Does Knowing Your FICO Score Change Financial Behavior? Evidence from a Field Experiment with Student Loan Borrowers

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Abstract

This paper evaluates the impact of providing access to an individual's FICO® Score on financial behavior. We conduct a field experiment with over 400,000 Sallie Mae student loan borrowers in which treatment group members received direct communications about score availability. Using administrative credit report data, we find that borrowers in the treatment group are less likely to have any payments past due, more likely to have at least one revolving credit account, and have higher FICO Scores after one year. Survey data find treatment group members were more likely to accurately report their own FICO Score; specifically, they were less likely to overestimate their score. These effects are particularly encouraging given the limited success of traditional higher cost financial education interventions.

Introduction

Consumers struggle when making financial decisions. Research consistently documents the challenges people have understanding fundamental concepts of personal financial management. These

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difficulties often translate to costly mistakes across domains of household finance, from investment and retirement savings decisions to mortgage choice and debt management (Benartzi and Thaler, 2001; Choi et al., 2009; Gross and Souleles, 2002; Ponce, Seira and Zamarripa, 2017). Given the direct implications for consumer welfare, improving financial decision-making has become a key focus in recent decades with actors in the public, private, and nonprofit sectors implementing a wide range of interventions designed to increase financial knowledge and equip individuals with the tools and information they need to make better financial decisions. Yet these efforts often fall short in improving financial outcomes (Hastings, Madrian and Skimmyhorn, 2013; Fernandes, Lynch Jr and Netemeyer, 2014).

In this paper, we test a novel intervention in which we provide individuals with quarterly reminders to view their FICO Score, a personalized, quantifiable, and behaviorally-responsive measure of their creditworthiness. We present evidence from a large-scale field experiment with over 400,000 clients of Sallie Mae, a national financial institution specializing in student loans. Beginning in June 2015, Sallie Mae offered borrowers access to unlimited views of their FICO Score. We exogenously vary the likelihood of viewing by randomly assigning borrowers to receive additional communications about the program's availability. To estimate the effect of viewing one's FICO Score on financial outcomes, we then link information on FICO Score views to individual-level credit report data provided by TransUnion.

Borrowers assigned to the treatment group received an informational email each quarter for eight quarters notifying them that an updated FICO Score was available to be viewed through the loan provider's website. During the first year of the intervention, 32 percent of treatment group members viewed their score at least once, a 12 percentage point increase over the control group. We find that treatment group members are significantly less likely to have any payments past due and are more likely to have at least one revolving credit account – outcomes associated with higher FICO Scores. Specifically, treatment group members were 0.7 percentage points less likely to have an account that was 30 days or more past due, a 4 percent decrease. While this estimate is small in magnitude, it is important to remember that it is the effect of receiving an email, not of actually viewing one's score. In addition to the intent-to-treat estimates (ITT), we instrument the likelihood of ever viewing one's score on the provider's site with treatment status to estimate the effect of actually viewing one's score on financial outcomes. The treatment-on-the-treated (TOT) estimates show that viewing one's FICO Score at least once is associated with a 9.0 percentage point decrease in the likelihood of having a delinquency. Additionally, treatment group members were 0.3 percentage points more likely to have at least one revolving trade account (e.g., credit card)—an important step towards establishing credit history—a TOT estimate of 3.6 percentage points on a base of 75.8 percent. These changes in behavior led to an increase in the borrower's FICO Score itself – a statistically significant increase of 0.7 points corresponding to a TOT estimate of 8.2 points. These effects largely persist through the end of our study period, two years from the start of the intervention.

We complement findings from this field experiment by analyzing responses to a survey conducted by Sallie Mae one year after the start of the intervention. The survey asked participants questions about their FICO Score knowledge and general financial literacy. We find that treatment group members were more likely to have accurate knowledge of their own FICO Score, specifically, treatment group members were less likely to overestimate their FICO Score. This is consistent with literature on overoptimism and overconfidence (Kahneman and Tversky, 1996; Fischhoff, Slovic and Lichtenstein, 1977; Svenson, 1981) and suggests the intervention may lead to behavior change by allowing people to properly calibrate their creditworthiness. In contrast, we find no differences in general financial literacy or the ability to identify actions associated with improving creditworthiness across experimental groups.

We test whether continued email reminders are necessary to maintain the effects on financial outcomes we observe in the first year of the intervention by using a separate sample – our "discontinued sample" – who only received emails for the first three quarters of the intervention. Consistent with an account of limited attention (Bordalo, Gennaioli and Shleifer, 2013; Chetty, Looney and Kroft, 2009; Malmendier and Lee, 2011), reminders have been shown to help people accomplish desired actions such as building savings or managing debt (Cadena and Schoar, 2011; Karlan et al., 2016; Bracha and Meier, 2014). However, we find no significant differences in financial outcomes between the main treatment group and the discontinued sample, evaluated a full year after the discontinued sample stopped receiving communications.

The effectiveness of our intervention is promising and somewhat surprising as even high-cost, high-touch interventions—such as classroom based financial literacy training or one-on-one counseling—are typically ineffective at changing behavior (Lusardi and Mitchell, 2007; Hathaway and

Khatiwada, 2008; Willis, 2008, 2009; Fernandes, Lynch Jr and Netemeyer, 2014; Hastings, Madrian and Skimmyhorn, 2013). Additionally, research examining efforts to improve decision-making through enhanced disclosures—such as those mandated by the Credit Card Accountability Responsibility and Disclosure (CARD) Act of 2009 and the Truth-in-Lending Act (TILA)–have found that these interventions often fail to influence outcomes as intended.[1]

Our intervention design builds on literature demonstrating the promise of interventions that correct for cognitive biases. For example, Bertrand and Morse (2011) find that the framing of fee disclosures influenced the likelihood of taking out a payday loan. In the context of creditworthiness, Perry (2008) finds that more than 30 percent of people overestimate their credit scores, suggesting that overoptimism could contribute to poor financial decision-making (Kahneman and Tversky, 1996; Fischhoff, Slovic and Lichtenstein, 1977; Svenson, 1981).[2] Related literature finds that personalized negative feedback can lead to positive behavior change. Agarwal et al. (2013) find individuals who incur credit card fees take steps that serve to dramatically reduce fees incurred over time. Similarly, Seira, Elizondo and Laguna-Muggenburg (2017) find that disclosures highlighting a borrower's high credit risk improved borrowing decisions. Consistent with this literature, our findings suggest that interventions may prove more effective if they are designed to help consumers correct biases in self-assessment of creditworthiness or financial health.

The paper is structured as follows. Section I provides background on FICO Scores and the Open Access initiative. Section II presents an overview of the field experiment. Section III provides a description of our data. Section IV presents findings on the effect of the intervention on viewing behavior and financial outcomes. Section V discusses mechanisms. Section VI considers welfare effects of the intervention. Section VII concludes.

[1] For example, Agarwal et al. (2014) examine the CARD Act's 36-month disclosure requirement, which required lenders to state the amount consumers would need to pay each month to repay their bill in full in 3 years. This policy led to minimal changes in payment behavior overall, with changes being primarily driven by an increase in the share of accounts paying exactly the 36-month amount. Similarly, Lacko and Pappalardo (2010) find that mortgage cost disclosures required by TILA are ineffective, with many consumers misunderstanding key terms.

[2] For example, Biais et al. (2005) show that overconfident traders are more likely to demonstrate the winner's curse, and Camerer and Lovallo (1999) show that overestimating chances of success in a new venture can lead to increased market entry and financial loss.

I. Background on FICO Scores and Open Access Initiative

FICO Scores, a product of the Fair Isaac Corporation, are used by 90 of the top 100 largest financial institutions to make consumer credit decisions. FICO Scores are calculated using information collected by the major credit bureaus and are constructed using a proprietary algorithm that incorporates information about an individual's outstanding debt, payment history, length of credit usage, mix of credit used, and applications for new credit (see Figure 1). Although the FICO Score is traditionally used to assess creditworthiness by lenders, the score has become increasingly utilized outside of the financial services sector (Bartik and Nelson, 2016; Clifford and Shoag, 2016; Dobbie et al., 2016).

In recent years there has been a push by policymakers, regulators and financial service providers to increase consumer access to their credit information, including credit reports and credit scores. In November 2013, FICO joined this effort by launching the FICO Score "Open Access" initiative. Through this initiative, FICO partnered with financial institutions that purchase FICO Scores for use in risk management to make those scores available directly to the consumer, free of charge. As of January 2018, more than 250 million consumer credit and loan accounts in the US included free access to the FICO Scores used by lenders to manage those accounts.

II. Experiment Overview

On June 24, 2015, Sallie Mae, a national financial institution specializing in student loans, launched the FICO Score Open Access program and began providing free score access to customers through the their website. Clients who logged in to the website saw a visual display that included their FICO Score beside a barometer showing the range of possible FICO Scores (Figure 2). The display also listed two "reason codes" that explain the key factors contributing to the individual's score, such as limited credit history or account delinquency.

While all customers had the ability to log in and view this information, many borrowers may not have been aware of the new program. To test the effect of providing information about a borrower's FICO Score, we experimentally vary knowledge of FICO Score availability through additional communication about the program.

A. Sample Population

The sample for the experiment consists of the 406,994 student loan borrowers who held a loan with Sallie Mae at the start of the FICO Score Open Access program and continued to hold that loan for the following two years. Table 1, Panel A presents summary statistics of the demographic characteristics of our experimental population provided by Sallie Mae. The average age of borrowers in our sample is 25 years old with just over half currently attending school, while the remainder are out of school and, therefore, have started paying off their student loan debt.

