁸ The even-numbered columns in Table 5 add these Lasso-selected *Post*covariate* terms to our main heterogeneous treatment specifications from Table 4 (those main specifications are reproduced in the odd-numbered columns in Table 5). We then test whether adding the *Post*covariate* terms reduces the HTEs with respect to baseline borrowing status by comparing HTEs across the two specifications (i.e., across the pairs of columns without and with the additional *Post*covariate* terms).²⁹

Comparing the four pairs of columns in Table 5, we find little if any evidence that HTEs are driven by anything other than baseline (installment) borrowing status *per se*. We base this inference on two key patterns of results. First, the point estimates and standard errors on level treatment effects are very similar across the two pairs of specifications; e.g., the largest difference across specifications between the four pairs of estimated treatment effects on the credit score is 1.5 points on a base of 561 (Columns 5-8). Second, and unsurprisingly given the first, adding covariates does not change our estimates of the *difference* in treatment effects between the baseline borrower and non-borrower groups in each specification. That inference is formed by comparing p-values across specifications, for each of the four specification pairs: the p-value pairs are 0.01 and 0.01, 0.02 and 0.03, 0.10 and 0.18, and 0.04 and 0.03. We emphasize however that these results control only for observed heterogeneity: unobserved heterogeneity could be driving the baseline borrowing HTEs.

Table 6 examines whether credit *behaviors* — specifically, factors used as inputs to the FICO scoring model — differ across baseline (installment) borrowers versus non-borrowers, within the CBL Arm. Specifically, we test the hypothesis that the CBL induces different behaviors for those

²⁸ Specifically, this model selection approach performs two steps: first, it uses a Lasso model to select covariates that are predictive of the treatment variable(s); second, it uses a Lasso model to select covariates that are predictive of the outcome variable. We then estimate OLS treatment effects including all covariates selected in either step (either 15 or 16 *Post*covariate* terms, depending on the specification; please see the notes to Table 5 for details).

²⁹ Appendix Table 4 does the same exercise, estimating separate treatment effects for each endline.

with different baseline borrowing status. This helps to identify what drives the observed heterogeneous treatment effects. If we find no differences in treatment effects on behavior, the alternative hypothesis is that those with different baseline borrowing status respond similarly to the CBL, but that their similar behavior is scored differently by FICO. This alternative hypothesis is viable given the limited modeling information that Fair-Isaac publicly reveals: "For particular groups—for example, people who have not been using credit long—the relative importance of these categories [the factors] may be different." ³⁰

We examine CBL treatment effects on credit behaviors by constructing indices, detailed in the Data Appendix, for four of the five behavior factors FICO states it uses in its scoring model: "New Credit", "Payment History" (including a measure that isolates treatment effects on non-CBL loans, as described below), "Amounts Owed" (which includes our "Utilization" measure), and "Credit Mix." (We lack a direct measure of the fifth factor: "Length of Credit History".) For each measure of each factor we compare CBL effects on baseline (installment) borrowers vs. non-borrowers in Table 6 Panel A (Panel B).³¹

The p-values in each panel indicate some evidence of HTEs across baseline (installment) borrowing status for three of the four scoring factors we observe. Looking at each of the four factors individually, there is little evidence of heterogeneity in New Credit (Column 1); the index components here are the number of inquiries in the last 12 months and the number of new loans in the last 6 months, with higher values indicating more new credit.

Columns 2 and 3 show some evidence that the CBL causes deterioration in overall payment history, for those with an (installment) loan at baseline: the treatment effect coefficients indicate declines in timely repayment ranging from 0.08 to 0.13 standard deviations. Column 2's index components are ten measures of delinquency, collections, and other serious derogatory indicators, with higher values indicating less timely repayment. Column 3's index removes the short-term delinquency components, and hence isolates treatment effects on *non*-CBL delinquency, since SLCCU CBLs are always paid off from escrow and closed before being reported as more than 30-days late (Section 2-A). We find no evidence that CBL affects payment history for those without a loan at baseline, although these null estimates are imprecise. The four p-values on the difference in treatment effects across the borrowing vs. no borrowing groups, for any loan and installment loan-only groups, are: 0.05, 0.10, 0.24, and 0.41.

Turning to the Amounts Owed factor, we have indices of two contributing sub-factors: Outstanding Balances (Columns 4) and Utilization (Column 5).³² The pattern here suggests the

³⁰ <u>http://www.myfico.com/credit-education/whats-in-your-credit-score/</u>, accessed September 21, 2017.

³¹ Appendix Table 5 repeats the analysis in Table 6 for the sub-sample with a credit score at baseline, and

Appendix Table 6 repeats the analysis in Table 6 estimating separate treatment effects for each endline. ³² We measure Balances with an index of standardized revolving, auto loan, and other installment loan balances. We measure Utilization with an index of 4 discrete measures of credit limit usage, outstanding balances, and the number of open installment loans.

CBL induces borrowing increases for those without baseline debt, at least relative to those with baseline debt. The four p-values on the difference in treatment effects across the baseline debt status groups are: 0.02, 0.04, 0.10, and 0.74.

Column 6 suggests substantial heterogeneity in Credit Mix (defined as having open loans of both installment and revolving types): the CBL effect on those without baseline debt is much more likely to be a transition into having both types, with a 0.06 p-value on the difference in treatment effects across any baseline borrowing vs. no borrowing groups (p-value of 0.01 for installment baseline borrowing).

Summarizing Table 6, we find evidence consistent with the hypothesis that the CBL's heterogeneous treatment effect on credit scores is due to HTEs on credit behaviors, although as noted at the outset we cannot rule out that any effect on scores is due to the proprietary FICO formula scoring identical behaviors differently for borrowers with different baseline characteristics. Having said that, CBL HTEs on credit behaviors are interesting in their own right. Our results suggest that those without baseline debt increase their overall debt usage and mix, and do so without compromising their creditworthiness. Meanwhile, those with any baseline debt tend toward the opposite pattern; of particular note are the results suggesting that CBL increases their *non*-CBL delinquencies by an estimated 0.05 standard deviations (se=0.03).

Table 7 examines CBL treatment effects on the usage of other SLCCU products. These results help round out the picture of how consumer financial behavior changes as creditworthiness builds (or deteriorates), on whether the CBL helps individuals build savings (SLCCU does not focus on this extensively in its marketing, but other CBL providers do), and on the bottom-line viability of CBLs from the supply-side perspective. Odd-numbered columns estimate average treatment effects for the full sample across the three endlines, and even-numbered columns estimate treatment effects separately by baseline borrowing status.³³

Columns 1 and 2 show no evidence of treatment effects on membership retention, although the confidence intervals do not rule out economically meaningful effects on attrition given that only 7% of the full sample is no longer an SLCCU member by the 18-month endline (9% and 6% in the No-Loan at Baseline and Loan at Baseline groups). Column 3 shows no treatment effect of the CBL on non-CBL borrowing from SLCCU on average (1pp, se=2pp, control mean=32%), with some hint in Column 4 of a positive treatment effect on those without a loan at baseline (5pp, se= 3pp).

Columns 5-8 examine treatment effects on deposit account balances. These are key outcomes for understanding whether there is a flypaper effect of CBL proceeds. Positive treatment effects on balances would be consistent with members using CBL for what it is, mechanically, aside from its

³³ Appendix Tables 7a and 7b report treatment effects separately for each endline. Treatment effects by baseline installment borrowing status are similar to those by baseline borrowing status, and we report the installment borrowing results in Appendix Table 8 to save space in the main table.

credit reporting feature: a costly commitment savings device. The results are mixed. We see some evidence that CBL increases level savings balances, with the full sample result in Column 5 (\$253, se=\$124) being driven by baseline borrowers in Column 6 (\$347, se=\$161). Having said that, these results are not entirely robust to alternative functional forms for balances (Appendix Table 9),³⁴ and Columns 7 and 8 show that we cannot rule out balance shifting from checking to savings. Nor can we rule out substantial negative treatment effects for baseline non-borrowers in Column 6 (\$4, se=\$145).

Summarizing Table 7, we find little evidence that CBL backfires from the provider's perspective: treatment effects on measures of engagement with SLCCU's core products suggest positive effects if anything. From the consumer's perspective, there is some evidence that the CBL leads to more borrowing for the those without (installment) debt at baseline (Column 4; Appendix Table 8 Column 2), and that CBL leads to more savings for those with (installment) debt at baseline (Column 6; Appendix Table 9 Panels B and C). If CBL does indeed serve as a costly commitment savings device for some users, that would raise the question of whether the costs—which here includes a strictly negative yield, and weakly lower credit scores— exceed the benefits.

C. Effects on Market Information

Our first piece of evidence on how CBL affects the quality of information available to the market to lenders and other credit bureau users—comes from treatment effect estimates on the likelihood of being scored. As discussed above, increasing the number of consumers with credit scores can be valuable in the sense that FICO's willingness to assign a score to a consumer depends on its confidence in the predictive power of that score: there is more precise information available on a consumer with a credit score than on one without a score. Our results suggest that CBLs can increase the number of scored consumers, particularly those without pre-existing debt.

We now further investigate how the CBL affects the quality of information available to the market with three predictive analyses.

The first analysis tests for selection on unobserved consumer characteristics: do those who takeup the CBL subsequently have higher credit scores? Table 8 restricts the sample frame to the CBL Arm, since the CBL Arm faced the usual take-up process, and replaces the random assignment in (1) with an indicator for whether someone took-up a CBL. We do this for each of our two main credit score outcomes: having a score (Columns 1 and 2) and credit score conditional on having one at baseline (Column 3 and 4). Normally this "naïve" specification would capture an unidentifiable combination of treatment and selection effects, but since we find a precise null for average treatment effects (Table 4, Columns 1 and 4) the naïve specification identifies selection

³⁴ We do not use log(balances) because 12% and 11% have zero savings balances and savings + checking balances at baseline.

in the full sample (Table 8 Panel A).³⁵ The two specifications per outcome take different but complementary approaches to identifying selection. Odd-numbered columns assume the relevant margin for selection on unobservables is anything not captured by baseline levels (recall that our empirical models include person fixed effects whenever we have multiple observations per person, as we do here). Even-numbered columns assume the relevant margin for selection on unobservables is anything not captured by baseline levels and trends that can vary with the baseline score level: as in Table 5, we use post double selection Lasso, this time to select which *Post*baseline credit score bin* terms to include.

Table 8 Panel A shows strong evidence of positive selection on CBL take-up, for both outcomes and both approaches to controlling for observables. Column 1 shows that CBL takers are 13pp more likely (se=2pp) to have a credit score in the endline period than non-takers in the parsimonious specification. This difference increases to 18pp (se=3pp) with the richer controls for observables in Column 2.³⁶ Columns 3 and 4 show that CBL takers who enter the sample with a credit score have scores that are 14 or 15 points higher at endline in the two specifications (se=4 points in both). Figure 3 suggests that this is due to CBL takers catching up to CBL non-takers; specifically, CBL takers increase their scores over the first six months while non-taker scores remain roughly constant over the endlines.

In all, Table 8 implies that CBLs attract consumers who are on an upward trajectory that is not fully captured by baseline observables. This has market implications: lenders can use CBLs to induce positive selection on improving creditworthiness. We speculate that our estimates are lower bounds on the potential for advantageous selection,³⁷ and that credit bureaus could facilitate advantageous selection by distinguishing CBLs from standard installment loans in their data.

The second and third predictive tests focus on whether the CBL-influenced credit score is better, or worse, at predicting default, as measured by the score's gradient (second test) and its fit (third test). CBLs might capture valuable information and thereby improve the predictive power of the credit score or distort information and thereby reduce the score's predictive power. As noted at the outset, distortion seems like a real possibility given that the CBL is not a loan in an economic

³⁵ In contrast, the heterogeneous treatment effects by baseline borrowing status imply that we cannot identify a pure selection effect separately for those groups, but we present results for those groups, in Table 8 Panels B and C, for completeness.

³⁶ Recall, from the transition matrix in Table 2, that this increase in the likelihood of being scored from baseline to endline must be driven by increases in transitions into being scored, not decreases in transitions out of being scored.

³⁷ Our positive selection is identified by comparing CBL takers to those who expressed ex-ante interest in the CBL but did not take-up; it seems plausible that CBL takers might be even more positively selected on future credit score improvements compared to a broader population (that is not interested in CBL or other credit building products/services). Unfortunately, we lack the requisite data, on anyone who is not interested in improving their scores, to test that hypothesis (recall that even our Uninterested Group is interested in improving their scores, just not interested in learning more about the CBL at the moment of the baseline survey).

sense—it functions like a commitment contract for saving—yet is reported to credit bureaus as a standard installment loan. These tests compare the 12-month endline credit score's default gradient or fit for 18-month default, across the CBL versus Extra Step arms. Focusing on the predictive power of 12-month endline scores allows time for the CBL to exert any salutary or distortionary influence on the predictive content of the credit score. If the CBL changes the predictive power, then the 12-month score*CBL Arm coefficient or fit will differ from the 12-month score*Extra-Step Arm coefficient or fit.

Table 9 presents results our second predictive test, the gradient test, for our summary index of ten measures of loan delinquency (Appendix Table 10 shows results for each component of the index). Column 1 shows no statistical difference in the default-score gradient across the CBL and Extra-Step arms (p=0.26), and the point estimate on the difference is small in economic terms: a 0.01 standard deviation difference per 100-point change in credit score. This result suggests that, on average, CBLs do not distort or otherwise change the predictive power of the credit score. Columns 2 and 3 decompose this average gradient for our baseline borrowing and non-borrowing groups, and again finds no economically or statistically meaningful differences (p-values range from 0.17 to 0.67).³⁸ The key takeaway from Table 9 is a precisely estimated null result: the CBL does not change the default-credit score gradient, at least over the short timeframe we can observe.

Figure 4 presents the results of third predictive test, of fit. Specifically, we test whether the CBL changes the 12-month endline credit score's ability to explain the variance of loan default, using receiver operator characteristic (ROC) curves. A greater area under the curve (AUC) indicates a better fit. The reference line shows what the ROC curve would be if the 12-month endline credit score had no power to predict default 6 months later. Our measure of default at the 18-month endline is a binary version of our default index; because a ROC curve requires a discrete predicted (outcome) variable, we cut the index at its median, with those above the median defaulting more. We then compare the AUCs for the CBL vs. Extra Step arms, calculating standard errors and p-values using the DeLong et al (1988) method. Examining the full sample, there is little difference in the AUCs across the CBL vs. Extra-Step arms (p-value=0.62). We obtain similar results within each of our four sub-samples of interest: those with and without a (installment) loan at baseline. None of the AUC differences between the two arms is economically large, and the smallest p-value is 0.34. As such, we find no evidence to support the hypothesis that CBL weakens the informational content of the credit score by weakening its ability to fit default, at least over the short timeframe we can observe.

³⁸ The other interesting pattern in Columns 2 and 3 is the steeper gradient for the no-(installment) loan-atbaseline groups relative to the (installment) loan at baseline groups; here we are comparing rows (iii) and (iv) to rows (v) and (vi), and rows (vii) and (viii) to rows (ix) and (x). For those without (installment) debt at baseline, 12-month credit scores are stronger predictors of downstream behavior, by about 0.1 standard deviations, perhaps because the dearth of activity at baseline means that the baseline credit score captures less information.

All told, predictive tests suggest that CBLs reveal information (Table 8) and do not distort it (Table 9 and Figure 4).

4. Conclusion

We use a randomized encouragement design and predictive modeling to examine impacts of a credit-builder loan (CBL) on borrowers, providers, and credit market information. The results are mixed, but promising.

The CBL studied here has null average treatment effects on consumer credit scores, but these average effects obscure important heterogeneity on a readily observable margin: baseline borrowing. Effects tend to be more positive for consumers without pre-existing debt, and there is some evidence of negative effects on consumers with pre-existing debt. Perhaps most strikingly, the CBL increases overall *non*-CBL delinquency among baseline borrowers. Together with high delinquency rates on the CBL itself (approximately 40%), this suggests that adding CBL's seemingly modest liquidity requirement is too much for many consumers to manage.

CBL effects at the market level are more uniformly positive. The strong positive treatment effects on the likelihood of FICO assigning a credit score, among consumers without a loan at baseline, suggest that the CBL improves the precision of credit risk assessment for "credit invisibles". We also find that CBL takers are substantially more likely to obtain or improve their credit scores over the next 6-18 months on average, conditional on their baseline score, implying that lenders can use CBLs to advantageously select borrowers who are on an upward trajectory. As such our results also illustrate how merely comparing outcomes before versus after product take-up, a common advertising strategy of lenders offering this product, is misleading. Meanwhile, CBLs do not change the gradient of the default-score relationship, nor do they reduce the ability of the credit score to explain variance in (fit) default, suggesting that CBLs do not distort the predictive value of credit scores.

With respect to overall efficiency, our estimates of the CBL's effects on consumers, providers, and the market suggest that CBLs could be efficient, and perhaps Pareto-improving, with some modest design changes. Providers should consider remediating or screening out those with pre-existing debt. Credit bureaus should consider requiring providers to report CBLs as a distinct category rather than as a traditional installment loan (as they do with distinct categories for unsecured vs. secured credit cards). In short, our results suggest a path to CBL designs that make nearly everyone better off while doing little harm to anyone else.

Expanding a bit on implications for providers, we see two potential product/program design implications to explore going forward. First, it may be counterproductive to try building consumers' financial knowledge with "product-linked" financial education. We find that a modest financial education requirement decreases product (CBL) take-up by nearly 20 percentage points, even among our sample of consumers that had expressed interest in credit building generally and the CBL specifically. Second, providers should test various approaches to dealing with the

possibility that CBLs backfire for those with pre-existing debt. Possibilities include: screening out existing borrowers; offering or requiring a scaffolded approach that focuses first on timely repayment of existing obligations and then segues into another traditional loan or CBL; offering or requiring help with cash flow management; informing and/or reminding users that they need only part with \$54 for a few minutes on the payment due date, as \$50 of each payment is available to be returned to the customer upon demand.

Testing CBL design changes, together with testing whether our results replicate, offers exciting possibilities for revealing insights into fundamental aspects of consumer decision making. The differential effects we find for those with versus without pre-existing debt beg for particular scrutiny. Is coming up with a very short-term outlay of \$54 really so disruptive to customers with a pre-existing loan, and if so... why? And why don't consumers with a pre-existing loan anticipate this disruption and simply decline the CBL?

We suspect our results are best explained by a behavioral model with limited attention to future liquidity constraints and/or over-confidence about making future payments, or limited capacity to manage multiple tasks due to scarcity in time, effort, and/or attention. Perhaps such biases or limitations are more prevalent among those with pre-existing debt, or more binding for those with more claims on future cash flows or more logistical claims on their time and effort. Concepts of scarcity as put forward by Mullainathan and Shafir (2013) can lead to predictions of both negative treatment effects (e.g., lack of capacity to manage one more obligation) and positive treatment effects (e.g., via tunneling and thus hyper-attention to particularly salient tasks, see Kaur et al. (2019); Lichand et al. (2019); Lichand and Mani (2019)), and so a key challenge going forward is developing testable models that sharpen understanding of whether and how scarcity leads to better or worse decision making.

Altogether our results highlight some key questions for future research and policy/product development. For research, we need to better understand how to model the decision making of very resource-constrained consumers. For policy and product development, efforts to help households build stronger credit records need to consider how to target more effectively and how such efforts affect market efficiency as well as consumers.

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Data Appendix. Indices Creation

- A. Index Construction Rules
 - 1. Standardize each component with respect to the Extra Step Arm
 - 2. Calculate the person-level mean across non-missing components (if someone is missing all components their index value is missing).
 - 3. Standardize each index with respect to the Extra Step Arm.
- B. Index Components and Definitions

Insecurity index (4 components, higher values indicate more insecurity)

1. Q: "My financial situation is a source of stress in my life."

A: 1 = strongly disagree, 2= disagree, 3 = feel neutrally, 4= agree, 5 = strongly agree

2. Q: "In a typical month, it is difficult for me to cover my expenses and pay all my bills."

A: 1 = strongly disagree, 2= disagree, 3 = feel neutrally, 4= agree, 5 = strongly agree

3. Q: "I am confident that I could come up with \$2000 if an unexpected need arose within the next month"

A: 1 = strongly agree, 2= agree, 3 = feel neutrally, 4= disagree, 5 = strongly disagree

4. Q: "How would you describe your overall financial situation? Would you say..."

A: 1 = excellent, 2 = Very good, 3 = okay, 4 = not very good, 5 = bad

Lacks Self-Control index (5 components, higher values indicate less self-control)

1. Q: "Before I buy something I carefully consider whether I can afford it."

A: 1 = strongly agree, 2= agree, 3 = feel neutrally, 4= disagree, 5 = strongly disagree

2. Q: "I tend to live for today and let tomorrow take care of itself."

A: 1 = strongly disagree, 2= disagree, 3 = feel neutrally, 4= agree, 5 = strongly agree

3. Q: "I set long term financial goals of five years or more and strive to achieve them."

A: 1 = strongly agree, 2= agree, 3 = feel neutrally, 4= disagree, 5 = strongly disagree

4. Q: "I often find that I regret spending money. I wish that when I had cash, I was better disciplined and saved my money rather than spent it."

A: 1 = strongly disagree, 2= disagree, 3 = feel neutrally, 4= agree, 5 = strongly agree

5. Q: "I have trouble finishing or completing my tasks."

A: 1 = strongly disagree, 2= disagree, 3 = feel neutrally, 4= agree, 5 = strongly agree

Financial Risk Taking Scale (1 question, higher values indicate greater risk tolerance)

1. Q: "I am willing to take a risk financially if there is a chance of substantial gain."

A: 1 = strongly disagree, 2= disagree, 3 = feel neutrally, 4= agree, 5 = strongly agree

Attention to Credit Status (2 components, higher values indicate more attention)

1. Q: "In the past 12 months, have you checked your credit score?"

A: 0 = No, 1 = Yes

2. Q: "In the past 12 months, have you obtained a copy of your credit report?"

A: 0 = No, 1 = Yes

Credit Process Knowledge (5 components, higher values indicate more knowledge, correct responses in bold parens)

1. Correctly answered "Could your credit rating affect the amount of interest you would pay on a bank loan?" (Yes)

A: 0 = No, 1 = Yes

2. Correctly answered: "Could your health affect the amount of interest you would pay on a bank loan?" (No)

A: 0 = No, 1 = Yes

3. Correctly answered: "Could your age affect the amount of interest you would pay on a bank loan?" (No)

A: 0 = No, 1 = Yes

4. Correctly answered: "Could how much you borrow overall affect the amount of interest you would pay on a bank loan?" (Yes)

A: 0 = No, 1 = Yes

5. Correctly answered: "Could how long you take to repay the loan affect the amount of interest you would pay on a bank loan?" (**Yes**)

A: 0 = No, 1 = Yes

Lack of liquidity (3 components, first from SLCCU data, other two from survey; higher values indicate less liquidity)

- 1. 1/0 Savings at baseline is less than \$60
- 2. 1/0 income was below sample median at baseline
- 3. "Have you had difficulty getting approved for loans in the past three years? Would you say...", recorded at baseline

0 = No, 1 = Yes, 2 = you have not tried to get approved for a loan

New Credit (2 components; higher values indicate more new credit)

- 1. Number of inquiries made in the last 12 months (bureau data)
- 2. The number of accounts (bureau data)

Amounts Owed: Balances (3 components, all from credit bureau data; higher values indicate more amounts owed)

- 1. Outstanding revolving loan balance
- 2. Outstanding installment loan balance
- 3. Outstanding auto loan balance

Amounts Owed: Utilization (5 components, all from credit bureau data; higher values indicate more utilization)

- 1. 1/0 revolving utilization is over 30% (missing if no credit line)
- 2. The number of open installment loans
- 3. 1/0 outstanding revolving loan balance
- 4. 1/0 outstanding auto loan balance
- 5. 1/0 outstanding installment loan balance

Credit Mix (1 component, comes from credit bureau data; higher values indicate more credit types open)

1. 1/0 has an open installment loan and an open revolving loan

Payment History/Default (as used in tables 5 and 8 and figure 4; 10 components, all from credit bureau data; higher values indicate more default, delinquency, collection activity on accounts)

- 1. 1/0 Has account 30 days past due in the last 12 months
- 2. 1/0 Has account 90 days past due in the last 12 months
- 3. 1/0 Has account in collection
- 4. 1/0 Has amount past due
- 5. 1/0 Has account with a major derogatory event
- 6. Number of accounts 30 days past due in the last 12 months
- 7. Number of accounts 90 days past due in the last 12 months
- 8. Number of accounts in collection
- 9. Amount past due
- 10. Number of accounts with a major derogatory event

SLCCU Deposit Index (as used in table 6; 3 components, all from credit bureau data; higher values indicate more SLCCU activity)

- 1. 1/0 Made a deposit
- 2. Balance of total deposits
- 3. 1/0 Individual remains an SLCCU member

	(1)	(2)	(3)
	Mea	n (SD)	Univariate diff:
C1	CBL Arm	Extra Step Arm	(2) - (1)
Sample	e: N=789	N=742	(SE)
Panel A. Baseline Survey Variables			
Missing Baseline Survey	0.015	0.020	-0.005
	(0.122)	(0.141)	(0.007)
Age	42.475	43.823	-1.348
	(15.328)	(15.056)	(0.777)
Female	0.655	0.642	0.014
	(0.476)	(0.480)	(0.024)
Married	0.229	0.241	-0.012
	(0.421)	(0.428)	(0.022)
# Adults in HH	1.629	1.611	0.019
	(0.791)	(0.788)	(0.041)
# Children in HH	0.807	0.845	-0.038
	(1.229)	(1.237)	(0.064)
Race - Black	0.883	0.875	0.008
	(0.322)	(0.331)	(0.017)
HH Income < \$30K	0.606	0.625	-0.020
	(0.489)	(0.484)	(0.025)
College or more	0.253	0.264	-0.011
	(0.435)	(0.441)	(0.023)
Financial Insecurity index (standardized)	-0.002	0.000	-0.002
	(0.951)	(1.000)	(0.050)
Lacks Self-Control index (standardized)	-0.009	0.000	-0.009
	(0.980)	(1.000)	(0.051)
Financial Risk-Taking scale (standardized)	0.039	0.000	0.039
-	(1.008)	(1.000)	(0.052)
Attention to Credit Status index (standardized)	0.042	0.000	0.042
	(1.012)	(1.000)	(0.052)
Credit Process Knowledge index (standardized)	0.047	0.000	0.047
	(0.961)	(1.000)	(0.051)
Panel B. Baseline SLCCU Variables			
1 = Remain an SLCCU member	1.000	1.000	0.000
	(0.000)	(0.000)	(0.000)
1 = Any non-CBL loan with SLCCU outstanding	0.313	0.322	-0.009
	(0.464)	(0.468)	(0.024)
Savings Balance (\$ hundreds)	2.645	4.987	-2.342
,	(10.507)	(30.668)	(1.158)
Savings and Checkings Balance (\$ hundreds)	5.512	7.435	-1.923
	(30.418)	(41.080)	(1.840)

Table 1. Baseline Characteristics and Randomization Balance for Experiment Sample

		(1)	(2)	(3)
		Mear	n (SD)	Univariate dif
	Sample	CBL Arm	Extra Step Arm	(2) - (1)
	Sample:	N=789	N=742	(SE)
Panel C. Baseline Credit Report Variables				
Missing Credit Report		0.022	0.016	0.005
		(0.145)	(0.126)	(0.007)
1 = Has FICO® Score 8		0.809	0.840	-0.031
		(0.394)	(0.367)	(0.020)
1 = (Has FICO [®] Score 8 and No loan at baseline)		0.358	0.457	-0.100
		(0.480)	(0.500)	(0.049)
1 = (Has FICO [®] Score 8 and 1 loan at baseline)		0.960	0.933	0.027
		(0.196)	(0.251)	(0.028)
$1 = (\text{Has FICO} \otimes \text{Score } 8 \text{ and } > 1 \text{ loan at baseline})$		0.995	0.985	0.010
· · · ·		(0.068)	(0.121)	(0.007)
FICO® Score 8 (100s) Has score		5.643	5.615	0.028
		(0.667)	(0.643)	(0.037)
FICO® Score 8 (100s) and No loan at baseline Has score		5.002	4.995	0.007
		(0.405)	(0.364)	(0.060)
FICO® Score 8 (100s) and 1 loan at baseline Has score		5.476	5.552	-0.077
		(0.534)	(0.555)	(0.069)
FICO® Score 8 (100s) and >1 loan at baseline Has score		5.807	5.767	0.040
		(0.658)	(0.633)	(0.045)
1 = Any Loan Open at Baseline		0.718	0.742	-0.025
		(0.450)	(0.438)	(0.023)
1 = Installment Loan Open at Baseline		0.605	0.636	-0.031
1 I		(0.489)	(0.482)	(0.025)
Amounts Owed: Balances index (standardized)		0.048	0.000	0.048
		(1.206)	(1.000)	(0.061)
Amounts Owed: Utilization index (standardized)		-0.030	0.000	-0.030
		(0.992)	(1.000)	(0.051)
Credit Mix scale (standardized)		-0.028	0.000	-0.028
()		(0.992)	(1.000)	(0.051)
Default index (standardized)		-0.074	0.000	-0.074
		(0.925)	(1.000)	(0.050)
New Credit index (standardized)		0.011	0.000	0.011
((1.036)	(1.000)	(0.052)
Panel D. Baseline Combined Survey and SLCCU Variables		(1.000)	(1.000)	(0.002)
Lack of Liquidity index (standardized)		-0.030	0.000	-0.030
		(1.013)	(1.000)	(0.051)

Unit of observation is an individual. Standard errors, in parenthesis in column (3), are Huber-White. Index variables are standardized to be mean zero and standard deviation one in the Extra Step Arm; see Data Appendix for details on index components and construction. Sample size varies across rows due to missing observations.