B. Experimental Conditions

Prior to the roll-out of the FICO Score Open Access Initiative through Sallie Mae, borrowers were randomly assigned to one of four experimental groups – three treatment groups and one control group. Roughly 90 percent of our sample was assigned to one of the three treatment groups, while the control group contained the remaining 10 percent of the sample. Borrowers assigned to the treatment groups received email communications from Sallie Mae alerting them to the availability of their FICO Score and providing instructions on how to access the information while control group members did not receive any communication about the program beyond what was provided on the provider's website.

All emails included a short description of the FICO Score and informed borrowers that their score was available to view. The email also included a link to log in via the loan provider's website. Treatment group members received these communications once per quarter on the date that scores were updated informing them that their FICO Score had been updated and, again, providing a link to log in to view the score. Due to privacy considerations, personalized information about FICO Scores were not included in the email itself.

Borrowers who received an email were randomly assigned to be in one of three conditions: (1) baseline, (2) economic consequences, and (3) social influence. In the baseline condition, borrowers received only the information described above (Figure 3). The two additional conditions included the same information as the baseline email as well as additional messaging. In the economic consequences condition (Figure 4a), clients received an email that was intended to emphasize the impact of the FICO Score on economic outcomes (e.g., "When you apply for credit – whether it's a credit card, car loan, student loan, apartment rental, or mortgage – lenders will assess your risk as a borrower...”). Building on research demonstrating the effectiveness of messaging informing individuals of prosocial actions of their peers (Allcott, 2011; Ayres, Raseman and Shih, 2012; Cialdini and Goldstein, 2004; Kast, Meier and Pomeranz, 2012), the social influence condition (Figure 4b) included messaging informing readers that their peers were taking actions to improve their credit (e.g., “Many of your peers are building strong financial futures. You can, too, by effectively managing your student loans.”).

C. Experiment Timeline

The three treatment groups in the main sample received eight quarterly emails starting in June of 2015. Each treatment group received their assigned message for three consecutive quarters (June, September, and December of 2015). However, beginning in 2016, all three treatment groups received only the content included in the baseline email message. In other words, clients in the economic consequences and social influence conditions began receiving the baseline message starting in March of 2016; clients in the baseline condition continued to receive the baseline message. The control group never received any direct communications about the program.

The experimental design included a separate population of 37,393 borrowers – the “discontinued sample” – that received quarterly emails for only three quarters. This sample was also split into three treatment message groups, and received quarterly email communications in June, September, and December of 2015. Our main analysis focuses on the 326,609 treatment group members who received quarterly communications through the end of the intervention in June of 2017. However, the discontinued sample allows us to test whether continued communication has an impact on the likelihood of viewing one’s score and on subsequent financial outcomes, and we discuss analysis of this sample in section V.C. See Figure 5 for a summary of the experimental timeline.

III. Data

A. FICO Score Page View Data

As described above, Sallie Mae offers all clients access to their FICO Score via their account profile which users access online by logging in with their username and password. Over the course of the study period, Sallie Mae tracked each time a borrower viewed the FICO Score page on the web portal. We use this information to construct indicators for whether the borrower viewed their FICO Score throughout the study period.

B. Credit Bureau Data

Each quarter, Sallie Mae receives updated credit report information for each of their borrowers as part of routine business practice. The credit report information is provided by TransUnion, one of three major national credit reporting agencies, and is used to calculate the borrowers FICO Score. The FICO Score is then made available to the borrower through the Open Access program. All borrowers in our sample hold a private student loan and, therefore, FICO Scores existed for all borrowers in our sample.

i. Credit Outcomes and Demographics

In addition to the FICO Score itself, the quarterly credit file includes information on other financial outcomes including late payments and credit account activity at the individual borrower level. The late payments data includes indicators for whether the individual had any account that was more than 30, 60, or 90 days past due in the last six months. The credit account data includes the number of revolving trade accounts (e.g., credit cards), credit utilization (i.e., the percent of the credit limit used), and the total credit balance amount.

ii. Summary Statistics

Panel B of Table 1 presents summary statistics on baseline credit measures for the 406,994 borrowers in our sample population as of June 2015 (i.e., prior to the launch of the experiment) by experimental condition. As mentioned in Section II.A, all individuals in our sample are student loan borrowers, with just over half still in school. Due to their young age, sample members are relatively new to credit with an average credit history of only 6.5 years. At the start of the experiment, the average FICO Score was 675, slightly lower than the national average of 700[3]. Just under 70 percent of the sample had at least one revolving trade account with the average borrower holding 2.5 revolving trade accounts. Borrowers with at least one revolving trade account utilize just under 40 percent

[3]Source: www.fico.com/en/blogs/risk-compliance/us-average-fico-score-hits-700-a-milestone-for-consumers/

of their account limit. Roughly 14 percent of borrowers have had at least one account balance 30 or more days past due within the prior six months with half of those borrowers holding at least one delinquent account (defined as 90 days or more past due). Individual demographics and baseline credit history are balanced across the control condition and all treatment conditions, consistent with a randomized design.

C. Financial Literacy Survey Data

In addition to collecting credit report data on the sample population, Sallie Mae conducted the FICO and Financial Literacy Survey to identify effects of the FICO Score Open Access initiative on respondent financial literacy and FICO Score-specific knowledge. In June 2016, one year after the program began, Sallie Mae solicited survey responses from all current borrowers in the experimental sample.[4] This data was linked to each borrower's treatment status to evaluate the effect of the intervention on survey responses.

i. Survey Questionnaire

The survey contained questions on the borrower's awareness and use of various financial communications and products provided by Sallie Mae with a specific focus on the FICO Score Open Access initiative. Questions asked each borrower about the number of FICO Score views in the last year, familiarity with the concept of a FICO Score, and awareness of her personal FICO Score.[5] Importantly, these self-reported scores could then be linked to an individual's actual FICO Score to assess the accuracy of the self-report. Additionally, the survey contained a wide variety of questions to assess the borrower's general financial literacy including awareness of positive credit behaviors. Additional details of these questions are in Appendix A. Lastly, participants responded to a series of demographic questions focusing on academic details such as college type, year and field of study, and student loan details.

[4] Responses were solicited via email and borrowers had up to one month to participate. Sallie Mae sent email reminders encouraging borrowers to take the survey but did not provide an incentive for participating.

[5] Possible responses included FICO Score ranges of 0-299, 300-449, 450-549, 550-649, 650-749, 750-850 and more than 850, or respondents could state that they did not know their FICO Score.

ii. Survey Response

Of the more than 400,000 borrowers who were asked to participate, only 3,511 individuals completed the survey. While this low response rate is in line with previous survey requests sent by the lender, it raises some questions about the external validity of this data source. Table 2, Panel A reveals several small but significant differences between survey respondents and non-respondents in baseline demographic and credit data drawn from the June 2015 TransUnion credit report. For example, survey respondents were slightly older (27 versus 25), more likely to be out of school (54 versus 45 percent), and had a higher FICO Score (696 versus 676) than non-respondents.

While the comparison of baseline characteristics reveals some differences between respondents and non-respondents, an examination of treatment status by survey response shows no such differences. Table 2, Panel B shows that borrowers assigned to one of the three treatment conditions were equally likely to participate in the survey: 89.0 percent of survey respondents were assigned to the treatment condition versus 89.4 percent of non-respondents. Response rates were also balanced across two of the the three treatment arms individually, with survey respondents being slightly less likely to have been assigned to the baseline treatment group. So while our sample of survey respondents is unlikely to be representative of our full sample population, these results suggest that experimental comparisons within this select sample are still likely to be internally valid.

IV. Analysis

This section presents the effects of our intervention on FICO Score views and subsequent financial outcomes. We first discuss the dynamics of FICO Score viewing patterns among our sample population. This analysis is primarily intended as a first stage to determine the effectiveness of the informational campaign on viewing. Next, we move to describe effects of the experiment on financial outcomes for the full sample and by subgroup.

A. Dynamics of FICO Score Viewing Patterns

i. Weekly FICO Score Viewing Patterns

We begin our analysis by investigating whether sending borrowers quarterly emails informing them that their score is available increases the likelihood of viewing their FICO Score using administrative data from the lender's website. Figure 6 presents weekly FICO Score viewing patterns for the main sample by experimental condition from June 26, 2015 to June 8, 2017[6] with quarter labels corresponding to the weeks in which the intervention emails were released. Figure 6A displays FICO Score view rates by week, while Figure 6B presents the percent of borrowers who had ever viewed their FICO Score through Sallie Mae's website from the intervention's start through the week in question. Viewing patterns are displayed separately for the treatment and control groups, with all three treatment message conditions combined.

These figures show that less than half a percent of control group members viewed their score in a given week with 19 percent of control group members viewing their score at least once by the end of the two-year intervention. This suggests that even in the absence of email communications about the program, some borrowers were aware of the availability of FICO Scores and did view them. However, the figures also show that receiving a quarterly email boosts FICO Score views even further. Treatment group members saw a large spike in the number of FICO Score views in the first week after each email was sent ranging between three and six percent of borrowers viewing their scores in the week of the email release. Additionally, these effects do not fade over time: continued viewing is driven by a combination of borrowers who have already viewed their scores doing so again as well as additional borrowers checking their score for the first time late in the study period, as shown in Figure 6B. By the end of the intervention, 31.4 percent of treatment group members viewed their score at least once.

ii. Quarterly FICO Score Views

Table 3 presents regression estimates of the effect of the email treatments on FICO Score views through Sallie Mae's website over time. The regression model is as follows:

[6] Our estimates of the fraction of borrowers viewing their scores will be lower bound estimates since we did not capture score views on the first two days of the campaign, see section III.

$$Y = \alpha_0 + \alpha_1 T + \varepsilon$$

where T is an indicator for being randomly assigned to any one of the three treatment conditions. We consider four outcomes of interest. The first is an indicator of ever having viewed one's FICO Score within the intervention quarter in the column header (Panel A). The second outcome is an indicator for ever having viewed one's FICO Score between the start of the intervention (the first date scores were available) and the end of the column header's quarter (Panel B). These two measures are very similar to those shown in Figures 6A and 6B, but at the quarterly, rather than weekly level. The last two outcomes of interest mirror these measures, but estimate the number of views rather than an indicator for ever viewing (Panels C and D).

Panel A of Table 3 shows that between 2.9 and 5.2 percent of control group members viewed their score in each of the first eight quarters of the Open Access program, again suggesting that at least a fraction of control group members were aware of the availability of access to their scores through banner ads or other sources. However, treatment group members were significantly more likely to view their score in every quarter – these quarterly treatment effects ranged from 1.5 to 5.9 percentage points. To consider whether the persistent effects are due to repeat viewing by a consistent set of viewers or whether the intervention causes new borrowers to view later in the intervention, Panel B of Table 3 estimates the likelihood of ever having viewed one's score by the given quarter. Control group viewing rates increase steadily over the intervention from 12.4 percent at the end of the first year to 19.2 percent at the end of the second. However, treatment group view rates increase by even more – the treatment effect estimates grew from an 8.1 percentage point increase in year one to a 12.4 percentage point increase by the end of the intervention. Our two estimates of the treatment effects of the number of views follow similar patterns. By the end of the intervention, the average number of views in the control group was just under half a view per person, while treatment group members viewed their score almost twice as often.

While these estimates suggest that our intervention led to a significant increase in the likelihood of viewing one's score through the Sallie Mae's website, this does not necessarily tell us about the effects of the intervention on *overall* views. For example, treatment and control group members could be equally likely to have viewed their scores during the study period, but the the intervention simply caused treatment group borrowers to view their scores through the Sallie Mae's website rather than through a different source. We address this concern in Appendix B using survey data on views from all sources during the first year of the intervention and find treatment effects on the likelihood of ever having viewed one's FICO Score through any source that are nearly identical – 8.0 versus 8.1 percentage points.

B. First-Year Effects on Financial Outcomes

The previous section demonstrated that the email intervention significantly affected the likelihood that a borrower viewed his or her FICO Score on the loan provider's website – a 65 percent increase in ever viewing during the experimental period. This section uses this exogenous variation in FICO Score views to determine the effect of the intervention on a variety of economic outcomes by linking FICO Score view data to individual-level credit bureau records.

Our primary specification is a reduced form regression comparing outcomes by experimental group using first-differences to control for an individual's credit history prior to the experiment – the intent-to-treat (ITT) estimate. As in the previous section, our main specification combines all three treatment message groups into one treatment group. Therefore, the econometric model takes the form of the regression in Equation (1), where the dependent variable is the difference in the economic outcome between the quarter prior to the experiment (June 2015) and the post-intervention quarter of interest. For our main specification, we consider the first-year impacts of the intervention; Section IV.C considers longer-term impacts. It is important to remember that while FICO Score views were significantly more common in the treatment groups than in the control group, all sample members had access to their scores on the loan provider's website. Therefore, the coefficient of interest, α_1, can be interpreted as the causal impact of sending quarterly emails about FICO Score availability on the within-person change in credit record outcomes, i.e., the difference-in-differences estimate comparing treatment and control groups before and after the start of the intervention. These estimates are presented in Panel A of the following tables.

To estimate the effects of viewing one's FICO Score on credit outcomes – rather than simply being sent an email, but not necessarily logging onto the website or even opening the email – we also include estimates of the treatment-on-the-treated (TOT). Here we use an instrumental variables regression where treatment status is the instrument for ever having viewed one's score by the quarter of interest. These results are presented in Panel B of the following tables.

i. Late Payments and Delinquencies

Repayment behavior has important implications for borrowers' creditworthiness and overall financial health. Table 4 presents the effect of the intervention on the change in likelihood of having at least one account balance past due for over 30, 60, or 90 days within the past six months. Treatment group members were significantly less likely to have an account that was 30 days or more past due – a 0.7 percentage point decrease with a treatment-on-the-treated effect of 9.0 percentage points. This is a relatively large effect given that only 17.5 percent of control group members had a balance 30 or more days past due. We observe similar impacts on the likelihood of having an account 60 or more days past due, though slightly smaller – a 0.5 percentage point decrease with a treatment-on-the-treated effect of 5.7 percentage points. While the estimates of the effect of the treatment on the likelihood of having a delinquent account (i.e., an account balance that is more than 90 days past due) are directionally consistent, the results are not statistically significant.

ii. Revolving Credit Account Activity

Another determinant of borrowers' creditworthiness pertains to their account status and credit utilization. While the number of accounts an individual holds can impact her creditworthiness in many ways – for example, too many accounts can signal over-utilization while too few accounts can prevent a borrower from establishing credit history – given that our sample is relatively young, we might expect that the more common concern is not having enough account activity to establish credit. Our analysis focuses on revolving trade activity (most commonly, credit card accounts) since these are trade accounts that are plausibly easy to open or close in response to learning about one's FICO Score unlike, for example, a mortgage or an auto loan. The first two columns in Table 5 present estimates of the effect of the treatment on the likelihood of having any open revolving credit account and on the number of accounts held, respectively. In line with our hypothesis about the credit history of our student borrower population, we find that the intervention caused a small but significant increase in the number of open accounts. Treatment group members were 0.3 percentage points more likely to have at least one account with a TOT estimate of 3.6 percentage points (on a base of 76 percent among control group members). We observe a similarly small but significant increase in the number of accounts held.

While having no credit history can harm one's creditworthiness, very high credit utilization (i.e., the percentage of revolving credit used) or carrying a balance (i.e., making minimum payments but not paying off the full balance) can also be detrimental. To examine whether the treatment affected these types of credit behaviors, we turn to the estimates in Columns 3 and 4. The point estimates for both credit utilization and balance amount are small and statistically insignificant.

iii. FICO Score

The results so far have shown that viewing one's FICO Score is associated with both a reduction in the number of past due accounts and an increase in the likelihood of holding a revolving trade account. But, what is the effect of viewing one's FICO Score on the FICO Score itself? An individual's FICO Score is generated using a proprietary algorithm which makes it difficult to predict the net effect of any specific behavior or change in financial condition on the score. However, Figure 1, which describes some of the key components impacting an individual's FICO Score suggests that we may expect some movement in the FICO Score itself as a result of the intervention given that we observe a treatment effect for several inputs including the total number of accounts and the number of past due accounts on the credit report.

Table 6 presents the estimated effects of the treatment on the individual's FICO Score. Borrowers in the control group have an average FICO Score of 676. Our results show that receiving the quarterly emails increased the average FICO Score of treatment group members by two-thirds of a point with a TOT estimate of 8.3 points. Results from models applying a log-transformation to the FICO Score in Column 2 yield substantively identical results. It is important to underscore that the FICO Score is designed as a measure of creditworthiness to be used in underwriting and is therefore not necessarily an accurate measure of financial health or well-being. Nevertheless, it does appear that viewing one's FICO Score drives financial behaviors which, on net, improve the creditworthiness of individuals. Column 3 looks at the effect of the treatment on the likelihood of having a FICO Score greater than 620, a common definition of a subprime borrower. We discuss these results in Section VI.

C. Long-Term Effects

The estimated treatment effects presented above are for one year from the start of the intervention, from June 2015 to June 2016. To examine both the longer-term treatment effects and how the effects evolve over time, Figure 7 presents ITT estimates quarterly for the full two-year study period from June 2015 to June 2017.

Figure 7A presents quarterly treatment effects for the likelihood having a late payment of 30 or more days past due. Our results show that the size of the treatment effect is greatest approximately 12 to 15 months from the start of the intervention. After 15 months, the treatment effect attenuates and by the end of the two-year period is no longer statistically significant. Figure 7B presents the effect of the treatment on whether the borrower has any revolving credit account. Here again we see the estimated treatment effect is largest one year from the start of the intervention and then attenuates towards zero in later months. Finally, Figure 7C presents the estimated effect of the treatment on borrowers' FICO Scores in each quarter. Here again we see the estimated coefficient is largest one year from the start of the intervention, however, the effect remains fairly consistent through the end of the two-year study period.

D. Subgroup Analysis

The treatment effects detailed above are estimated on the full sample of student loan borrowers. This includes individuals with relatively high FICO Scores as well as individuals who started off with relatively low scores or had a delinquency on their credit report at the start of the intervention. It similarly combines younger borrowers, many of whom have limited experience handling their own finances or understanding the consequences of certain actions, with older, more experienced borrowers. This section presents estimates of treatment effects on our financial outcomes by subgroup.

i. Baseline FICO Score

One question is whether the intervention was effective for the people who needed help the most – those with lower FICO scores – or whether the treatment only moved behavior among those who were already performing well on this metric. To examine treatment effects by pre-intervention FICO

Score, we split our sample into two groups: a "low" FICO Score group comprised of those with initial FICO Scores below the sample median of 675 and a "high" FICO Score group comprised of those with initial scores above 675. We then re-estimated our models including an interaction between assignment to treatment and a binary indicator for whether the individual started the study period with a high FICO Score. Results are presented in Table 7. For all of our outcomes, the interaction term is not significant, though the point estimates suggest that the estimated effect of the treatment on creditworthiness (lower likelihood of late payments and increased likelihood of having a credit account) is larger for borrowers with a lower pre-intervention FICO Score.[7]

ii. Baseline Late Payments

A second question is whether the treatment solely prompts people to take actions to remedy existing problems (e.g., repay accounts with existing delinquencies) or whether it also serves as a more general motivation to improve future financial behaviors (e.g., avoid having delinquent accounts in the future). Table 8 addresses this question by presenting treatment effects by baseline late payments, interacting treatment status with an indicator for having a payment of thirty or more days past due in the past six months at the start of the intervention. The sign of the interaction term coefficient suggests that the treatment effects on FICO Score, 30-day late payments, and having a revolving credit account are larger for individuals with baseline late payments, though the interaction term is only significant for having a revolving account. It is also interesting to note that the intervention led to a statistically significant decrease in the likelihood of having a 30-day late payment at the end of the first year among treatment group members with no late payments at baseline. This suggests that the decrease in late payments is not solely driven by individuals reconciling previous past due accounts, but that the intervention reduced the likelihood that an individual who was not previously delinquent entered into delinquency during the study period.[8]

[7] Splitting the sample by high versus low FICO Scores may obscure important variation in treatment effects at different points in the distribution. Appendix Table C.1 examines interactions by baseline FICO Score quartile; results are substantively similar to those presented here and indicate results are not being driven by one specific FICO Score quartile.