Table	e 2. Tra	nsition	Matrix for Ha	ving a Credit Score	9		
		(1)	(2)	(3)	(4)	(5)	(6)
			CBI	L Arm		Extra S	tep Arm
			Have score at	Didn't have		Have score at	Didn't have
			18-month	score at 18-		18-month	score at 18-
		N=	endline	month endline	N=	endline	month endline
Panel A. Full Sample							
	N=		668	91		632	85
Have score at baseline		622	96.95%	3.05%	609	95.07%	4.93%
Didn't have score at baseline		137	47.45%	52.55%	108	49.07%	50.93%
Panel B. Sample that had no loan at baseline							
	N=		128	80		104	76
Have score at baseline		78	87.18%	12.82%	86	74.42%	25.58%
Didn't have score at baseline		130	46.15%	53.85%	94	42.55%	57.45%
Panel C. Sample that had any loan at baseline							
	N=		540	11		528	9
Have score at baseline		544	98.35%	1.65%	523	98.47%	1.53%
Didn't have score at baseline		7	71.43%	28.57%	14	92.86%	7.14%

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Unit of observation is an individual. Sample here is limited to persons with a credit report at our 18-month endline.

		(1)	(2)	(3)	(4)	(5)	(6)	(7) Non-experimenta
				Experimen	t Sample			Sample Uninterested
			Full		Hav	e score at bas	eline	in CBL
		CBL	Extra Step	Difference	CBL	Extra Step		
Panel A: Take-up Rates = First-Stage for the Experiment Samp	le	Arm	Arm	(SE)	Arm	Arm	(SE)	
All	ic	0.299	0.118	0.181	0.306	0.108	0.198	0.043
All	N=	772	730	(0.021)	625	613	(0.022)	719
No loan open at baseline (1)	N=	0.303 218	0.101 188	0.202 (0.038)	0.372 78	0.058 86	0.314 (0.060)	0.055 128
Any loan open at baseline (2)	N=	0.298 554	0.124 542	0.174 (0.024)	0.296 547	0.116 527	0.180 (0.024)	0.041 591
Diff-in-Diffs (2) - (1)	14	551	512	-0.027 (0.045)	517	521	-0.133 (0.065)	571
No installment loan open at baseline (3)	N=	0.282 305	0.109 266	0.173 (0.032)	0.296 162	0.081 160	0.215 (0.042)	0.041 245
Installment loan open at baseline (4)	N=	0.310 467	0.123 464	0.188 (0.026)	0.309 463	0.117 453	0.192 (0.026)	0.044 474
Diff-in-Diffs (4) - (3)				0.015 (0.042)			-0.023 (0.050)	
Panel B: Delinquency Rates, Conditional on Take-up								
All	N=	0.416 231	0.302 86	0.113 (0.061)	0.403 191	0.303 66	0.100 (0.069)	0.387 31
No loan open at baseline (5)	N=	$\begin{array}{c} 0.470\\ 66\end{array}$	0.368 19	0.101 (0.127)	0.517 29	0.600 5	-0.083 (0.240)	0.429 7
Any loan open at baseline (6)	N=	0.394 165	0.284 67	0.110 (0.067)	0.383 162	0.279 61	0.104 (0.069)	0.375 24
Diff-in-Diffs (6) - (5)				0.009 (0.144)			0.187 (0.250)	
No installment loan open at baseline (7)	N=	0.465 86	0.379 29	0.086 (0.106)	0.479 48	0.538 13	-0.059 (0.157)	0.400 10
Installment loan open at baseline (8)	N=	0.386 145	0.263 57	0.123 (0.071)	0.378 143	0.245 53	0.132 (0.072)	0.381 21
Diff-in-Diffs (8) - (7)				0.037 (0.127)			0.192 (0.173)	

Unit of observation is an individual. Standard errors, in parenthesis in columns (3) and (6), are Huber-White. We include the Uninterested individuals for descriptive purposes; this group is not part of the experimental sample frame and thus not in the treatment effect analysis. Delinquency is the proportion of CBL users with any CBL payment >30 days late in the prior 18 months per the credit union's data, calculated 18 months after the start of the experiment.

mun Eneces and Neterogeneny	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	1 = Ha	s FICO® S	Score 8	FI	CO® Scor	e 8
Sample:		Full		Have	score at ba	aseline
CBL Arm * Post	0.018			-1.888		
	(0.015)			(2.730)		
CBL Arm * Post * 1 = No Loan Open at Baseline (i)		0.102			8.861	
		(0.045)			(6.665)	
CBL Arm * Post * 1 = Any Loan Open at Baseline (ii)		-0.016			-3.183	
		(0.010)			(2.903)	
CBL Arm * Post * 1 = No Installment Loan Open at Baseline (iii)			0.068			7.822
			(0.035)			(5.554)
CBL Arm * Post * 1 = Installment Loan Open at Baseline (iv)			-0.016			-5.268
			(0.010)			(3.079)
P-value of (i) = (ii) or (iii) = (iv)		0.011	0.021		0.098	0.039
Observations	5966	5966	5966	4865	4865	4865
Individuals	1502	1502	1502	1238	1238	1238
Mean Dependent Variable in Extra Step Arm at Baseline	0.840	0.840	0.840	561	561	561

Table 4. CBL Treatment Effects on Credit Score and on Likelihood of Having a Credit Score: Main Effects and Heterogeneity by Baseline Borrowing Status

Unit of observation is a person-credit report, with four observations for most persons: baseline, and three endlines at 6, 12, and 18 months post-treatment assignment, all three of which are included in the *Post* indicator for the experiment period. Number of observations is lower than the number of individuals x 4 credit reports, because a small number of credit reports lack information on one or more dependent variables, including whether the person is scored. Standard errors, in parentheses, are clustered at the person-level. Each column presents results from a single OLS regression of the dependent variable described in the column heading on the variables shown in the rows, *Post* + *No* (*Installment*) *Loan at Baseline* where appropriate, and person fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:		= Has FIC					Score 8	
Sample		Fi	ull]	Have score	at baselin	e
CBL Arm * Post * 1 = No Loan Open at Baseline (i)	0.102	0.094			8.861	7.729		
	(0.045)	(0.044)			(6.665)	(6.527)		
CBL Arm * Post * 1 = Any Loan Open at Baseline (ii)	-0.016	-0.018			-3.183	-1.732		
	(0.010)	(0.010)			(2.903)	(2.793)		
CBL Arm * Post * 1 = No Installment Loan Open at Baseline (iii)			0.068	0.060			7.822	8.808
			(0.035)	(0.034)			(5.554)	(5.197)
CBL Arm * Post * 1 = Installment Loan Open at Baseline (iv)			-0.016	-0.017			-5.268	-4.088
			(0.010)	(0.010)			(3.079)	(2.962)
Control for baseline variables * Post (see notes)	No	Yes	No	Yes	No	Yes	No	Yes
P-value of $(i) = (ii)$ or $(iii) = (iv)$	0.011	0.014	0.021	0.032	0.098	0.183	0.039	0.031
Observations	5966	5966	5966	5966	4865	4865	4865	4865
Individuals	1502	1502	1502	1502	1238	1238	1238	1238
Mean Dependent Variable in Extra Step Arm at Baseline	0.840	0.840	0.840	0.840	561	561	561	561

Table 5. Is CBL Treatment Effect Heterogeneity on Scores Driven by Baseline Borrowing per se, or by Mediators Correlated with Baseline Borrowing?

Unit of observation is a person-credit report, with four observations for most persons: baseline, and three endlines at 6, 12, and 18 months post-treatment assignment, all three of which are included in the *Post* indicator for the experiment period. Number of observations is lower than the number of individuals x 4 credit reports, because a small number of credit reports lack information on one or more dependent variables, including whether the person is scored. Standard errors, in parentheses, are clustered at the person-level. Each column presents results from a single OLS regression of the dependent variable described in the column heading on the variables shown in the rows, *Post* * *No* (*Installment*) *Loan at Baseline*, and person fixed effects. Index variables are standardized to be mean zero and standard deviation one in the Extra Step Arm at baseline; see Data Appendix for details on index components and construction. Even-numbered columns include controls for *Post* interacted with baseline variables chosen by the post-double selection lasso. All the even columns include *Post* interacted with these 13 variables: 1 = < 26 years old, female, married, # adults in HH, race-black, HH Income < \$30K, college educated, 1 = any non-CBL loan with SLCCU outstanding, savings balance (hundreds), amounts owed: utilization index, credit mix scale, default index, and new credit index. In addition to the 13 common variables, column (2) includes Post interacted with: # children in HH, attention to credit status index, and lack of liquidity index; column (6) includes Post interacted with: amounts owed: balances index and lack of liquidity index. We also include missing dummy variables for all control covariates so that missing observations would not be excluded.

	(1)	(2)	(3)	(4)	(5)	(6)
FICO® Score 8 Factor	New Credit	Paymer	nt History	Amou	nts Owed	Credit Mix
Dependent variable index includes	Inquiries, Number of Accounts	10 measures of delinquency, collections & derogatories (higher values = less timely repmt). Includes CBL delinquency.	8 measures of serious , delinquency, collections, & derogatories (higher values = less timely repmt). Excludes CBL delinquency.	Balances: Revolving, Auto loans, Other Installment	Utilization: 4 discrete measures of credit limit usage and outstanding balances; # open installment loans	1=(open installment and open revolving loan)
Sample			F	full		
Panel A. Heterogeneity by Baseline Borrowing Status						
CBL Arm * Post * 1 = No Loan Open at Baseline (i)	0.027	0.031	-0.018	0.096	0.133	0.066
	(0.055)	(0.069)	(0.073)	(0.078)	(0.068)	(0.045)
CBL Arm * Post * 1 = Any Loan Open at Baseline (ii)	-0.009	0.100	0.081	-0.090	-0.058	-0.069
	(0.045)	(0.048)	(0.043)	(0.046)	(0.050)	(0.056)
P-value of $(i) = (ii)$	0.618	0.405	0.240	0.040	0.024	0.061
Panel B. Heterogeneity by Baseline Installment Loan Status						
CBL Arm * Post * 1 = No Installment Loan Open at Baseline (iii)	0.005	0.003	-0.038	-0.036	0.080	0.097
•	(0.046)	(0.057)	(0.059)	(0.087)	(0.065)	(0.056)
CBL Arm * Post * 1 = Installment Loan Open at Baseline (iv)	-0.005	0.130	0.111	-0.068	-0.060	-0.122
• • • • •	(0.051)	(0.053)	(0.047)	(0.044)	(0.053)	(0.059)
P-value of (iii) = (iv)	0.883	0.103	0.047	0.740	0.098	0.007
Observations	5970	5970	5970	5482	5970	5970
Individuals	1502	1502	1502	1423	1502	1502
Mean Dependent Variable in Extra Step Arm at Baseline	0.000	0.000	0.000	0.000	0.000	0.000

Table 6. Is CBL Treatment Effect Heterogeneity by Baseline Borrowing Status Driven by Credit Behaviors?

Unit of observation is a person-credit report, with four observations for most persons: baseline, and three endlines at 6, 12, and 18 months post-treatment assignment, all three of which are included in the *Post* indicator for the experiment period. Standard errors, in parentheses, are clustered at the person-level. Each panel-column presents results from a single OLS regression of the dependent variable described in the column heading on the variables shown in the rows, *Post*, *Post* * *No* (*Installment*) *Loan at Baseline*, and person fixed effects. *Payment History* in column 2 is equivalent to the default index used in Tables 1 and 9 but is called Payment History here to be consistent with how FICO labels its score factors. Column 3 excludes 30-day delinquency measures and hence excludes CBL delinquencies, which never reach serious delinquency status by design: CBLs that are more than 30 days late are repaid using the remaining balance in the escrow account and then closed. Number of observations is lower than the number of individuals x 4 credit reports, because some credit reports lack information on one or more dependent variables. Index variables are standardized to be mean zero and standard deviation one in the Extra Step Arm at baseline; see Data Appendix for details on index components and construction.

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variab	le:	1 = Remain an SLCCU member		1 = Any non-CBL loan with SLCCU outstanding		Balances of all savings accounts (\$ hundreds)		all savings + accounts ndreds)
Sampl	e:				Full			
CBL Arm * Post	-0.008		0.011		2.533		1.322	
	(0.011)		(0.019)		(1.236)		(1.701)	
CBL Arm * Post * 1 = No Loan Open at Baseline (i)		-0.001		0.048		0.043		0.012
		(0.027)		(0.029)		(1.453)		(1.581)
CBL Arm * Post * 1 = Any Loan Open at Baseline (ii)		-0.010		-0.005		3.469		1.825
		(0.012)		(0.024)		(1.607)		(2.273)
P-value of $(i) = (ii)$		0.760		0.159		0.114		0.513
Observations	6008	6008	6008	6008	6008	6008	6008	6008
Individuals	1502	1502	1502	1502	1502	1502	1502	1502
Mean Dependent Variable in Extra Step Arm at Baseline	1.000	1.000	0.327	0.327	5.040	5.040	7.536	7.536

 Table 7. CBL treatment effects on usage of other SLCCU products:

 Main Effects and Heterogeneity by Baseline Borrowing Status

Unit of observation is a person-credit report, with four observations for most persons: baseline, and three endlines at 6, 12, and 18 months post-treatment assignment, all three of which are included in the *Post* indicator for the experiment period. Standard errors, in parentheses, are clustered at the person-level. Each column presents results from a single OLS regression of the dependent variable described in the column heading on the variables shown in the rows, *Post* * *No Loan Open at Baseline* where appropriate, and person fixed effects. All outcome variables are calculated from SLCCU administrative data. Balances are recorded as zero for those who leave the credit union.

Table 8. Selection into C	BL				
	(1)	(2)	(3)	(4)	
Dependent variable:	1 = Has FICO® Score 8		FICO®	Score 8	
Sample:	Full Cl	BL Arm	CBL Arm participants that have score at baseline		
Panel A. Main Effects Tookup CBL * Post	0.126 (0.023)	0.188 (0.028)	14.999 (3.987)	13.817 (4.273)	
Panel B. Heterogeneity by Baseline Borrowing Status Tookup CBL * Post * 1 = No Loan Open at Baseline (i)	0.400 (0.060)	0.441 (0.055)	60.027 (5.780)	42.801 (6.946)	
Tookup CBL * Post * 1 = Any Loan Open at Baseline (ii)	0.016 (0.011)	0.066 (0.016)	7.000 (4.185)	8.976 (4.526)	
P-value of (i) = (ii)	0.000	0.000	0.000	0.000	
Panel C. Heterogeneity by Baseline Installment Loan Status Tookup CBL * Post * 1 = No Installment Loan Open at Baseline (iii)	0.318 (0.052)	0.365 (0.049)	45.833 (6.094)	35.458 (6.354)	
Tookup CBL * Post * 1 = Installment Loan Open at Baseline (iv)	0.011 (0.010)	0.067 (0.014)	4.697 (4.496)	6.910 (4.778)	
P-value of (iii) = (iv)	0.000	0.000	0.000	0.000	
Controls for baseline variables * Post Number of people in sample that took up a CBL Observations	No 231 3065	Yes 231 3065	No 191 2466	Yes 191 2466	
Individuals Mean Dependent Variable in CBL Arm at Baseline	772 0.810	772 0.810	625 564	625 564	

Unit of observation is a person-credit report, with four observations for most persons: baseline, and three endlines at 6, 12, and 18 months post-treatment assignment, all three of which are included in *Post* indicator for the experiment period. Standard errors, in parentheses, are clustered at the person-level. Each panel-column presents results from a single OLS regression of the dependent variable described in the column heading on the variables shown in the panel-rows, *Post*, *Post* * *No* (*Installment*) *Loan Open at Baseline* where applicable, and person fixed effects. Heterogeneous treatment effects by baseline borrowing status (Tables 4-7) imply that we cannot identify a pure selection effect separately for those sub-groups, but we present results for those groups, in panels B and C, for completeness. Even-numbered columns in all three panels include *Post* interacted with: *baseline FICO*® *Score* 8, *1 = baseline FICO*® *Score* 8 in the 400s, and *1 = baseline FICO*® *Score* 8 in the 500s. Even-numbered columns in panels B and C as well as column (4) in panel A also include *Post* interacted with *1 = baseline FICO*® *Score* 8 in the 600s. Control variables chosen by post-double selection Lasso.

	0	(1)	(2)	(3)
Deper	ndent variable:	Standa	rdized Index of Default O (18 month endline)	utcomes
	Sample:		Have score at baseline	
FICO® Score 8 (hundreds) 12 month endline * CBL Arm (i)		-0.822		
		(0.051)		
FICO® Score 8 (hundreds) 12 month endline * Extra Step Arm (ii)		-0.831		
		(0.051)		
FICO® Score 8 (hundreds) 12 month endline * CBL Arm * No Loan at Baseline (iii)			-0.891	
			(0.050)	
FICO® Score 8 (hundreds) 12 month endline * Extra Step Arm * No Loan at Baseline (iv)			-0.917	
			(0.053)	
FICO® Score 8 (hundreds) 12 month endline * CBL Arm * Any Loan at Baseline (v)			-0.776	
			(0.051)	
FICO® Score 8 (hundreds) 12 month endline * Extra Step Arm * Any Loan at Baseline (vi)			-0.782	
			(0.050)	
FICO® Score 8 (hundreds) 12 month endline * CBL Arm * No Installment Loan at Baseline (vii)				-0.857
				(0.050)
FICO® Score 8 (hundreds) 12 month endline * Extra Step Arm * No Installment Loan at Baseline	(viii)			-0.863
				(0.051)
FICO® Score 8 (hundreds) 12 month endline * CBL Arm * Installment Loan at Baseline (ix)				-0.770
				(0.050)
FICO® Score 8 (hundreds) 12 month endline * Extra Step Arm * Installment Loan at Baseline (x)				-0.782
				(0.050)
P-value of $(i) = (ii)$		0.255		
P-value of (ii) = (iv) P-value of (iii) = (iv)		0.200	0.224	
P-value of $(w) = (w)$ P-value of $(v) = (v)$			0.402	
P-value of $(vi) = (vii)$				0.674
P-value of $(ix) = (x)$				0.170
Observations		1217	1217	1217
Mean Dependent Variable in Extra Step Arm		0.066	0.066	0.066

Table 9. Do CBLs Change the Predictive Power of Credit Scores?Testing for differences in the default-score gradient

Unit of observation is a person. Standard errors, in parenthesis, are Huber-White. Each column presents results from a single OLS regression of the dependent variable described in the column heading on the variables shown in the rows and FICO® Score 8 at baseline. Index variables are standardized to be mean zero and standard deviation one in the Extra Step Arm at baseline; see Data Appendix for details on index components and construction. Sample here is limited to persons for whom we could obtain a credit report at our 18-month endline and who have a credit score at baseline and the 12-month endline.

Figure 1. CBL Marketing Materials



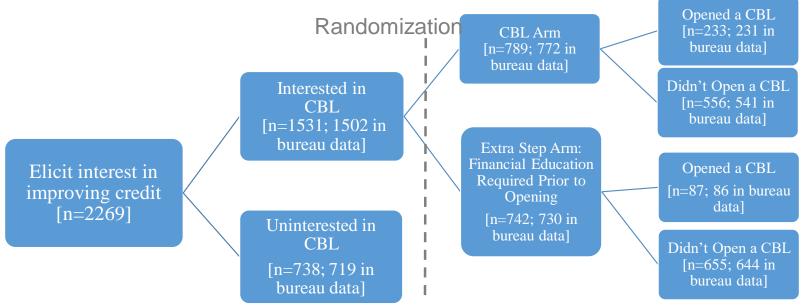
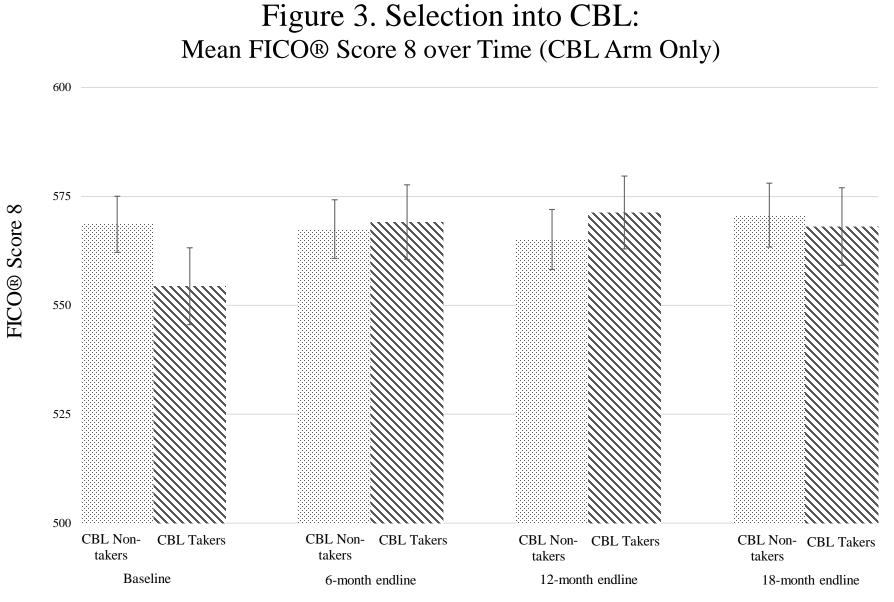


Figure 2. Sample Construction and Experimental Design

Note: "CBL"= Credit Builder Loan. Sample sizes include only those matched to the credit union's administrative data and hence inferred to be a credit union member at baseline. The sample sizes shown to be "in bureau data" are those in the study sample whom we were able to match to a credit report at baseline.



Note: The error bars show the 95% confidence intervals.

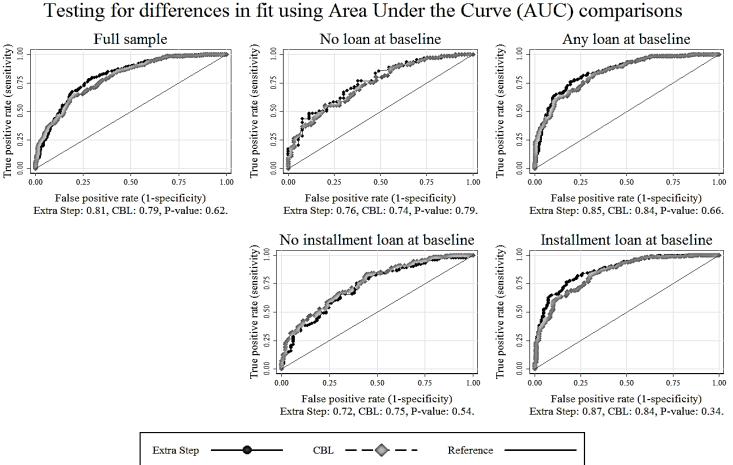


Figure 4.Do CBLs change credit scores' predictive power?

Note: Each graph shows receiver operating characteristic (ROC) curves used to assess credit score accuracy. We use each 12-month endline credit score as a cutoff to classify those with lower scores as more-risky and those above as less-risky; this jibes with what credit scores are constructed to do, which is to predict default ordinally. We then compare this classification with the 18-month endline discretized default index.- ROCs require a discrete classification of the outcome to be predicted, so we discretize our 18-month endline default index (see Data Appendix for details) at the median index value, with higher values indicating more default-- to calculate the true and false positive rates. The true positive rate, on the y-axis, is (number of people correctly classified as more-risky at 12 months)/ (number of observed more-risky people at 18 months). The false positive rate, on the x-axis, is (number of people incorrectly classified as more-risky at 12 months)/(number of observed less-risky people at 18 months). The false positive rate, on the x-axis, is (number of people incorrectly classified as more-risky at 12 months)/(number of observed less-risky people at 18 months). The areas under the curve (AUCs) for the Extra Step and CBL Arms are shown below each graph along with the p-value of a chi-squared test of their equality (Delong, Delong, Clarke-Pearson 1988). The Reference (45-degree) line shows a ROC with no predictive power.

	(1)	(2)	(3)
	Mea	an (SD)	Univariate diff:
Samp	CBL Arm	Extra Step Arm	(2) - (1)
· · · · · · · · · · · · · · · · · · ·	N=554	N=542	(SE)
Panel A. Baseline Survey Variables			
Missing Baseline Survey	0.016	0.018	-0.002
	(0.127)	(0.135)	(0.008)
Age	44.170	44.810	-0.640
	(15.173)	(15.091)	(0.914)
Female	0.677	0.677	-0.000
	(0.468)	(0.468)	(0.028)
Married	0.250	0.278	-0.028
	(0.433)	(0.448)	(0.027)
# Adults in HH	1.607	1.607	0.000
	(0.757)	(0.797)	(0.047)
# Children in HH	0.733	0.846	-0.112
	(1.119)	(1.238)	(0.072)
Race - Black	0.888	0.870	0.018
	(0.316)	(0.336)	(0.020)
HH Income < \$30K	0.542	0.559	-0.018
	(0.499)	(0.497)	(0.030)
College or more	0.303	0.318	-0.014
-	(0.460)	(0.466)	(0.028)
Financial Insecurity index (standardized)	-0.000	0.021	-0.022
	(0.953)	(1.021)	(0.060)
Lacks Self-Control index (standardized)	-0.032	0.054	-0.085
	(1.012)	(1.000)	(0.061)
Financial Risk-Taking scale (standardized)	0.068	-0.023	0.091
	(1.010)	(0.989)	(0.061)
Attention to Credit Status index (standardized)	0.198	0.155	0.043
	(1.040)	(1.019)	(0.063)
Credit Process Knowledge index (standardized)	0.120	0.047	0.073
e ()	(0.875)	(0.959)	(0.056)
Panel B. Baseline SLCCU Variables	``'	× /	、
1 = Remain an SLCCU member	1.000	1.000	0.000
	(0.000)	(0.000)	(0.000)
1 = Any non-CBL loan with SLCCU outstanding	0.431	0.441	-0.010
. 6	(0.496)	(0.497)	(0.030)
Savings Balance (\$ hundreds)	3.152	5.997	-2.844
	(10.990)	(34.490)	(1.539)
Savings and Checkings Balance (\$ hundreds)	6.723	8.968	-2.245
	(35.570)	(46.911)	(2.511)

Appendix Table 1a. Baseline characteristics for subsample with at least one loan at baseline (Same as Table 1 but sample here is only those with a loan at baseline)

		(1)	(2)	(3)
		Mea	n (SD)	Univariate diff
	Sample:	CBL Arm N=554	Extra Step Arm N=542	(2) - (1) (SE)
Panel C. Baseline Credit Report Variables				
$1 = \text{Has FICO} \ \mathbb{R}$ Score 8		0.987	0.972	0.015
		(0.112)	(0.164)	(0.008)
1 = (Has FICO® Score 8 and 1 loan at baseline)		0.960	0.933	0.027
		(0.196)	(0.251)	(0.028)
1 = (Has FICO® Score 8 and >1 loan at baseline)		0.995	0.985	0.010
		(0.068)	(0.121)	(0.007)
FICO® Score 8 (100s) Has score		5.734	5.716	0.018
		(0.647)	(0.622)	(0.039)
FICO® Score 8 (100s) and 1 loan at baseline Has score		5.476	5.552	-0.077
		(0.534)	(0.555)	(0.069)
FICO® Score 8 (100s) and >1 loan at baseline Has score		5.807	5.767	0.040
		(0.658)	(0.633)	(0.045)
Amounts Owed: Balances index (standardized)		0.202	0.133	0.069
		(1.261)	(1.030)	(0.070)
Amounts Owed: Utilization index (standardized)		0.287	0.285	0.002
		(0.949)	(0.950)	(0.057)
Credit Mix scale (standardized)		0.262	0.266	-0.004
		(1.036)	(1.036)	(0.063)
Default index (standardized)		0.061	0.121	-0.060
		(0.947)	(1.023)	(0.060)
New Credit index (standardized)		0.251	0.235	0.016
· · · ·		(1.096)	(1.050)	(0.065)
Panel D. Baseline Combined Survey and SLCCU Variables				
Lack of Liquidity index (standardized)		-0.176	-0.115	-0.061
		(1.027)	(1.010)	(0.062)

Unit of observation is an individual. Index variables are standardized to be mean zero and standard deviation one in the Extra Step Arm; see Data Appendix for details on index components and construction. Sample size varies across rows due to missing observations. Further, we restricted the table to only those individuals that had at least one loan at baseline.