[8] Results are substantively similar if we use an indicator for whether the individual had a delinquency reason code at baseline instead of a current late payment on their credit report, see Appendix Table D.1.

iii. Borrower Age

Finally, it is possible that the treatment had differential effects on borrowers of different age groups. Younger borrowers are less likely to have financial experience and may be less aware of how to improve their own creditworthiness; therefore, we might expect that our intervention would be particularly successful in this population. Alternatively, older borrowers may respond more to the intervention since they have more actions available to take as a result of having more established finances. Table 9 presents treatment effects by age, comparing borrowers who are above or below the median age of 23 years old at the start of the intervention. We find no significant differences in the likelihood of having a late payment or having an open revolving trade account by age, though the point estimates suggest that the treatment effects on these outcomes are slightly larger among the older borrowers. However, we do find significant differences by age group on number of revolving trade accounts and credit utilization.

V. Mechanisms

The previous section shows that our informational campaign led to several improved measures of creditworthiness. However, these communications and the information provided on the lender's FICO Score web page contained several different informational components. For example, individuals who logged on to Sallie Mae's website to view their score were directed to a web page that included not only personalized information on the borrower's current FICO Score and reason codes, but also links to additional financial literacy materials provided by the lender. Those who read the email but did not log on to the website received general information about FICO Scores. Additionally, borrowers in the social influence and economics consequences treatment groups received information about peer credit behavior and financial consequences of low FICO Scores, respectively. Lastly, treatment messages may have simply reminded borrowers about late payments or other financial actions independently from the information about their FICO Score. This section considers the effect of the different components of the intervention and provides suggestive evidence on which elements may have been most effective at improving borrowers' financial outcomes.

A. Financial Knowledge

In this section, we use information from our second data source, the FICO Financial Literacy Survey, to test the effect of our intervention on various financial knowledge outcomes.

i. Personal FICO Score Knowledge

Previous research has shown that people are often overly confident about their own knowledge and ability in a range of domains (Kahneman and Tversky, 1996; Fischhoff, Slovic and Lichtenstein, 1977), including evidence of overestimation in the context of credit scores (Perry, 2008). Survey respondents were asked several questions about their knowledge of personal financial information, specifically, their own FICO Score. Respondents were asked if they knew their FICO Score and, if so, were asked to indicate their score within a 100 to 150 point range. Using data from our administrative credit reports, we can then verify the accuracy of these self-reported scores. Column 1 of Table 10 shows that while over three-quarters of control group members reported knowing their FICO Score range, treatment group members were 4.3 percentage points more likely to report knowing their score. A larger difference emerges when comparing the accuracy of these responses to the corresponding data from respondents' TransUnion credit reports. Column 2 shows that treatment group members are 7.1 percentage points more likely to report an accurate FICO Score range on a base of 51.5 percent accuracy among control group members – a 14 percent increase. Columns 3 and 4 decompose this measure of reported accuracy to examine the effects of the intervention on the likelihood of overestimating versus underestimating one's FICO Score, respectively. We find that receiving a treatment message significantly decreased the likelihood of borrowers reporting an overestimate of their FICO Score by 3.4 percentage points, but had no significant impact on the likelihood of underestimating one's score. These findings suggest that the intervention provided borrowers with important feedback that they could use to calibrate their personal creditworthiness. Our findings are consistent with existing evidence of overoptimism in knowledge of personal creditworthiness (Perry, 2008) and with evidence that over-confidence and over-optimism negatively affect performance in other areas (Biais et al., 2005; Camerer and Lovallo, 1999). Our evidence suggests that debiasing these misperceptions may lead to improvements in financial behaviors.

ii. Other Financial Knowledge Measures

The survey also contains questions on knowledge of several financial concepts including knowledge of good credit behaviors, familiarity with FICO Scores, and a financial literacy quiz. We test whether receiving the FICO Score communications translates to differences in other types of financial knowledge beyond one's own FICO Score. For example, the intervention could make people more familiar with the concept of a credit score or good types of credit behavior. To the extent that people were previously unaware that a metric like a credit score existed, that awareness could, in and of itself, lead people to take actions to improve it. Separately, receiving communications about one's FICO Score could lead people to become more engaged with their finances overall, resulting in higher levels of financial literacy.

Table 11 investigates this issue by estimating the effect of the intervention on respondents' ability to correctly identify positive credit behaviors such as paying bills on time, having neither too many nor too few credit cards, and keeping a low balance and credit utilization. We find no effects of the treatment on borrowers' ability to correctly identify any individual credit behavior as positive or negative, nor on their likelihood of accurately assigning all behaviors. It is interesting to note that the control means for accurately identifying each behavior are quite high – over 90 percent for all but one measure – suggesting that many respondents were already aware of the activities necessary to improve their credit. Table 12 complements this analysis using questions on borrowers' self-reported familiarity with the concept of a FICO Score as well as answers to a three-question financial literacy quiz involving questions related to interest rates and student loan options. Columns 1 and 2 show that just under a third of control group members report being very aware of the concept of a FICO Score (i.e., are confident they could explain what a credit score is to a friend) while 86 percent report being at least somewhat familiar with the concept. However, neither measure of general FICO Score knowledge is significantly affected by the intervention. Similarly, we find no impact of the treatment on accuracy of the financial literacy quiz either on individual questions or perfect accuracy (columns 3 to 6).

B. Treatment Effects by Message Type

The results in Section IV focus on the effect of receiving any treatment message. However, two experimental groups – the economic consequences and social influence groups – received additional information in their email messages for the first three quarters of the intervention. If borrowers were unaware of how FICO Scores impact the cost of credit, the economic consequences message may prompt additional changes in behavior. At the same time, borrowers may be additionally motivated to improve their FICO Score if they are told people like them are doing so (Allcott, 2011; Ayres, Raseman and Shih, 2012; Cialdini and Goldstein, 2004; Kast, Meier and Pomeranz, 2012).

Figure 8 mirrors the analysis in Figure 6, but displays FICO Score view rates separately for the three treatment messages for the first year of the intervention. The figure shows that the viewing rates – both in a given week and the likelihood of ever viewing – are very similar across treatment messages. If anything, the baseline message outperformed the two messages that contained additional information. Table 13 presents ITT estimates for the financial outcomes measured in Tables 4-6 separately by treatment message type: baseline, economic consequences, and social influence. The F-test for equality of treatment effects across the three messages suggests that the estimates are not significantly different across treatment groups for all but one outcome: the number of revolving accounts held. This is somewhat unsurprising given the relatively similar FICO Score view rates across the three treatment groups. While research has shown nudges of this type can be effective in some contexts, we find no evidence these additional messages impacted behavior.

C. Reminders

Consistent with an account of limited attention (Bordalo, Gennaioli and Shleifer, 2013; Chetty, Looney and Kroft, 2009; Malmendier and Lee, 2011), a final possibility is that our intervention did not provide borrowers with any new information, but simply served as a reminder about late payments or other financial actions (Cadena and Schoar, 2011; Karlan et al., 2016). In this section, we examine a separate sample – our "discontinued sample" – who were randomly assigned to received quarterly email communications for only three quarters rather than throughout the two-year intervention as in our main treatment sample. This sample allows us to test the impact of additional email communications on viewing rates and financial outcomes to determine if these reminders lead to improved outcomes.

Figure 9 presents weekly FICO Score view rates for the control group, discontinued sample, and the main treatment sample. The figure shows that the FICO Score view rates for the main treatment sample and the discontinued sample are virtually indistinguishable for the first year of the email campaign, which is expected since the two groups received the same treatment during this time period. However, starting in March 2016—when the discontinued sample stopped receiving email communications—the discontinued group's view rates began to closely track the control group rather than the treatment group.

Table 14 presents a modified version of the regression in Panel B of Table 3 which estimates the effect of treatment assignment on the likelihood of ever viewing one's FICO Score separately for the main treatment sample and the discontinued sample by intervention quarter. For example, Column 3 presents treatment effects for the two treatment samples on the likelihood of viewing one's score before March 2016, the last quarter in which the two groups had received the same treatment. Unsurprisingly, we see no difference in treatment effects between the two groups prior to March 2016 – each treatment group was 6.3 percentage points more likely to have viewed their score relative to the control group. However, starting in the following quarter we see the two groups diverge. One year after the discontinued group stopped receiving the quarterly emails, the treatment effects on viewing rates for the main sample were twice as large as those for the discontinued group – 10.9 versus 5.3 percentage points. This suggests that sending additional communications did increase the likelihood that the borrower would eventually view her score.