		(1)	(2)	(3)
		Mea	an (SD)	Univariate diff
	Sample:	CBL Arm	Extra Step Arm	(2) - (1)
	Sample.	N=218	N=188	(SE)
Panel A. Baseline Survey Variables				
Missing Baseline Survey		0.009	0.027	-0.017
		(0.096)	(0.161)	(0.013)
Age		38.872	41.367	-2.495
		(14.813)	(14.656)	(1.467)
Female		0.596	0.548	0.048
		(0.492)	(0.499)	(0.049)
Married		0.171	0.132	0.039
		(0.378)	(0.339)	(0.036)
# Adults in HH		1.662	1.617	0.045
		(0.864)	(0.760)	(0.082)
# Children in HH		0.968	0.809	0.159
		(1.392)	(1.219)	(0.132)
Race - Black		0.875	0.885	-0.010
		(0.331)	(0.320)	(0.033)
HH Income < \$30K		0.780	0.809	-0.029
		(0.415)	(0.395)	(0.040)
College or more		0.121	0.120	0.001
c		(0.327)	(0.326)	(0.033)
Financial Insecurity index (standardized)		-0.009	-0.065	0.056
		(0.942)	(0.938)	(0.095)
Lacks Self-Control index (standardized)		0.047	-0.138	0.185
		(0.904)	(1.001)	(0.095)
Financial Risk-Taking scale (standardized)		-0.059	0.068	-0.126
8		(1.012)	(1.039)	(0.104)
Attention to Credit Status index (standardized)		-0.342	-0.410	0.067
()		(0.819)	(0.816)	(0.082)
Credit Process Knowledge index (standardized)		-0.110	-0.110	0.001
		(1.136)	(1.081)	(0.112)
Panel B. Baseline SLCCU Variables		()	()	()
1 = Remain an SLCCU member		1.000	1.000	0.000
		(0.000)	(0.000)	(0.000)
Savings Balance (\$ hundreds)		1.521	2.281	-0.760
		(9.525)	(16.525)	(1.317)
Savings and Checkings Balance (\$ hundreds)		2.770	3.408	-0.638
Surmas and chockings bulance (@ numereds)		(11.069)	(17.119)	(1.413)

Appendix Table 1b. Baseline characteristics for subsample with no loan at baseline (Same as Table 1 but sample here is only those with no loan at baseline)

Credit Building or Credit Crumbling?

		(1)	(2)	(3)
		Mea	Univariate diff:	
	Sample:	CBL Arm N=218	Extra Step Arm N=188	(2) - (1) (SE)
Panel C. Baseline Credit Report Variables				
$1 = \text{Has FICO} \ \mathbb{R}$ Score 8		0.358	0.457	-0.100
		(0.480)	(0.500)	(0.049)
FICO® Score 8 (100s) Has score		5.002	4.995	0.007
		(0.405)	(0.364)	(0.060)
Amounts Owed: Balances index (standardized)		-0.717	-0.639	-0.078
		(0.292)	(0.464)	(0.052)
Amounts Owed: Utilization index (standardized)		-0.838	-0.822	-0.016
		(0.535)	(0.610)	(0.057)
Credit Mix scale (standardized)		-0.766	-0.766	0.000
		(0.000)	(0.000)	(0.000)
Default index (standardized)		-0.415	-0.347	-0.067
		(0.769)	(0.841)	(0.080)
New Credit index (standardized)		-0.584	-0.626	0.042
		(0.434)	(0.423)	(0.043)
Panel D. Baseline Combined Survey and SLCCU Variables				
Lack of Liquidity index (standardized)		0.332	0.309	0.023
		(0.899)	(0.907)	(0.090)

Unit of observation is an individual. Index variables are standardized to be mean zero and standard deviation one in the Extra Step Arm; see Data Appendix for details on index components and construction. Sample size varies across rows due to missing observations. Further, we restricted the table to only those individuals that had no loan at baseline.

		(1)	(2)	(3)
	_		n (SD)	Univariate dif
	Sample:	CBL Arm	Extra Step Arm	(2) - (1)
	Sample.	N=467	N=464	(SE)
Panel A. Baseline Survey Variables				
Missing Baseline Survey		0.019	0.019	-0.000
		(0.138)	(0.138)	(0.009)
Age		43.343	44.616	-1.274
		(15.023)	(15.198)	(0.990)
Female		0.687	0.694	-0.007
		(0.464)	(0.461)	(0.030)
Married		0.258	0.288	-0.030
		(0.438)	(0.453)	(0.030)
# Adults in HH		1.627	1.571	0.055
		(0.759)	(0.702)	(0.048)
# Children in HH		0.747	0.901	-0.154
		(1.131)	(1.286)	(0.080)
Race - Black		0.897	0.877	0.020
		(0.304)	(0.329)	(0.021)
HH Income < \$30K		0.507	0.541	-0.033
		(0.500)	(0.499)	(0.033)
College or more		0.330	0.334	-0.004
C C		(0.471)	(0.472)	(0.031)
Financial Insecurity index (standardized)		0.002	0.028	-0.026
· · · · · ·		(0.958)	(0.995)	(0.065)
Lacks Self-Control index (standardized)		-0.032	0.054	-0.087
		(1.019)	(0.976)	(0.066)
Financial Risk-Taking scale (standardized)		0.096	-0.005	0.102
		(1.025)	(0.993)	(0.067)
Attention to Credit Status index (standardized)		0.237	0.171	0.067
		(1.048)	(1.022)	(0.069)
Credit Process Knowledge index (standardized)		0.127	0.065	0.062
6 ()		(0.901)	(0.921)	(0.060)
Panel B. Baseline SLCCU Variables		()		· · · · ·
1 = Remain an SLCCU member		1.000	1.000	0.000
		(0.000)	(0.000)	(0.000)
1 = Any non-CBL loan with SLCCU outstanding		0.415	0.418	-0.003
,		(0.493)	(0.494)	(0.032)
Savings Balance (\$ hundreds)		3.011	5.938	-2.927
		(9.252)	(35.990)	(1.720)
Savings and Checkings Balance (\$ hundreds)		6.444	8.628	-2.184
6		(37.031)	(48.965)	(2.844)

Appendix Table 1c. Baseline characteristics for subsample with at least one installment loan at baseline (Same as Table 1 but sample here is only those with installment loan at baseline)

	(1) Mea	(2) un (SD)	(3) Univariate diff:
Sample	CBI Arm	Extra Step Arm N=464	(2) - (1) (SE)
Panel C. Baseline Credit Report Variables			
$1 = \text{Has FICO} \ \mathbb{R}$ Score 8	0.991	0.976	0.015
	(0.092)	(0.152)	(0.008)
1 = (Has FICO [®] Score 8 and 1 loan at baseline)	0.977	0.961	0.016
	(0.151)	(0.195)	(0.019)
$1 = (\text{Has FICO} \otimes \text{Score } 8 \text{ and } > 1 \text{ loan at baseline})$	1.000	0.986	0.014
	(0.000)	(0.118)	(0.007)
FICO® Score 8 (100s) Has score	5.720	5.728	-0.007
	(0.630)	(0.619)	(0.041)
FICO® Score 8 (100s) and 1 loan at baseline Has score	5.651	5.715	-0.064
	(0.716)	(0.554)	(0.069)
FICO® Score 8 (100s) and >1 loan at baseline Has score	5.760	5.736	0.025
	(0.573)	(0.657)	(0.051)
Amounts Owed: Balances index (standardized)	0.282	0.217	0.065
	(1.143)	(1.058)	(0.072)
Amounts Owed: Utilization index (standardized)	0.395	0.374	0.021
	(0.921)	(0.935)	(0.061)
Credit Mix scale (standardized)	0.453	0.439	0.014
	(1.020)	(1.022)	(0.067)
Default index (standardized)	0.137	0.163	-0.026
	(0.956)	(1.043)	(0.066)
New Credit index (standardized)	0.303	0.271	0.032
	(1.148)	(1.103)	(0.074)
Panel D. Baseline Combined Survey and SLCCU Variables	. /		. /
Lack of Liquidity index (standardized)	-0.157	-0.086	-0.071
- • • •	(1.028)	(1.019)	(0.067)

Unit of observation is an individual. Index variables are standardized to be mean zero and standard deviation one in the Extra Step Arm; see Data Appendix for details on index components and construction. Sample size varies across rows due to missing observations. Further, we restricted the table to only those that had at least one installment loan at baseline.

Appendix Table 1d. Baseline characteristics for subsample with no installment loan at baseline (Same as Table 1 but sample is only those with no installment loan at baseline)

(Same as Table 1 but sam		(1)	(2)	(3)
			an (SD)	Univariate diff:
	Sample:	CBL Arm N=305	Extra Step Arm N=266	(2) - (1) (SE)
Panel A. Baseline Survey Variables				
Missing Baseline Survey		0.007	0.023	-0.016
		(0.081)	(0.149)	(0.010)
Age		41.649	42.714	-1.065
		(15.562)	(14.726)	(1.273)
Female		0.603	0.556	0.047
		(0.490)	(0.498)	(0.041)
Married		0.182	0.158	0.023
		(0.386)	(0.366)	(0.032)
# Adults in HH		1.617	1.677	-0.060
		(0.833)	(0.915)	(0.074)
# Children in HH		0.881	0.723	0.158
		(1.311)	(1.125)	(0.104)
Race - Black		0.865	0.869	-0.005
		(0.343)	(0.338)	(0.029)
HH Income < \$30K		0.764	0.767	-0.003
		(0.425)	(0.424)	(0.036)
College or more		0.132	0.150	-0.018
8		(0.340)	(0.358)	(0.029)
Financial Insecurity index (standardized)		-0.010	-0.051	0.041
		(0.938)	(1.010)	(0.082)
Lacks Self-Control index (standardized)		0.026	-0.082	0.108
((0.925)	(1.044)	(0.083)
Financial Risk-Taking scale (standardized)		-0.066	0.010	-0.076
Thimfold Turing Soure (Suman and a)		(0.985)	(1.018)	(0.085)
Attention to Credit Status index (standardized)		-0.247	-0.271	0.024
Then to creat Status mack (standardized)		(0.878)	(0.899)	(0.075)
Credit Process Knowledge index (standardized)		-0.054	-0.095	0.041
Creat Trocess Knowledge Index (sunduruzed)		(1.037)	(1.103)	(0.090)
Panel B. Baseline SLCCU Variables		(1.057)	(1.105)	(0.070)
1 = Remain an SLCCU member		1.000	1.000	0.000
		(0.000)	(0.000)	(0.000)
Savings Balance (\$ hundreds)		2.202	3.473	-1.271
Savings Bulance (@ nundreds)		(12.418)	(19.015)	(1.329)
Savings and Checkings Balance (\$ hundreds)		4.326	5.633	-1.307
Savings and Checkings Dalance (& nunuleus)		(17.096)	(22.824)	(1.675)
		(17.090)	(22.024)	(1.075)

Credit Building or Credit Crumbling?

Appendix	Table Id	l, continued	(2)	(2)
		(1) Mar	(2) an (SD)	(3)
	<u> </u>	WIC	Univariate diff:	
Sa	ample:	CBL Arm N=305	Extra Step Arm N=266	(2) - (1) (SE)
Panel C. Baseline Credit Report Variables				
$1 = \text{Has FICO} \otimes \text{Score 8}$		0.531	0.602	-0.070
		(0.500)	(0.491)	(0.042)
FICO® Score 8 (100s) Has score		5.420	5.295	0.125
		(0.722)	(0.602)	(0.074)
Amounts Owed: Balances index (standardized)		-0.502	-0.527	0.026
		(1.175)	(0.564)	(0.094)
Amounts Owed: Utilization index (standardized)		-0.682	-0.652	-0.030
		(0.701)	(0.743)	(0.060)
Credit Mix scale (standardized)		-0.766	-0.766	0.000
		(0.000)	(0.000)	(0.000)
Default index (standardized)		-0.395	-0.284	-0.111
		(0.772)	(0.850)	(0.068)
New Credit index (standardized)		-0.425	-0.436	0.011
		(0.580)	(0.569)	(0.048)
Panel D. Baseline Combined Survey and SLCCU Variables		. ,		. /
Lack of Liquidity index (standardized)		0.157	0.132	0.025
		(0.975)	(0.955)	(0.081)

Unit of observation is an individual. Index variables are standardized to be mean zero and standard deviation one in the Extra Step Arm; see Data Appendix for details on index components and construction. Sample size varies across rows due to missing observations. Further, we restricted the table to only those individuals that had no installment loan at baseline.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		CBL Arr			Extra-Step A		
	Takeup	Takeup -	P-value of	Takeup	Takeup -	P-value of	P-value
	Mean	No Takeup	Takeup =	Mean	No Takeup	Takeup =	of
	(SE)	Mean	No Takeup	(SE)	Mean	No Takeup	(1)=(4)
Sample	e:			Full			
Age	43.017	0.491	0.683	42.581	-1.521	0.379	0.812
	(0.997)	(1.191)		(1.634)	(1.740)		
Female	0.623	-0.044	0.241	0.605	-0.044	0.420	0.761
	(0.031)	(0.038)		(0.051)	(0.055)		
Married	0.231	0.006	0.859	0.274	0.038	0.448	0.440
	(0.028)	(0.033)		(0.046)	(0.049)	0.150	
# Adults in HH	1.598	-0.035	0.573	1.718	0.122	0.178	0.242
	(0.052)	(0.062)	0.070	(0.085)	(0.091)	0.705	0 770
# Children in HH	0.921	0.173	0.070	0.871	0.039	0.785	0.772
Race - Black	(0.081) 0.908	(0.096)	0.176	(0.132) 0.859	(0.141)	0.651	0.205
Kace - Black		0.034	0.176		-0.017	0.651	0.205
HH Income < \$30K	(0.022) 0.576	(0.026) -0.047	0.219	(0.035) 0.640	(0.038) 0.018	0.741	0.306
III Income < \$50K	(0.032)	(0.038)	0.219	(0.052)	(0.056)	0.741	0.500
College or more	0.266	0.021	0.539	0.376	0.124	0.015	0.058
	(0.029)	(0.035)	0.557	(0.047)	(0.051)	0.015	0.050
Financial insecurity index (standardized)	0.018	0.030	0.692	0.058	0.066	0.568	0.755
manenar misecurity maex (standardized)	(0.064)	(0.077)	0.092	(0.106)	(0.113)	0.200	0.700
Lacks Self-Control index (standardized)	-0.034	-0.036	0.647	0.064	0.068	0.559	0.456
	(0.066)	(0.078)		(0.108)	(0.115)		
Financial Risk-Taking scale (standardized)	0.136	0.149	0.064	0.011	0.012	0.919	0.341
<i>2 x y</i>	(0.067)	(0.080)		(0.110)	(0.117)		
Attention to Credit Status index (standardized)	0.000	-0.064	0.421	0.186	0.200	0.084	0.146
	(0.066)	(0.079)		(0.109)	(0.116)		
Credit Process Knowledge index (standardized)	-0.026	-0.116	0.128	0.092	0.097	0.401	0.336
	(0.065)	(0.077)		(0.106)	(0.113)		
l = Remain an SLCCU member	1.000	0.000		1.000	0.000		
A second CDL has set the CL CCL set to a line	0.247	0.000	0.007	0.200	0.124	0.012	0 407
l = Any non-CBL loan with SLCCU outstanding	0.247	-0.099	0.007	0.209	-0.134	0.013	0.487
Servines Delense (Chundrede)	(0.031)	(0.037)	0.097	(0.050) 1.158	(0.053)	0.215	0 1 9 0
Savings Balance (\$ hundreds)	2.682 (1.503)	-0.013 (1.796)	0.987	(2.464)	-4.400 (2.623)	0.215	0.180
Savings and Checkings Balance (\$ hundreds)	(1.303)	3.093	0.201	3.026	-5.112	0.282	0.398
Savings and Checkings Datanee (\$ hundreds)	(2.389)	(2.854)	0.201	(3.915)	(4.168)	0.282	0.598
1 = Has FICO® Score 8	0.827	0.025	0.426	0.767	-0.082	0.052	0.231
	(0.025)	(0.030)	0.120	(0.041)	(0.044)	0.052	0.201
FICO® Score 8 (100s) Has score	5.544	-0.142	0.014	5.610	-0.005	0.949	0.434
	(0.047)	(0.057)		(0.081)	(0.085)		
l = Any Loan Open at Baseline	0.714	-0.005	0.893	0.779	0.041	0.409	0.248
	(0.029)	(0.035)		(0.048)	(0.051)		
l = Installment Loan Open at Baseline	0.628	0.033	0.398	0.663	0.031	0.578	0.565
-	(0.032)	(0.038)		(0.052)	(0.056)		
Amounts Owed: Balances index (standardized)	-0.020	-0.097	0.340	-0.032	-0.036	0.767	0.934
	(0.078)	(0.093)		(0.126)	(0.135)		
Amounts Owed: Utilization index (standardized)	-0.076	-0.064	0.410	0.113	0.128	0.266	0.125
	(0.066)	(0.078)		(0.107)	(0.114)		
Credit Mix scale (standardized)	-0.058	-0.042	0.590	-0.044	-0.049	0.668	0.910
	(0.066)	(0.078)		(0.107)	(0.114)		
Default index (standardized)	0.022	0.136	0.061	0.013	0.015	0.895	0.946
	(0.063)	(0.076)		(0.104)	(0.110)	0.000	a
New Credit index (standardized)	-0.071	-0.123	0.127	-0.027	-0.046	0.690	0.731
	(0.067)	(0.080)	0.001	(0.110)	(0.117)	0.011	0.001
Lack of Liquidity index (standardized)	0.025	0.011	0.801	0.182	0.213	0.064	0.084

Each pair of columns shows the baseline mean of those that took up a CBL in the specified sample and then the difference between those that tookup and those that did not take up. Standard errors are shown in parenthesis below the means. Column (7) shows the p-value of the t-test of the take-up rate between the CBL Arm and the Extra Step Arm in the full sample.

0.011

(0.079)

-0.025

(0.066)

Lack of Liquidity index (standardized)

0.891

0.182

(0.109)

0.213

(0.116)

0.064

0.084

(Same as Table 4 but here Post br					(5)	(())
D	(1)	(2) Has FICO® Score	(3)	(4)	(5) FICO® Score 8	(6)
Dependent variable			8			
CBL Arm * 6 month endline (i)		Full		2 429	Have score at baselin	ne
CBL Arm * 6 month endline (1)	0.008			-2.428		
CBL Arm * 12 month endline (ii)	(0.014)			(2.615)		
_BL Arm * 12 month endline (1)	0.020			-1.267		
CBL Arm * 18 month endline (iii)	(0.017) 0.028			(3.262) -1.981		
CDL Arm · 18 monul endline (III)						
CBL Arm * 6 month endline * 1 = No Loan Open at Baseline (iv)	(0.020)	0.068		(3.745)	10.573	
ΔBL Arm ' 6 month endline ' I – No Loan Open at Baseline (IV)		(0.043)			(6.502)	
CDL Arm * 12 month on dline * 1 - No Leon Onen et Deseline (x)		0.099				
CBL Arm * 12 month endline * 1 = No Loan Open at Baseline (v)		(0.053)			8.197	
CBL Arm * 18 month endline * 1 = No Loan Open at Baseline (vi)					(8.145)	
JEL Arm + 18 month endline + 1 – No Loan Open at Baseline (VI)		0.140			6.719 (8.378)	
CBL Arm * 6 month endline * 1 = Any Loan Open at Baseline (vii)		(0.065) -0.017			-4.091	
BL Arm * 6 month endline * I = Any Loan Open at Baseline (VII)						
CDL A		(0.010)			(2.799)	
CBL Arm * 12 month endline * 1 = Any Loan Open at Baseline (viii)		-0.015			-2.368	
		(0.011)			(3.476)	
CBL Arm * 18 month endline * 1 = Any Loan Open at Baseline (ix)		-0.018			-3.081	
DI Am * ((0.013)	0.041		(4.026)	10 505
CBL Arm * 6 month endline * 1 = No Installment Loan Open at Baseline (x)			0.041			10.595
			(0.033)			(5.132)
CBL Arm * 12 month endline * 1 = No Installment Loan Open at Baseline (xi)			0.063			7.496
			(0.040)			(6.745)
CBL Arm * 18 month endline * 1 = No Installment Loan Open at Baseline (xii)			0.100			4.746
			(0.050)			(7.486)
CBL Arm * 6 month endline * 1 = Installment Loan Open at Baseline (xiii)			-0.015			-6.957
			(0.010)			(2.992)
CBL Arm * 12 month endline * 1 = Installment Loan Open at Baseline (xiv)			-0.013			-4.359
			(0.011)			(3.670)
CBL Arm * 18 month endline * 1 = Installment Loan Open at Baseline (xv)			-0.021			-4.463
			(0.011)			(4.287)
	0.014			0.650		
P-value of (i) = (ii)	0.314			0.652		
P-value of (i) = (iii)	0.277			0.895		
P-value of (ii) = (iii)	0.596	o 41 4	o 10 1	0.809	0.000	0.531
P-value of $(iv) = (v)$ or $(x) = (xi)$		0.414	0.424		0.696	0.531
P-value of (iv) = (vi) or (x) = (xii)		0.242	0.190		0.603	0.383
P-value of $(v) = (vi)$ or $(xi) = (xii)$		0.432	0.333		0.819	0.622
P-value of (vii) = (viii) or (xiii) = (xiv)		0.754	0.694		0.539	0.388
P-value of $(vii) = (ix)$ or $(xiii) = (xv)$		0.931	0.490		0.785	0.526
P-value of (viii) = (ix) or (xiv) = (xv)		0.752	0.319		0.826	0.976
P-value of $(iv) = (vii)$ or $(x) = (xiii)$		0.056	0.102		0.039	0.003
P-value of $(v) = (viii)$ or $(xi) = (xiv)$		0.035	0.068		0.233	0.123
P-value of $(vi) = (ix)$ or $(xii) = (xv)$		0.018	0.017	10.5-	0.292	0.286
Dbservations	5966	5966	5966	4865	4865	4865
Individuals	1502	1502	1502	1238	1238	1238
Mean Dependent Variable in Extra Step Arm at Baseline	0.840	0.840	0.840	561	561	561

Appendix Table 3. CBL Treatment Effects on Credit Score and on Likelihood of Having a Credit Score: Main Effects and Heterogeneity by Baseline Borrowing Status

Unit of observation is a person-credit report, with four observations for most persons: baseline, and three endlines at 6, 12, and 18 months post-treatment assignment. Number of observations is lower than the number of individuals x 4 credit reports, because a small number of credit reports lack information on one or more dependent variables. Standard errors, in parentheses, are clustered at the person-level. Each column presents results from a single OLS regression of the dependent variable described in the column heading on the variables shown in the rows, indicators for 6, 12, and 18-month observations, interactions between *No (Installment) Loan at Baseline* and each endline indicator (e.g., *No Loan at Baseline * 6 month endline*) where appropriate, and person fixed effects.

	N	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable:		1 = Has FICO				FICO®		
	Sample:	0.0(0	Full			10.572	Have score	at baseline	
CBL Arm * 6 month endline * 1 = No Loan Open at Baseline (i)		0.068	0.065			10.573	10.031		
		(0.043)	(0.043)			(6.502)	(6.473)		
CBL Arm * 12 month endline * 1 = No Loan Open at Baseline (ii)		0.099	0.091			8.197	7.665		
		(0.053)	(0.051)			(8.145)	(7.997)		
CBL Arm * 18 month endline * 1 = No Loan Open at Baseline (iii)		0.140	0.128			6.719	6.436		
		(0.065)	(0.064)			(8.378)	(8.460)		
CBL Arm * 6 month endline * 1 = Any Loan Open at Baseline (iv)		-0.017	-0.017			-4.091	-3.671		
		(0.010)	(0.010)			(2.799)	(2.794)		
CBL Arm * 12 month endline * 1 = Any Loan Open at Baseline (v)		-0.015	-0.017			-2.368	-0.667		
		(0.011)	(0.012)			(3.476)	(3.391)		
CBL Arm * 18 month endline * 1 = Any Loan Open at Baseline (vi)		-0.018	-0.019			-3.081	-1.622		
		(0.013)	(0.013)			(4.026)	(3.891)		
CBL Arm * 6 month endline * 1 = No Installment Loan Open at Baseline (vii)				0.041	0.037			10.595	10.154
				(0.033)	(0.032)			(5.132)	(5.047)
CBL Arm * 12 month endline * 1 = No Installment Loan Open at Baseline (viii)			0.063	0.057			7.496	8.293
				(0.040)	(0.039)			(6.745)	(6.397)
CBL Arm * 18 month endline * 1 = No Installment Loan Open at Baseline (ix)				0.100	0.088			4.746	6.129
				(0.050)	(0.049)			(7.486)	(7.272)
CBL Arm * 6 month endline * 1 = Installment Loan Open at Baseline (x)				-0.015	-0.013			-6.957	-6.274
				(0.010)	(0.010)			(2.992)	(2.990)
CBL Arm * 12 month endline * 1 = Installment Loan Open at Baseline (xi)				-0.013	-0.014			-4.359	-2.678
				(0.011)	(0.012)			(3.670)	(3.581)
CBL Arm * 18 month endline * 1 = Installment Loan Open at Baseline (xii)				-0.021	-0.019			-4.463	-3.308
				(0.011)	(0.012)			(4.287)	(4.129)
Control for baseline variables * 6 month endline (see notes)		No	Yes	No	Yes	No	Yes	No	Yes
Control for baseline variables * 12 month endline (see notes)		No	Yes	No	Yes	No	Yes	No	Yes
Control for baseline variables * 18 month endline (see notes)		No	Yes	No	Yes	No	Yes	No	Yes
P-value of (i) = (iv) or (vii) = (x)		0.056	0.062	0.102	0.139	0.039	0.052	0.003	0.005
P-value of (ii) = (v) or (viii) = (xi)		0.035	0.041	0.068	0.084	0.233	0.339	0.123	0.134
P-value of (iii) = (vi) or (ix) = (xii)		0.018	0.024	0.017	0.032	0.292	0.387	0.286	0.259
Observations		5966	5966	5966	5966	4865	4865	4865	4865
Individuals		1502	1502	1502	1502	1238	1238	1238	1238
Mean Dependent Variable in Extra Step Arm at Baseline		0.840	0.840	0.840	0.840	561	561	561	561

Appendix Table 4. Is CBL Treatment Effect Heterogeneity Driven by Baseline Borrowing per se, or by Mediators Correlated with Baseline Borrowing? (Same as Table 5 but here *Post* broken down by 6, 12, and 18 month endlines)

Unit of observation is a person-credit report, with four observations for most persons: baseline, and three endlines at 6, 12, and 18 months post-treatment assignment. Number of observations is lower than the number of individuals x 4 credit reports, because a small number of credit reports lack information on one or more dependent variables. Standard errors, in parentheses, are clustered at the person-level. Each column presents results from a single OLS regression of the dependent variable described in the column heading on the variables shown in the rows, indicators for 6, 12, and 18 month observations, interactions between *No (Installment) Loan at Baseline* and each endline indicator (e.g., *No Loan at Baseline * 6 month endline*) where appropriate, and person fixed effects. Index variables are standardized to be mean zero and standard deviation one in the Extra Step Arm at baseline; see Data Appendix for details on index components and construction. Even-numbered columns include controls for 6 month, 12 month, and 18 month endlines interacted with 11 variables: *female, married, # adults in HH, race-black, HH Income < \$30K, college educated, 1 = any non-CBL loan with SLCCU outstanding, savings balance (hundreds), amounts owed: utilization index, credit mix scale, and new credit index . In addition to the 11 common variables, column (2) includes 6 month interacted with: 1 = < 26 years old, # children in HH, attention to credit status index, and lack of liquidity index , and lack of liquidity index and lack of*

11		8	e that have a score at b			
	(1)	(2)	(3)	(4)	(5)	(6)
FICO® Score 8 Factor:	New Credit	Paymer	nt History	Amoun	ts Owed	Credit Mix
Dependent variable index includes	Inquiries, Number of Accounts	10 measures of delinquency, collections, & derogatories (higher values = less timely repmt)	8 measures of serious delinquency, collections, & derogatories (higher values = less timely repmt)	Balances: Revolving, Auto loans, Other Installment	Utilization: 4 discrete measures of credit limit usage and outstanding balances; # open installment loans	1=(open installment and open revolving loan)
Sample:			Have score	at baseline		
Panel A. Heterogeneity by Baseline Borrowing Status						
CBL Arm * Post * 1 = No Loan Open at Baseline (i)	0.018	0.031	-0.026	0.096	0.215	0.065
	(0.067)	(0.086)	(0.077)	(0.094)	(0.127)	(0.075)
CBL Arm * Post * 1 = Any Loan Open at Baseline (ii)	-0.001	0.101	0.082	-0.088	-0.053	-0.058
	(0.046)	(0.048)	(0.043)	(0.047)	(0.050)	(0.057)
P-value of $(i) = (ii)$	0.817	0.478	0.220	0.080	0.050	0.188
Panel B. Heterogeneity by Baseline Installment Loan Status						
CBL Arm * Post * 1 = No Installment Loan Open at Baseline (iii)	-0.017	-0.007	-0.051	-0.061	0.075	0.150
	(0.053)	(0.068)	(0.062)	(0.103)	(0.100)	(0.085)
CBL Arm * Post * 1 = Installment Loan Open at Baseline (iv)	0.006	0.132	0.114	-0.066	-0.054	-0.109
	(0.051)	(0.053)	(0.047)	(0.045)	(0.053)	(0.059)
P-value of (iii) = (iv)	0.755	0.109	0.035	0.967	0.256	0.012
Observations	4945	4945	4945	4929	4945	4945
Individuals	1238	1238	1238	1238	1238	1238
Mean Dependent Variable in Extra Step Arm at Baseline	0.139	0.156	0.135	0.057	0.151	0.139

Appendix Table 5. CBL Treatm	ent Effect Heterogeneity on Credit Behaviors:
Same as Table 6 but here sample	is restricted to those that have a score at haseline)

Unit of observation is a person-credit report, with four observations for most persons: baseline, and three endlines at 6, 12, and 18 months post-treatment assignment, all three of which are included in the *Post* indicator for the experiment period. Number of observations is lower than the number of individuals x 4 credit reports, because a small number of credit reports lack information on one or more dependent variables. Standard errors, in parentheses, are clustered at the person-level. Each column presents results from a single OLS regression of the dependent variable described in the column heading on the variables shown in the rows, *Post*, *Post* * *No* (*Installment*) *Loan at Baseline* where appropriate, and person fixed effects. Index variables are standardized to be mean zero and standard deviation one in the Extra Step Arm at baseline; see Data Appendix for details on index components and construction. Sample sizes are lower for *Amounts Owed* because of cases where all variables in other tables because we are not missing observations on these dependent variables at endlines but we are for dependent variables in other tables. *Payment History* in column (2) is equivalent to the default index used in Tables 1 and 9 but is called *Payment History* here to be consistent with the names used by FICO for their score factors. Index means may differ from 0.000 because individuals in our sample that are not matched to credit data are excluded from these regression samples.