While our results show that individuals who continue to receive reminders to view their FICO Score are more likely to do so than individuals who received reminders for a limited time, it is not necessarily true that continued reminders will lead to larger changes in economic outcomes. For example, if the individuals who view their score only after receiving several emails are unlikely to respond to the information contained in the email, discontinuing communications may have no impact on average financial behavior. Table 15 presents the ITT estimates for the two treatment samples relative to the control group on a borrower's financial behavior as of March 2017, one year after the discontinued group stopped receiving communications. First, as we saw in Section IV.C, our main treatment group results are attenuated, but largely persistent almost two years after the program's inception. Similarly, the estimates for the discontinued sample are only slightly smaller than those in the main treatment group: there is no statistically significant difference between the financial outcomes of those who continued to receive emails and those who stopped receiving emails a year prior.

VI. Economic Consequences

In our experiment, we observe that the average FICO Score of treatment group members increased by 0.67 points with a TOT estimate of 8.2 points one year after the intervention began. One question is how meaningful this increase is in terms of consumer welfare. To calibrate the size of the effect, a 10 point increase in credit scores is equivalent to the removal of a bankruptcy flag from a credit report after seven years (Dobbie et al., 2016). Dobbie et al. (2016) further find that increases in credit scores correspond to improvements in credit access. However, differential treatment as a function of credit scores is not linear. Instead, banks frequently change lending terms at discrete cutoffs. For example, Fannie Mae requires a minimum credit score of 620 for most mortgages, their definition of a subprime borrower. Table 6 looks at the effect of the intervention on having a FICO Score above 620 and shows that treatment group members are significantly less likely to be subprime borrowers – the treatment leads to an increase of just under half a percentage point in the likelihood of having a score over 620.

Credit information is used in nearly all lending decisions, but also in other contexts. For example, credit reports are frequently used as inputs by landlords to determine eligibility for rental apartments, or by employers in hiring decisions (Bartik and Nelson, 2016; Clifford and Shoag, 2016; Dobbie et al., 2016). Beyond improving one's credit profile, increasing on-time payments is likely to be beneficial in and of itself. For example, making the minimum payment towards an account balance reduces the incidence and severity of finance charges and fees associated with delinquencies.

VII. Conclusion

Findings from our field experiment indicate that viewing one's FICO Score influences financial behaviors. People who were randomly assigned to receive communications informing them that their score was available to view were less likely to have past-due credit accounts and were more likely to have at least one revolving credit account. These changes contributed to an overall increase in creditworthiness as measured by an increase in the FICO Score itself, an effect that largely persisted throughout the full two-year intervention. Survey results provide evidence that people in the treatment group were less likely to overestimate their score relative to those in the control group, while providing no evidence of changes on other metrics such as general financial literacy or knowledge of which actions to take to improve one's creditworthiness. It is particularly encouraging that this intervention appears to spur positive behavior change among a relatively young population that is new to credit and may therefore yield long term benefits from immediate behavior change. Future work should examine how this research generalizes to the broader population.

The FICO Score provides a single number that allows for easy tracking of a disparate set of actions related to creditworthiness. This personalized, quantified, dynamic measure allows individuals to monitor and track their progress over time, analogous to the role of a Fitbit in encouraging exercise (Cadmus-Bertram et al., 2015).This holistic financial metric may be particularly well suited for goal-setting. For example, a large body of literature documents goal-setting behavior in which people try to achieve a certain level of performance as a function of a numeric cue, such as a race finishing time or personal best score in a game (Anderson and Green, 2017; Locke and Latham, 2002; Markle et al., 2015; Pope and Simonsohn, 2011). However, these types of goals can only be set and managed when they are able to be tracked through a single number.[9] Similar metrics that summarize a broad set of outcomes may be effective in other areas as well, such as promoting overall health scores to encourage better health habits or promoting overall efficiency scores to encourage better time management.

Our findings demonstrate the potential for targeted, low-cost, scalable interventions to positively impact financial decision making and improve consumer financial welfare. They are particularly encouraging given the limited success of traditional higher cost financial education interventions and suggest that these interventions may prove more effective if they also encourage individuals to track a personalized metric of financial health. More generally, our findings point to possible benefits of personalizing financial literacy content, consistent with individual self-reports that personal experience is a key driver of financial learning (Hilgert, Hogarth and Beverly 2003) and with recents efforts to promote "just in time" interventions that are timed to personal financial events (Fernandes,

[9] For example, see Erez (1977); Seligman and Darley (1977); Walford et al. (1978) for studies in the health and medical literature documenting positive behavioral responses to monitoring.

Lynch Jr and Netemeyer, 2014).

A limitation of our experiment is that we are unable to see borrowers' full financial pictures. Since we only see information reported to credit bureaus, we cannot rule out the possibility that the intervention is encouraging people to prioritize financial behaviors that are directly tied to their credit score to the detriment of other aspects of their financial lives we do not observe, such as income and savings (Beshears et al., 2017; Medina, 2017; Sussman and O'Brien, 2016). While our intervention shows positive effects on behaviors recorded in credit bureau data, future work should examine the impact of viewing one's score on other aspects of financial health.

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Table 1: Summary Statistics

			Treatment by Message Type			Discontinued		
	Control	Treatment	Baseline	Economic	Social	Sample	F-stat	prob>F
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Demographics								
Age	25.0	25.0	25.0	25.0	25.0	25.0	1.01	0.314
Currently in School (%)	56.1	56.7	56.8	56.7	56.7	56.9	2.58	0.108
Panel B: Credit History								
Months in Credit File	77.0	77.5	77.6	77.5	77.3	77.1	1.41	0.236
Balance Past Due (%)								
30+ Days	13.5	13.7	13.8	13.8	13.6	13.4	1.54	0.215
60+ Days	9.2	9.2	9.2	9.2	9.2	9.1	0.00	0.945
90+ Days	6.7	6.7	6.7	6.7	6.7	6.6	0.11	0.743
Revolving Trade Activity								
Any Account (%)	69.7	69.3	69.4	69.3	69.3	69.1	0.34	0.558
Number of Accounts	2.5	2.5	2.5	2.5	2.5	2.5	0.07	0.791
Credit Utilization (%)	39.6	39.7	39.7	39.8	39.6	39.9	0.16	0.686
FICO Score	675	674	674	674	675	674	0.27	0.606
N	42,964	326,609	108,759	108,813	109,065	37,393		

Source: Sallie Mae and TransUnion, June 2015.

Means shown for the control group (col 1), main treatment sample combined (col 2) and by message type including baseline, economic consequences, and social influence messages (col 3-5).

Means for the discontinued sample shown separately (col 6).

F-statistic and p-value for the F-test of equality for treatment versus control group means.

Balance past due measures assessed over the prior six months.

Credit utilization evaluated only for borrowers with at least one revolving account.

Table 2: Treatment Status and Demographics by Survey Response

	Respondents	Non-Respondents	F-stat	prob>F
	(1)	(2)	(3)	(4)
Panel A: Baseline Characteristics				
Age	27.1	25.2	310.20	0.00
Out-of-School	54.0	45.0	115.72	0.00
FICO Score	696	676	435.04	0.00
Panel B: Treatment Status				
Any Treatment	89.0	89.4	0.89	0.34
T: Baseline	28.3	29.8	3.67	0.06
T: Economic	30.1	29.8	0.11	0.74
T: Social	30.6	29.8	0.91	0.34
N	3,511	451,183		

Source: FICO Financial Literacy Survey, June 2016; TransUnion, June 2015.
Columns 1 & 2 report means for respondents and non-respondents of the June 2016 survey, respectively.
Columns 3 & 4 report results from the F-test for equality across survey response.

Table 3: First Stage: FICO Score Viewing Patterns

	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q5 (5)	Q6 (6)	Q7 (7)	Q8 (8)
Panel A: Ever View in the Quarter								
Treatment (T)	0.0146***	0.0483***	0.0341***	0.0512***	0.0535***	0.0417***	0.0385***	0.0586***
	(0.0011)	(0.0011)	(0.0012)	(0.0010)	(0.0010)	(0.0009)	(0.0012)	(0.0011)
Control Mean	0.047	0.039	0.050	0.034	0.036	0.029	0.052	0.039
Panel B: Ever View by Quarter End								
Treatment (T)	0.0146***	0.0516***	0.0626***	0.0813***	0.0977***	0.1057***	0.1082***	0.1238***
	(0.0011)	(0.0014)	(0.0016)	(0.0017)	(0.0018)	(0.0019)	(0.0020)	(0.0021)
Control Mean	0.047	0.076	0.107	0.124	0.141	0.153	0.177	0.192
Panel C: Number of Views in the Quarter								
Treatment (T)	0.0203***	0.0609***	0.0490***	0.0629***	0.0658***	0.0504***	0.0524***	0.0751***
	(0.0016)	(0.0017)	(0.0020)	(0.0018)	(0.0020)	(0.0018)	(0.0023)	(0.0019)
Control Mean	0.060	0.051	0.067	0.049	0.053	0.043	0.073	0.053
Panel D: Number of Views by Quarter End								
Treatment (T)	0.0203***	0.0811***	0.1302***	0.1931***	0.2589***	0.3093***	0.3617***	0.4367***
	(0.0016)	(0.0027)	(0.0040)	(0.0051)	(0.0063)	(0.0073)	(0.0088)	(0.0098)
Control Mean	0.060	0.111	0.178	0.227	0.280	0.322	0.396	0.449
N	369,601	369,601	369,601	369,601	369,601	369,601	369,601	369,601

Source: Sallie Mae, June 2015 to June 2017.

Quarters in reference to the start of the intervention in column headers.

Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Balance Past Due

	30+ Days	60+ Days	90+ Days
	(1)	(2)	(3)
Panel A: ITT			
Treatment (T)	-0.0073***	-0.0046**	-0.0021
	(0.0021)	(0.0019)	(0.0017)
Panel B: TOT			
Ever View	-0.0896***	-0.0568**	-0.0254
	(0.0258)	(0.0230)	(0.0208)
Control Mean	0.175	0.127	0.097
N	369,601	369,601	369,601

Source: Sallie Mae and TransUnion, June 2015 to June 2016.
Outcome: indicator for having a balance at least 30, 60, or 90 days past due in past six months.
All outcomes are first-differences between June 2015 and June 2016.
Treatment group includes all borrowers who received messages for eight quarters.
Panel A, Intent-to-Treat (ITT): OLS comparing treatment and control groups.
Panel B, Treatment-on-Treated (TOT): IV instrumenting ever viewing FICO Score in year one with treatment assignment.
Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Revolving Credit Account Activity

	Any Account	# Accounts	% Credit Used	Balance Amount
	(1)	(2)	(3)	(4)
Panel A: ITT				
Treatment (T)	0.0029*	0.0131**	0.0469	22.7892
	(0.0017)	(0.0067)	(0.1803)	(25.8924)
Panel B: TOT				
Ever View	0.0356*	0.1615**	0.4909	280.3666
	(0.0204)	(0.0819)	(1.8853)	(318.5089)
Control Mean	0.758	2.778	39.542	3717.136
N	369,601	369,601	232,503	369,601

Source: Sallie Mae and TransUnion, June 2015 to June 2016.
Outcome: indicator for any open revolving trade account, number of accounts, percent of credit used among borrowers with at least one account, and balance amount.
All outcomes are first-differences between June 2015 and June 2016.
Treatment group includes all borrowers who received messages for eight quarters.
Panel A, Intent-to-Treat (ITT): OLS comparing treatment and control groups.
Panel B, Treatment-on-Treated (TOT): IV instrumenting ever viewing Fico Score in year one with treatment assignment.
Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: FICO Score

	FICO	log(FICO)	FICO > 620
	(1)	(2)	(3)
Panel A: ITT			
Treatment (T)	0.6700***	0.0011***	0.0042**
	(0.2265)	(0.0004)	(0.0018)
Panel B: TOT			
Ever View	8.2425***	0.0132***	0.0514**
	(2.7872)	(0.0044)	(0.0219)
Control Mean	676	676	0.822
N	369,601	369,601	369,601

Source: Sallie Mae and TransUnion, June 2015 to June 2016.

Outcome: FICO Score in points, logs, and indicator for FICO Score of at least 620.

All outcomes are first-differences between June 2015 and June 2016.

Treatment group includes all borrowers who received messages for eight quarters.

Panel A, Intent-to-Treat (ITT): OLS comparing treatment and control groups.

Panel B, Treatment-on-Treated (TOT): IV instrumenting FICO Score views with treatment assignment.

Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Subgroup Analysis: Initial FICO Score

		Balance Past Due				Revolving Trade Activity		
	FICO	30+ Days	60+ Days	90+ Days	Any Acct	# Accts	% Credit Used	Balance Amt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (T)	0.3984	-0.0101***	-0.0073**	-0.0025	0.0045	0.0233**	0.2322	49.7464*
	(0.3266)	(0.0036)	(0.0034)	(0.0031)	(0.0028)	(0.0104)	(0.3346)	(26.8229)
T x High FICO	0.5378	0.0056	0.0052	0.0009	-0.0031	-0.0201	-0.3186	-53.2278
	(0.4474)	(0.0042)	(0.0038)	(0.0034)	(0.0033)	(0.0133)	(0.3926)	(51.1117)
High FICO	-14.5536***	0.0706***	0.0334***	0.0139***	-0.0390***	0.1659***	9.8131***	967.7929***
	(0.4214)	(0.0040)	(0.0036)	(0.0032)	(0.0031)	(0.0126)	(0.3693)	(47.9324)
Control Mean	676	0.175	0.127	0.097	0.758	2.778	39.542	3,717
N	369,601	369,601	369,601	369,601	369,601	369,601	232,503	369,601

Source: Sallie Mae and TransUnion, June 2015 to June 2016.

Outcomes: FICO Score (col 1), indicator for 30, 60, 90 days or more past due in past six months (col 2-4), indicator for having any revolving trade accounts (col 5), number of revolving accounts (col 6), credit utilization (col 7), and balance amount (col 8).

High FICO is an indicator for having a FICO Score above the median (675) at the start of the intervention.

All outcomes are first-differences between June 2015 and June 2016.

Treatment group (T) includes all borrowers who received messages for eight quarters.

Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Subgroup Analysis: Baseline 30-Day Delinquency

		Balance Past Due				Revolving Trade Activity		
	FICO	30+ Days	60+ Days	90+ Days	Any Acct	# Accts	% Credit Used	Balance Amt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (T)	0.5946**	-0.0052***	-0.0039***	-0.0018	0.0020	0.0069	0.0939	19.2667
	(0.2386)	(0.0018)	(0.0015)	(0.0013)	(0.0017)	(0.0067)	(0.1911)	(28.0492)
T x Delinquency	0.3150	-0.0060	0.0001	0.0013	0.0087*	0.0564**	-0.3036	45.0037
	(0.7053)	(0.0072)	(0.0091)	(0.0090)	(0.0051)	(0.0238)	(0.5658)	(70.8241)
Delinquency	14.6898***	-0.5975***	-0.3437***	-0.2156***	-0.1278***	-0.6784***	-3.6547***	-1209.8004***
	(0.6658)	(0.0068)	(0.0085)	(0.0085)	(0.0048)	(0.0224)	(0.5315)	(63.8086)
Control Mean	675.901	0.175	0.127	0.097	0.758	2.778	39.542	3717.136
N	369,601	369,601	369,601	369,601	369,601	369,601	232,503	369,601

Source: Sallie Mae and TransUnion, June 2015 to June 2016.

Outcomes: FICO score (col 1), indicator for 30, 60, 90 days or more past due in past six months (col 2-4), indicator for having any revolving trade accounts (col 5), number of revolving accounts (col 6), credit utilization (col 7), and balance amount (col 8).

Delinquency is an indicator for 30 days or more past due in past six months as of June 2015.

All outcomes are first-differences between June 2015 and June 2016.

Treatment group (T) includes all borrowers who received messages for eight quarters.

Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Subgroup Analysis: Age

		Balance Past Due			Revolving Trade Activity			
	FICO	30+ Days	60+ Days	90+ Days	Any Acct	# Accts	% Credit Used	Balance Amt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (T)	0.8227**	-0.0082**	-0.0054*	-0.0045	0.0048**	0.0272**	-0.2182	19.1412
	(0.3423)	(0.0035)	(0.0031)	(0.0029)	(0.0019)	(0.0119)	(0.2227)	(53.4868)
T x Below Median Age	-0.2597	0.0018	0.0014	0.0045	-0.0030	-0.0246*	0.6400*	5.2413
	(0.4562)	(0.0043)	(0.0039)	(0.0035)	(0.0032)	(0.0139)	(0.3719)	(56.4021)
Below Median Age	3.6648***	0.0185***	0.0089**	0.0019	0.0903***	0.1848***	1.0579***	-288.4760***
	(0.4298)	(0.0041)	(0.0036)	(0.0033)	(0.0030)	(0.0131)	(0.3498)	(52.9432)
Control Mean	676	0.175	0.127	0.097	0.758	2.778	39.542	3,717
N	369,601	369,601	369,601	369,601	369,601	369,601	232,503	369,601

Source: Sallie Mae and TransUnion, June 2015 to June 2016.

Outcomes: FICO Score (col 1), indicator for 30, 60, 90 days or more past due in past six months (col 2-4), indicator for having any revolving trade accounts (col 5), number of revolving accounts (col 6), credit utilization (col 7), and balance amount (col 8).

Below Median Age is an indicator for being 23 years old or under at the start of the intervention.

All outcomes are first-differences between June 2015 and June 2016.

Treatment group (T) includes all borrowers who received messages for eight quarters.

Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Personal FICO Score Knowledge

	Reported Knowledge	Accurate Knowledge	Overestimate	Underestimate
	(1)	(2)	(3)	(4)
Treatment (T)	0.0433*	0.0712***	-0.0343**	0.0065
	(0.0224)	(0.0269)	(0.0165)	(0.0192)
Control Mean	0.773	0.515	0.108	0.149
N	3,511	3,511	3,511	3,511

Source: FICO and Financial Literacy Survey, June 2016.
Outcomes: indicators for reporting awareness of personal FICO Score (col 1),
recalling accurate personal 100-150 point FICO Score range (col 2), and
reporting overestimated or underestimated FICO Score (col 3-4).
Treatment group includes borrowers who received a message at any point in the intervention.
Each column indicates the proportion of the total population suveyed responding as stated.
Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Knowledge of Creditworthy Behaviors

	Positive Behavior Knowledge		Negative Behavior Knowledge				
	Pay Bills	Low CC Bal	No CC	Many CCs	High CC Bal	High CC Util	All Correct
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment (T)	0.0030	-0.0225	-0.0040	0.0014	-0.0009	-0.0044	-0.0316
	(0.0076)	(0.0213)	(0.0144)	(0.0137)	(0.0047)	(0.0056)	(0.0253)
Control Mean	0.979	0.809	0.923	0.930	0.992	0.990	0.675
N	3,511	3,511	3,511	3,511	3,511	3,511	3,511

Source: FICO and Financial Literacy Survey, June 2016.

Outcomes: indicator for correctly identifying positive credit behaviors, such as paying bills on time (col 1) and keeping a low balance on credit cards (col 2), and negative behaviors, such as having no credit cards (col 3), lots of credit cards (col 4), keeping a high balance on credit cards (col 5), and maximizing credit utilization (col 6).