		(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
FICO® Score 8 Factor	(1) r: Ne	ew Credit		(4) nt History	(5)	Amoun		(8)		redit Mix
Dependent variable index include:	s: Inquiries, N	umber of Accounts	collections, (higher valu	of delinquency, & derogatories es = less timely pmt)		evolving, Auto er Installment	measures o usage and balances; # o	n: 4 discrete of credit limit l outstanding open installment oans		stallment and open lving loans)
Sample	Full	Have score at baseline	Full	Have score at baseline	Full	Have score at baseline	Full	Have score at baseline	Full	Have score at baseline
Panel A. Heterogeneity by Baseline Borrowing Status CBL Arm * 6 month endline * 1 = No Loan Open at Baseline (i)	0.037	0.030	0.004	-0.036	0.054	0.036	0.174	0.245	0.046	0.029
CBL Arm * 12 month endline * 1 = No Loan Open at Baseline (ii)	(0.051) -0.012 (0.069)	(0.065) 0.033 (0.087)	(0.062) 0.042 (0.081)	(0.076) 0.071 (0.102)	(0.074) 0.067 (0.082)	(0.084) 0.088 (0.096)	(0.062) 0.140 (0.080)	(0.111) 0.232 (0.145)	(0.034) 0.105 (0.059)	(0.051) 0.118 (0.106)
CBL Arm * 18 month endline * 1 = No Loan Open at Baseline (iii)	0.057 (0.075)	-0.008 (0.096)	0.047 (0.091)	0.058 (0.126)	0.168 (0.094)	0.163 (0.123)	0.083 (0.097)	0.168 (0.176)	0.046 (0.081)	0.049 (0.120)
CBL Arm * 6 month endline * 1 = Any Loan Open at Baseline (iv)	0.030 (0.037)	0.033 (0.038)	0.093 (0.043)	0.099 (0.044)	-0.064 (0.040)	-0.064 (0.040)	-0.025 (0.049)	-0.022 (0.050)	-0.056 (0.054)	-0.051 (0.054)
CBL Arm * 12 month endline * 1 = Any Loan Open at Baseline (v)	0.023 (0.056)	0.033 (0.056)	0.097 (0.057)	0.094 (0.058)	-0.068 (0.050)	-0.068 (0.051)	-0.051 (0.058)	-0.044 (0.059)	-0.063 (0.068)	-0.050 (0.068)
CBL Arm * 18 month endline * 1 = Any Loan Open at Baseline (vi)	-0.079 (0.064)	-0.068 (0.064)	0.111 (0.066)	0.111 (0.067)	-0.137 (0.065)	-0.132 (0.066)	-0.098 (0.063)	-0.093 (0.064)	-0.086 (0.077)	-0.074 (0.078)
P-value of (i) = (ii) P-value of (i) = (iii)	0.274 0.780	0.966 0.711	0.501 0.576	0.223 0.426	0.766 0.049	0.332 0.126	0.582 0.295	0.902 0.608	0.326 0.995	0.383 0.859
P-value of (ii) = (iii) P-value of (iv) = (v)	0.279 0.851	0.654 0.988	0.934 0.936	0.886 0.913	0.071 0.894	0.282 0.917	0.436 0.547	0.589 0.609	0.429 0.889	0.508 0.996
P-value of $(iv) = (vi)$ P-value of $(v) = (vi)$	0.069 0.036	0.097 0.040	0.767 0.778	0.836 0.732	0.159 0.113	0.195 0.140	0.177 0.312	0.197 0.305	0.672 0.706	0.747 0.699
P-value of (i) = (iv) $P-value of (ii) = (v)$ $P-value of (iii) = (v)$	0.908 0.693 0.166	0.973 0.996 0.604	0.236 0.582 0.571	0.127 0.847 0.710	0.159 0.161 0.008	0.281 0.151 0.034	0.012 0.055 0.119	0.029 0.078 0.163	0.111 0.062 0.237	0.282 0.179 0.392
Panel B. Heterogeneity by Baseline Installment Loan Status										
CBL Arm * 6 month endline * 1 = No Installment Loan Open at Baseline (vii) CBL Arm * 12 month endline * 1 = No Installment Loan Open at Baseline (viii)	0.004 (0.041) -0.017	-0.026 (0.048) -0.002	-0.012 (0.050) 0.008	-0.043 (0.057) 0.008	-0.074 (0.079) -0.057	-0.111 (0.090) -0.067	0.100 (0.062) 0.101	0.090 (0.097) 0.118	0.098 (0.060) 0.123	0.163 (0.094) 0.175
CBL Arm * 12 month endline * $1 = N0$ Installment Loan Open at Baseline (vii)	(0.058) 0.028	-0.002 (0.070) -0.021	(0.069) 0.012	(0.084) 0.013	(0.088) 0.024	(0.101) -0.006	(0.075) 0.036	(0.113) 0.017	(0.069) 0.068	(0.105) 0.110
CBL Arm * 6 month endline * 1 = Installment Loan Open at Baseline (x)	(0.065) 0.047	(0.080) 0.051	(0.079) 0.119	(0.102) 0.126	(0.106) -0.032	(0.129) -0.031	(0.087) -0.017	(0.126) -0.016	(0.078) -0.116	(0.108) -0.110
CBL Arm * 12 month endline * 1 = Installment Loan Open at Baseline (xi)	(0.042) 0.028	(0.043) 0.043	(0.049) 0.128	(0.049) 0.127	(0.038) -0.042	(0.039) -0.041	(0.051) -0.061	(0.052) -0.056	(0.053) -0.116	(0.053) -0.100
CBL Arm * 18 month endline * 1 = Installment Loan Open at Baseline (xii)	(0.063) -0.090 (0.071)	(0.063) -0.075 (0.072)	(0.063) 0.143 (0.073)	(0.064) 0.143 (0.074)	(0.051) -0.130 (0.066)	(0.051) -0.125 (0.066)	(0.062) -0.101 (0.067)	(0.063) -0.089 (0.068)	(0.071) -0.134 (0.084)	(0.071) -0.118 (0.085)
P-value of (vii) = (viii) P-value of (vii) = (ix)	0.589 0.711	0.618 0.951	0.680 0.729	0.460 0.557	0.639 0.071	0.325 0.126	0.983 0.399	0.700 0.496	0.659 0.712	0.893 0.630
P-value of $(vii) = (ix)$ P-value of $(xii) = (ix)$	0.442 0.661	0.802 0.847	0.949 0.844	0.942 0.982	0.097 0.787	0.289 0.802	0.308 0.348	0.238 0.398	0.449 0.999	0.516 0.872
P-value of $(x) = (xi)$ P-value of $(x) = (xi)$	0.040 0.026	0.059 0.027	0.716 0.792	0.799 0.776	0.088 0.067	0.106 0.082	0.146 0.428	0.211 0.517	0.818 0.781	0.908 0.777
P-value of $(vii) = (x)$ P-value of $(viii) = (xi)$	0.474 0.600	0.228 0.631	0.062	0.025 0.258	0.630 0.889	0.418 0.820	0.148 0.096	0.335 0.178	0.008 0.016	0.011 0.030
P-value of $(ix) = (xii)$	0.221	0.616	0.225	0.303	0.215	0.410	0.214	0.458	0.078	0.096
)bservations ndividuals	5970 1502	4945 1238	5970 1502	4945 1238	5482 1423	4929 1238	5970 1502	4945 1238	5970 1502	4945 1238

Appendix Table 6. CBL Treatment Effect Heterogeneity on Credit Behaviors:

Unit of observation is a person-credit report, with four observations for most persons: baseline, and three endlines at 6, 12, and 18 months post-treatment assignment. Number of observations is lower than the number of individuals x 4 credit reports, because a small number of credit reports lack information on one or more dependent variables. Standard errors, in parentheses, are clustered at the person-level. Each panel-column presents results from an OLS regression of the dependent variable described in the column heading on the variables shown in the panel-rows, indicators for 6, 12, and 18-month observations, interactions between *No (Installment) Loan at Baseline* where appropriate and each endline indicator (e.g., *No Loan at Baseline * 6 month endline)* where appropriate, and person fixed effects. Index variables are standardized to be mean zero and standard deviation one in the Extra Step Arm at baseline; see Data Appendix for details on index components and construction. Sample sizes are lower for *Amounts Owed* because of cases where all variables for outstanding balances are missing values.

		(1)	(2)	(3)		(4)	(5)	(6)
Depe	ndent variable:	$1 = \mathbf{R}$	emain an SLCCU n	nember		1 = Any non-C	BL loan with SLC	CU outstanding
	Sample:				Full			
CBL Arm * 6 month endline (i)		-0.000				0.009		
CBL Arm * 12 month endline (ii)		(0.009) -0.012				(0.018) 0.001		
CBL Arm * 18 month endline (iii)		(0.013) -0.013				(0.022) 0.022		
		(0.015)				(0.025)		
CBL Arm * 6 month endline * 1 = No Loan Open at Baseline (iv)			0.006 (0.023)				0.026 (0.028)	
CBL Arm * 12 month endline * 1 = No Loan Open at Baseline (v)			-0.003 (0.031)				0.043 (0.035)	
CBL Arm * 18 month endline * 1 = No Loan Open at Baseline (vi)			-0.007 (0.033)				0.074 (0.039)	
CBL Arm * 6 month endline * 1 = Any Loan Open at Baseline (vii)			-0.001				0.001	
CBL Arm * 12 month endline * 1 = Any Loan Open at Baseline (viii)			(0.009) -0.014				(0.022) -0.017	
CBL Arm * 18 month endline * 1 = Any Loan Open at Baseline (ix)			(0.013) -0.015				(0.027) 0.001	
• • • • • • • • • • • • • • • • • • • •			(0.017)	0.004			(0.031)	0.020
CBL Arm * 6 month endline * 1 = No Installment Loan Open at Baseline (x)				0.004 (0.016)				0.029 (0.024)
CBL Arm * 12 month endline * 1 = No Installment Loan Open at Baseline (xi)				-0.012 (0.023)				0.045 (0.030)
CBL Arm * 18 month endline * 1 = No Installment Loan Open at Baseline (xii)				-0.011				0.093
CBL Arm * 6 month endline * 1 = Installment Loan Open at Baseline (xiii)				(0.025) -0.002				(0.035) -0.005
CBL Arm * 12 month endline * 1 = Installment Loan Open at Baseline (xiv)				(0.011) -0.010				(0.024) -0.028
CBL Arm * 18 month endline * 1 = Installment Loan Open at Baseline (xv)				(0.015) -0.015				(0.030) -0.022
CDL AIII * 18 monul endine * 1 – instanment Loan Open at Basenne (xv)				(0.019)				(0.034)
P-value of (i) = (ii)		0.215				0.627		
P-value of (i) = (iii)		0.276				0.526		
P-value of (ii) = (iii) P-value of (iii) = (iii)		0.841	0.70/	0.252		0.168	0.552	0.402
P-value of (iv) = (v) or (x) = (xi) P-value of (x) = (xi)			0.706	0.353			0.552	0.493
P-value of $(iv) = (vi)$ or $(x) = (xii)$			0.613 0.690	0.457 0.885			0.190 0.302	0.039 0.065
P-value of $(v) = (vi)$ or $(xi) = (xii)$			0.890	0.885			0.346	0.065
P-value of (vii) = (viii) or (xiii) = (xiv) P-value of (vii) = (iv) or (xiii) = (viv)							0.983	0.287
P-value of (vii) = (ix) or (xiii) = (xv) P-value of (viii) = (ix) or (xiii) = (xv)			0.339	0.423				
P-value of (viii) = (ix) or (xiv) = (xv) P-value of (iii) = ((iii) or (xiv) = (xviii)			0.899	0.719			0.332	0.751
P-value of (iv) = (vii) or (x) = (xiii) P-value of (iv) = (viii) ar (vii) = (viii)			0.764	0.762			0.494	0.327
P-value of $(v) = (viii)$ or $(xi) = (xiv)$			0.748	0.943			0.171	0.083
P-value of $(vi) = (ix)$ or $(xii) = (xv)$		(000	0.818	0.909		(000	0.143	0.020
Observations		6008	6008	6008		6008	6008	6008
Individuals		1502	1502	1502		1502	1502	1502
Mean Dependent Variable in Extra Step Arm at Baseline		1.000	1.000	1.000		0.327	0.327	0.327

Appendix Table 7a. CBL treatment effects on usage of non-CBL SLCCU products Main Effects and Heterogeneity by Baseline Borrowing Status (Same as Table 7 and Appendix Table 7 but here *Post* broken down by 6, 12, and 18 month endlines)

Unit of observation is a person-credit report, with four observations for most persons: baseline, and three endlines at 6, 12, and 18 months post-treatment assignment. Standard errors, in parentheses, are clustered at the personlevel. Each column presents results from an OLS regression of the dependent variable described in the column heading on the variables shown in the rows, indicators for 6, 12, and 18-month observations, interactions between *No (Installment) Loan at Baseline* and each endline indicator (e.g., *No Loan at Baseline * 6 month endline*) where appropriate, and person fixed effects. All outcome variables are calculated from SLCCU administrative data.