Column 7 is an indicator for correctly identifying the effects of all credit behaviors.

Treatment group includes borrowers who received a message at any point in the intervention.

Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Other Financial Knowledge Outcomes

	FICO Knowledge		Financial Literacy Test			
	Familiar	Very Familiar	Q1	Q2	Q3	All 3
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (T)	0.0104	0.0240	0.0022	-0.0024	-0.0019	-0.0001
	(0.0184)	(0.0250)	(0.0107)	(0.0206)	(0.0224)	(0.0257)
Control Mean	0.863	0.312	0.959	0.822	0.778	0.647
N	3,511	3,511	3,511	3,511	3,511	3,511

Source: FICO and Financial Literacy Survey, June 2016.

Outcomes: indicator for reporting being familiar or very familiar with the concept of a FICO Score (col 1-2), accurately responding to individual questions in a financial literacy test (col 3-5) or all questions (col 7).

Treatment group includes borrowers who received a message at any point in the intervention.

Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Financial Outcomes by Treatment Message

		Balance Past Due			Revolving Trade Activity			
	FICO	30+ Days	60+ Days	90+ Days	Any Acct	# Accts	% Credit Used	Balance Amt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T: Baseline	0.7177***	-0.0080***	-0.0058***	-0.0021	0.0023	0.0063	0.1435	27.6935
	(0.2505)	(0.0023)	(0.0021)	(0.0019)	(0.0018)	(0.0074)	(0.2001)	(28.5904)
T: Economic	0.6122**	-0.0068***	-0.0036*	-0.0019	0.0041**	0.0194***	0.0369	15.6714
	(0.2512)	(0.0023)	(0.0021)	(0.0019)	(0.0018)	(0.0074)	(0.2001)	(28.6177)
Social	0.6801***	-0.0070***	-0.0045**	-0.0022	0.0022	0.0137*	-0.0393	25.0001
	(0.2504)	(0.0023)	(0.0021)	(0.0019)	(0.0018)	(0.0074)	(0.1997)	(29.2725)
Control Mean	676	0.175	0.127	0.097	0.758	2.778	39.542	3,717
Prob>F	0.849	0.757	0.364	0.973	0.310	0.055	0.471	0.841
N	369,601	369,601	369,601	369,601	369,601	369,601	232,503	369,601

Source: Sallie Mae and TransUnion, June 2015 to June 2016.

Outcome: FICO Score (col 1), indicator for 30, 60, 90 days or more past due in past six months (col 2-4), indicator for having any revolving trade accounts (col 5), number of revolving accounts (col 6), credit utilization (col 7), and balance amount (col 8).

All outcomes are intent-to-treat first-differences between June 2015 and June 2016.

Treatment groups (T) includes borrowers who received messages for eight quarters separately by message type (baseline, economic consequences, and social influence messaging).

F-statistic test for equality of treatment effects across the three email messages.

Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Main vs. Discontinued Sample: Ever View by Quarter End

	Q1	Q2	Q3	Q4	Q5	Q6	Q7
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T: Main	0.0146***	0.0516***	0.0626***	0.0813***	0.0977***	0.1057***	0.1082***
	(0.0011)	(0.0014)	(0.0016)	(0.0017)	(0.0018)	(0.0019)	(0.0020)
T: Discontinued	0.0145***	0.0524***	0.0633***	0.0609***	0.0597***	0.0580***	0.0530***
	(0.0016)	(0.0021)	(0.0025)	(0.0026)	(0.0027)	(0.0027)	(0.0028)
Control Mean	0.047	0.076	0.107	0.124	0.141	0.153	0.177
Prob>F	0.934	0.639	0.733	0.000	0.000	0.000	0.000
N	406,994	406,994	406,994	406,994	406,994	406,994	406,994

Source: Sallie Mae, June 2015 to March 2017.

Outcome: indicator for ever viewing one's score by quarter end;

quarter in reference to the start of the intervention in column headers.

Treatment group (T) members in the main sample received messages for eight quarters;

treatment group members in the discontinued sample received messages for three quarters.

F-statistic test for equality of treatment effects main vs. discontinued treatment samples.

Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Main vs. Discontinued Sample, March 2017

			Balance Past Due			Revolving Trade Activity		
	FICO	30+ Days	60+ Days	90+ Days	Any Acct	# Accts	% Credit Used	Balance Amt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T: Main	0.5310*	-0.0051**	-0.0032	-0.0027	0.0023	0.0150	-0.2021	-31.5645
	(0.2768)	(0.0023)	(0.0020)	(0.0018)	(0.0020)	(0.0094)	(0.2062)	(37.6500)
T: Discontinued	0.3639	-0.0035	-0.0038	-0.0021	0.0016	0.0188	-0.4438	-47.7589
	(0.3802)	(0.0031)	(0.0028)	(0.0025)	(0.0028)	(0.0128)	(0.2850)	(50.3109)
Control Mean	676	0.188	0.139	0.108	0.795	2.978	40.807	4,406
Prob>F	0.568	0.503	0.786	0.752	0.740	0.698	0.273	0.671
N	406,994	406,994	406,994	406,994	406,994	406,994	250,212	406,994

Source: Sallie Mae and TransUnion, June 2015 to March 2017.

Outcome: FICO Score (col 1), indicator for 30, 60, 90 days or more past due in past six months (col 2-4), indicator for having any revolving trade accounts (col 5), number of revolving accounts (col 6), credit utilization (col 7), and balance amount (col 8).

Treatment group (T) members in the main sample received messages for eight quarters;
treatment group members in the discontinued sample received messages for three quarters.

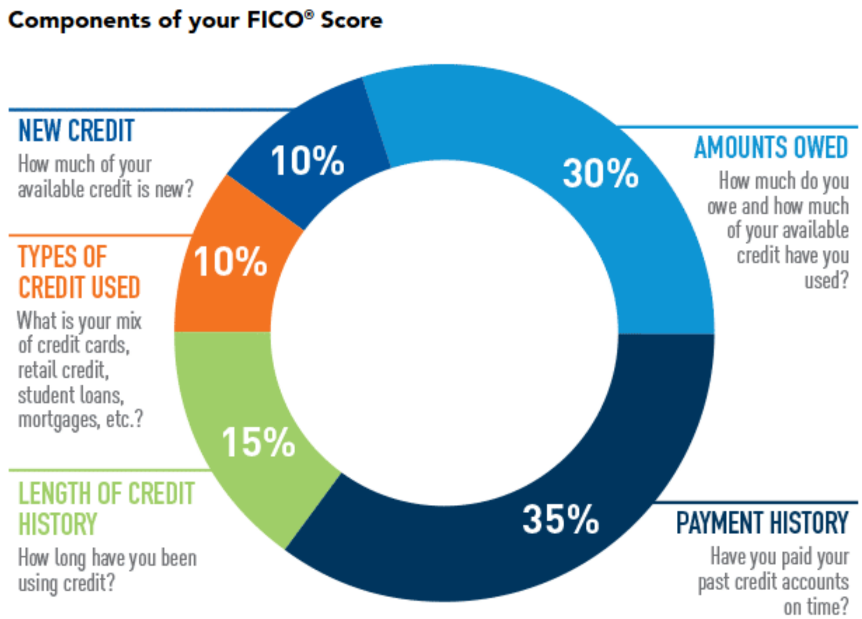
All outcomes are first-differences between June 2015 and March 2017,
one year after the discontinued sample stopped receiving treatment messages.

F-statistic test for equality of treatment effects main vs. discontinued treatment samples.

Robust standard errors in parentheses.

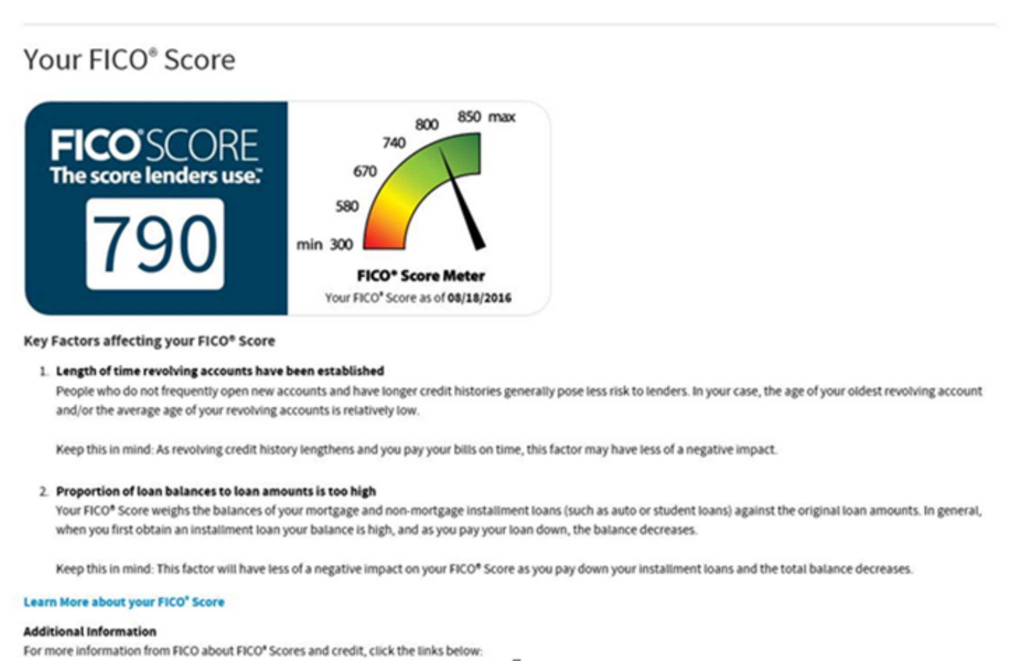
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Components of FICO Score