	(1)	(2)	(3)		(4)	(5)	(6)
Dependent variabl	Balanc	es of all savings a	ccounts		Balances of a	Ill savings + chec	king accounts
Dependent variable	le.	(\$ hundreds)				(\$ hundreds)	
Sampl	e:			Full			
BL Arm * 6 month endline (i)	2.831				1.729		
	(1.721)				(2.078)		
CBL Arm * 12 month endline (ii)	2.595				1.672		
	(1.407)				(1.842)		
BL Arm * 18 month endline (iii)	2.172				0.564		
	(1.449)				(1.939)		
BL Arm * 6 month endline * 1 = No Loan Open at Baseline (iv)		0.420				1.435	
		(1.384)				(1.571)	
BL Arm * 12 month endline * 1 = No Loan Open at Baseline (v)		0.179				0.327	
		(1.608)				(1.713)	
BL Arm * 18 month endline * 1 = No Loan Open at Baseline (vi)		-0.469				-1.725	
DI Amer * (mandle and line * 1 - Amer I and Onen at Databling (ciii)		(1.721)				(1.959)	
BL Arm * 6 month endline * 1 = Any Loan Open at Baseline (vii)		3.723				1.849	
BL Arm * 12 month endline * 1 = Any Loan Open at Baseline (viii)		(2.322) 3.513				(2.816) 2.190	
BL Arm * 12 month endline * 1 – Any Loan Open at Basenne (vin)		(1.851)				(2.471)	
BL Arm * 18 month endline * 1 = Any Loan Open at Baseline (ix)		3.172				1.436	
BL Ann \sim 18 month endline \sim 1 – Any Loan Open at Basenne (ix)		(1.876)				(2.567)	
BL Arm * 6 month endline * 1 = No Installment Loan Open at Baseline (x)		(1.870)	0.859			(2.507)	1.772
DE Arm 0 monur endine T = N0 mstanment Eoan Open at Dasenne (x)			(1.083)				(1.475)
BL Arm * 12 month endline * 1 = No Installment Loan Open at Baseline (xi)			0.673				1.030
BE Ann 12 month channe 1 No instantinent Eotar Open at Basenne (XI)			(1.275)				(1.524)
BL Arm * 18 month endline * 1 = No Installment Loan Open at Baseline (xii)			-0.371				-0.997
			(1.964)				(2.278)
BL Arm * 6 month endline * 1 = Installment Loan Open at Baseline (xiii)			4.056				1.734
			(2.730)				(3.277)
BL Arm * 12 month endline * 1 = Installment Loan Open at Baseline (xiv)			3.815				2.116
			(2.160)				(2.870)
BL Arm * 18 month endline * 1 = Installment Loan Open at Baseline (xv)			3.717				1.542
			(2.015)				(2.836)
P-value of (i) = (ii)	0.872				0.971		
-value of (i) = (iii)	0.703				0.527		
P-value of (ii) = (iii)	0.777				0.483		
-value of $(iv) = (v)$ or $(x) = (xi)$		0.814	0.828			0.362	0.530
-value of $(iv) = (vi)$ or $(x) = (xii)$		0.464	0.464			0.035	0.163
-value of $(v) = (vi)$ or $(xi) = (xii)$		0.472	0.499			0.088	0.240
-value of $(vii) = (viii)$ or $(xiii) = (xiv)$		0.916	0.918			0.873	0.877
-value of $(vii) = (ix)$ or $(xiii) = (xv)$		0.815	0.898			0.868	0.945
-value of (viii) = (ix) or (xiv) = (xv)		0.867	0.965			0.724	0.808
-value of (iv) = (vii) or (x) = (xiii)		0.222	0.276			0.898	0.992
-value of $(v) = (viii)$ or $(xi) = (xiv)$		0.174	0.211			0.536	0.738
-value of $(vi) = (ix)$ or $(xii) = (xv)$	6000	0.153	0.147		60.00	0.328	0.485
bservations	6008	6008	6008		6008	6008	6008
ndividuals	1502	1502	1502		1502	1502	1502
Mean Dependent Variable in Extra Step Arm at Baseline	5.040	5.040	5.040		7.536	7.536	7.536

Appendix Table 7b. CBL treatment effects on SLCCU account balances Main Effects and Heterogeneity by Baseline Borrowing Status (Same as Table 7 and Appendix Table 7 but here *Post* broken down by 6, 12, and 18 month endlines)

Unit of observation is a person-credit report, with four observations for most persons: baseline, and three endlines at 6, 12, and 18 months post-treatment assignment. Standard errors, in parentheses, are clustered at the person-level. Each column presents results from an OLS regression of the dependent variable described in the column heading on the variables shown in the rows, indicators for 6, 12, and 18 month observations, interactions between *No (Installment) Loan at Baseline* and each endline indicator (e.g., *No Loan at Baseline * 6 month endline*) where appropriate, and person fixed effects. All outcome variables are calculated from SLCCU administrative data. Balances are recorded as zero for those who leave the credit union.

	neter ogenetty by Das	chine instantinent Lo		cu5	
$\begin{array}{c c} \begin{tabular}{lllllllllllllllllllllllllllllllllll$	(Same as Table 7 but here heterogene	ous groups based or	ı installment loan	status at baseline)	
$\begin{array}{c} \text{Dependent variable:} & 1 = \text{Remain an} \\ \text{SLCCU member} \\ \hline \\ \text{SLCU member} \\ \hline \\ \hline \\ \ \\ \text{SLCU member} \\ \hline \\ \hline \\ \ \\ \text{SLCU member} \\ \hline \\ \hline \\ \ \\ \ \\ \text{SLCU member} \\ \hline \\ \ \\ \ \\ \ \ \ \ \ \ \ \ \ \ \ \ \$		(1)	(2)	(3)	(4)
CBL Arm * Post * 1 = No Installment Loan Open at Baseline (i) -0.007 0.056 0.387 0.602 (D.20)(0.020)(0.025)(1.248)(1.518)CBL Arm * Post * 1 = Installment Loan Open at Baseline (ii) -0.009 -0.018 3.863 1.797 (D.013)(0.026)(1.847)(2.614)P-value of (i) = (ii) 0.917 0.044 0.119 0.692 Observations 6008 6008 6008 6008 Individuals 1502 1502 1502 1502	Dependent variable:		CBL loan with SLCCU	savings accounts	+ checking accounts
CBL Arm * Post * 1 = Installment Loan Open at Baseline (ii) (0.020) (0.025) (1.248) (1.518) CBL Arm * Post * 1 = Installment Loan Open at Baseline (ii) -0.009 -0.018 3.863 1.797 (0.013) (0.026) (1.847) (2.614) P-value of (i) = (ii) 0.917 0.044 0.119 0.692 Observations 6008 6008 6008 6008 Individuals 1502 1502 1502 1502	Sample:			Full	
CBL Arm * Post * 1 = Installment Loan Open at Baseline (ii) -0.009 -0.018 3.863 1.797 (0.013)(0.026)(1.847)(2.614)P-value of (i) = (ii)0.9170.0440.1190.692Observations6008600860086008Individuals1502150215021502	CBL Arm * Post * 1 = No Installment Loan Open at Baseline (i)	-0.007	0.056	0.387	0.602
P-value of (i) = (ii) 0.917 0.044 0.119 0.692 Observations 6008 6008 6008 6008 Individuals 1502 1502 1502 1502		(0.020)	(0.025)	(1.248)	(1.518)
P-value of (i) = (ii) 0.917 0.044 0.119 0.692 Observations 6008 6008 6008 6008 Individuals 1502 1502 1502 1502	CBL Arm * Post * 1 = Installment Loan Open at Baseline (ii)	-0.009	-0.018	3.863	1.797
Observations 6008 6008 6008 6008 Individuals 1502 1502 1502 1502		(0.013)	(0.026)	(1.847)	(2.614)
Individuals 1502 1502 1502 1502	P-value of $(i) = (ii)$	0.917	0.044	0.119	0.692
	Observations	6008	6008	6008	6008
Mean Dependent Variable in Extra Step Arm at Baseline1.0000.3275.0407.536	Individuals	1502	1502	1502	1502
	Mean Dependent Variable in Extra Step Arm at Baseline	1.000	0.327	5.040	7.536

Appendix Table 8. CBL treatment effects on usage of other SLCCU products: Heterogeneity by Baseline Installment Loan Borrowing Status

Unit of observation is a person-credit report, with four observations for most persons: baseline, and three endlines at 6, 12, and 18 months posttreatment assignment, all three of which are included in the *Post* indicator for the experiment period. Standard errors, in parentheses, are clustered at the person-level. Each column presents results from a single OLS regression of the dependent variable described in the column heading on the variables shown in the rows, *Post*, *Post* * *No Installment Loan Open at Baseline* where appropriate, and person fixed effects. All outcome variables are calculated from SLCCU administrative data. Balances are recorded as zero for those that leave the credit union.

Appendix Table 9. CBL treatment effects on SLCCU account balances Main Effects and Heterogeneity by Baseline Borrowing Status (Same as Table 7 Columns 5-8 but here outcome variables are transformed)

	Dependent variable:	(1) Balanaaa	(2) of all savings accounts	(3)	(4) Delenses of all	(5) savings + checking ac	(6)
	Dependent variable:	Datatices (of all savings accounts	(\$ nundreds)	balances of an	savings + checking ac	counts (\$ nundreds)
		Winsorized (95%)	Winsorized (99%)	Inverse Hyperbolic Sine	Winsorized (95%)	Winsorized (99%)	Inverse Hyperbolic Sine
	Sample:			Ful	11		
Panel A. Main Effects							
Opened a Loan * Post		0.331	0.998	0.068	0.136	1.055	0.043
		(0.282)	(0.625)	(0.058)	(0.501)	(0.924)	(0.085)
Panel B. Heterogeneity by Baseline Borrowing Status							
Opened a Loan * Post * 1 = No Loan Open at Baseline (i)		-0.061	-0.347	0.017	-0.018	-0.008	-0.008
		(0.441)	(1.114)	(0.103)	(0.731)	(1.563)	(0.154)
Opened a Loan * Post * 1 = Any Loan Open at Baseline (ii)		0.476	1.503	0.087	0.212	1.476	0.067
		(0.350)	(0.750)	(0.070)	(0.631)	(1.130)	(0.101)
P-value of $(i) = (ii)$		0.340	0.169	0.573	0.812	0.442	0.684
Panel C. Heterogeneity by Baseline Installment Loan Status							
Opened a Loan * Post * 1 = No Installment Loan Open at Baseline (iii)		0.356	0.120	0.070	0.563	0.671	0.073
		(0.398)	(0.920)	(0.088)	(0.718)	(1.446)	(0.131)
Opened a Loan * Post * 1 = Installment Loan Open at Baseline (iv)		0.316	1.542	0.068	-0.088	1.344	0.031
• • • • • • • • • • • • • • • • • • • •		(0.386)	(0.838)	(0.077)	(0.677)	(1.207)	(0.110)
P-value of $(iii) = (iv)$		0.943	0.254	0.981	0.510	0.721	0.809
Observations		6008	6008	6008	6008	6008	6008
Individuals		1502	1502	1502	1502	1502	1502
Mean Dependent Variable in Extra Step Arm at Baseline		2.160	3.724	0.739	4.053	6.088	1.016

Unit of observation is a person-credit report, with four observations for most persons: baseline, and three endlines at 6, 12, and 18 months post-treatment assignment. Standard errors, in parentheses, are clustered at the person-level. Each panelcolumn presents results from an OLS regression of the dependent variable described in the column heading on the variables shown in the panel-rows, indicators for 6, 12, and 18-month observations, interactions between *No (Installment) Loan at Baseline* and each endline indicator (e.g., *No Loan at Baseline * 6 month endline*) where appropriate, and person fixed effects. All outcome variables are calculated from SLCCU administrative data. Balances are recorded as zero for those who leave the credit union.

(Same as Table 9 but here	deatuit index is	s broken down in	to its componen	its)	
	(1)	(2)	(3)	(4)	(5)
	No of Accts 30	No of Accts 90	No of Accts	Amt Past	No of
Dependent variable at 18-month endline:	days past due last	days past due last	in Collections	Due	Derogatory Accts
	12 mos	12 mos		(\$ thousands)	<i>c i</i>
Panel A. Continuous components					
FICO® Score 8 (hundreds) 12 month endline * CBL Arm (i)	-1.291	-1.215	-1.728	-3.736	-1.421
	(0.170)	(0.153)	(0.232)	(1.181)	(0.203)
FICO® Score 8 (hundreds) 12 month endline * Extra Step Arm (ii)	-1.319	-1.239	-1.739	-3.633	-1.428
	(0.172)	(0.155)	(0.234)	(1.128)	(0.201)
P-value of $(i) = (ii)$	0.211	0.229	0.785	0.350	0.798
Observations	1217	1217	1217	1210	1211
Mean Dependent Variable in Extra Step Arm	1.481	1.019	4.143	3.687	2.388
	Has acct 30	Has acct 90	Has acct	Has Amt	Has derogatory
Dependent variable at 18-month endline:	days past due last	days past due last	in collection	Past Due	acct
	12 mos	12 mos			
Panel B. Binary components					
FICO® Score 8 (hundreds) 12 month endline * CBL Arm (iii)	-0.286	-0.361	-0.149	-0.302	-0.254
	(0.027)	(0.026)	(0.020)	(0.026)	(0.023)
FICO® Score 8 (hundreds) 12 month endline * Extra Step Arm (vi)	-0.287	-0.361	-0.161	-0.298	-0.258
	(0.027)	(0.026)	(0.020)	(0.026)	(0.023)
P-value of (iii) = (iv)	0.874	0.972	0.000	0.310	0.397
Observations	1217	1217	1217	1210	1211
Mean Dependent Variable in Extra Step Arm	0.528	0.377	0.836	0.576	0.669

Appendix Table 10. Do CBLs Change the Predictive Power of Credit Scores? Testing for differences in the default-score gradient in index components (Same as Table 9 but here deafult index is broken down into its components)

Unit of observation is a person. Standard errors, in parenthesis, are Huber-White. Each panel-column presents results from a single OLS regression of the dependent variable described in the panel-column heading at the 18 month endline on the variables shown in the panel-rows and *FICO® Score 8 (hundreds)* at baseline. Index variables are standardized to be mean zero and standard deviation one in the Extra Step Arm at baseline; see Data Appendix for details on index components and construction. Sample here is limited to persons for whom we could obtain a credit report at our 18-month endline and who have a credit score at baseline and the 12-month endline.