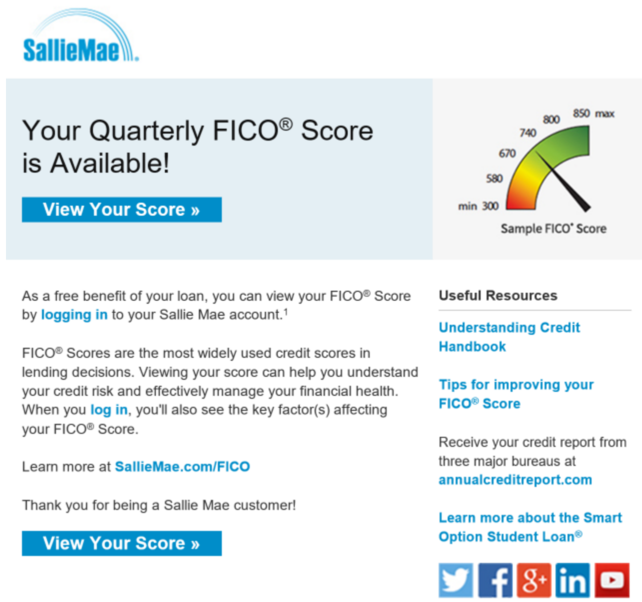
Source: www.myfico.com

Figure 2: Example Sallie Mae FICO Score Webpage View



Source: Sallie Mae

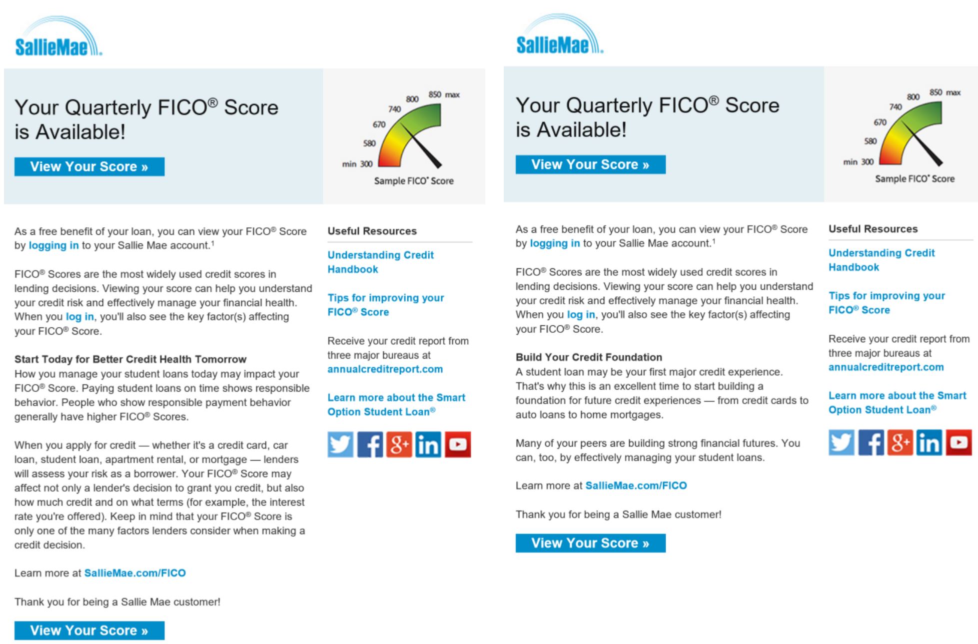
Figure 3: Example Baseline Email Message



Source: Sallie Mae

Figure 4: Example of Additional Email Messages

(a) Economic Consequences Message (b) Social Influence Message



Source: Sallie Mae

Figure 5: Experiment Timeline

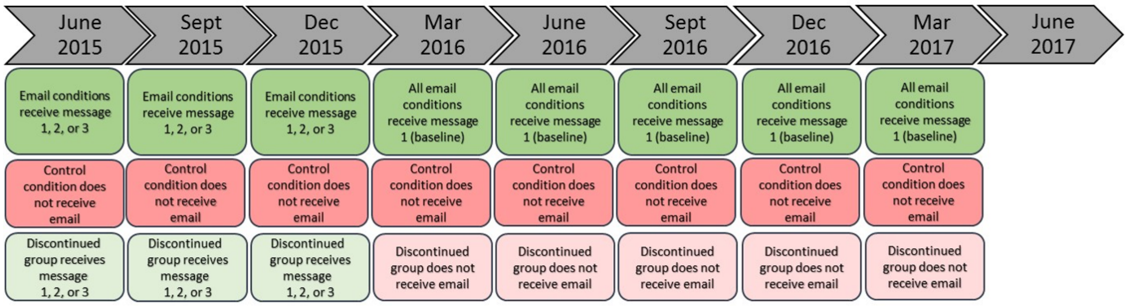
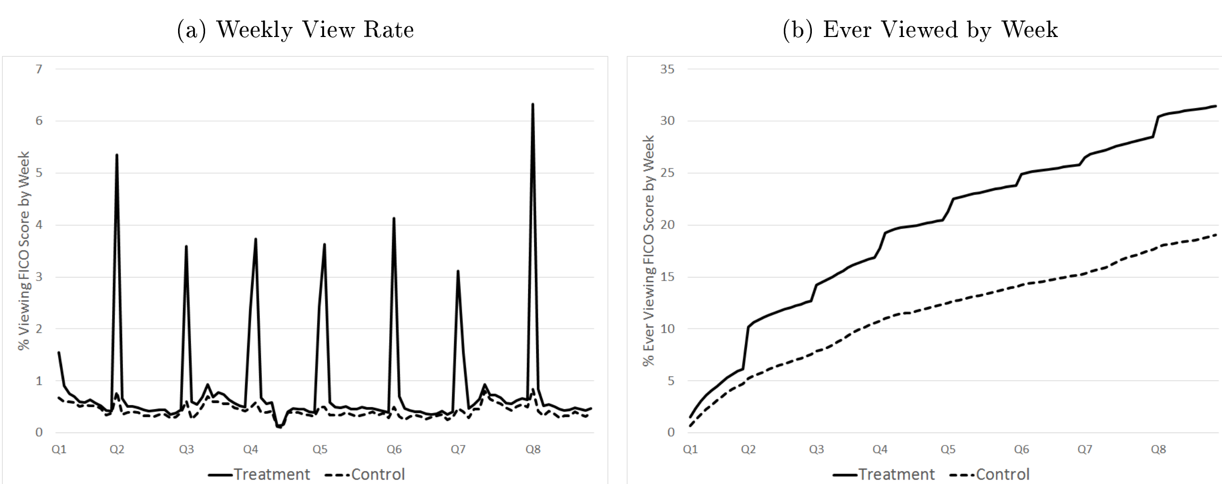


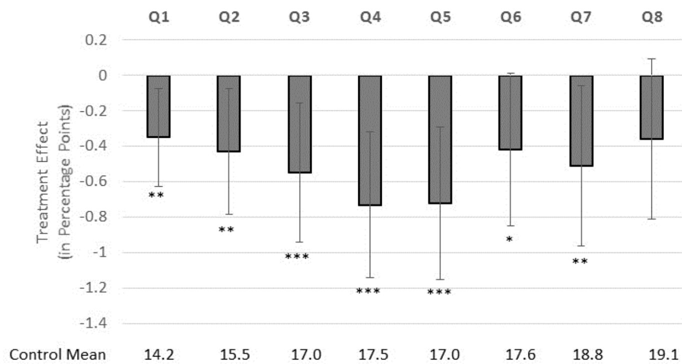
Figure 6: FICO Score Views by Experimental Group



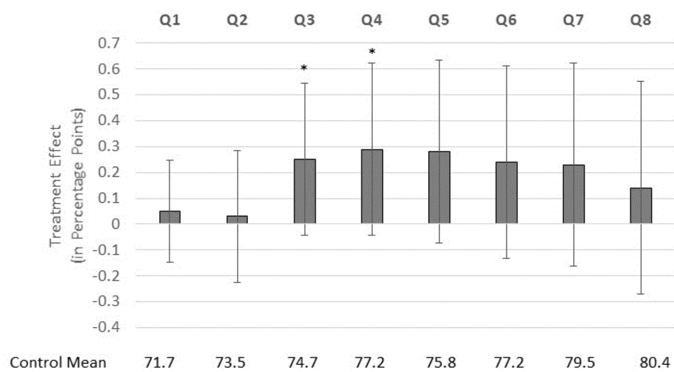
Source: Sallie Mae, June 2015 to June 2017.
Timeline labels correspond to release dates of quarterly communications.
Treatment group includes all borrowers who received messages for eight quarters.

Figure 7: Treatment Effects by Quarter

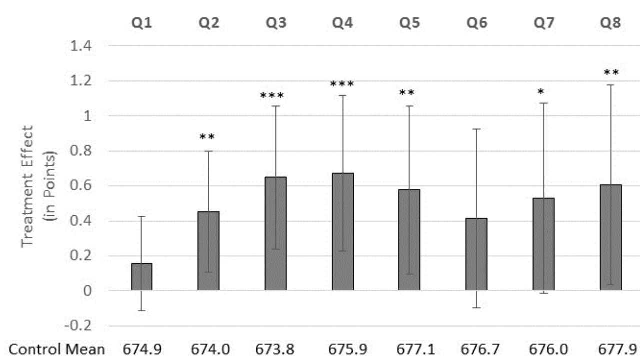
(a) Balance 30+ Days Past Due



(b) Any Revolving Credit Account



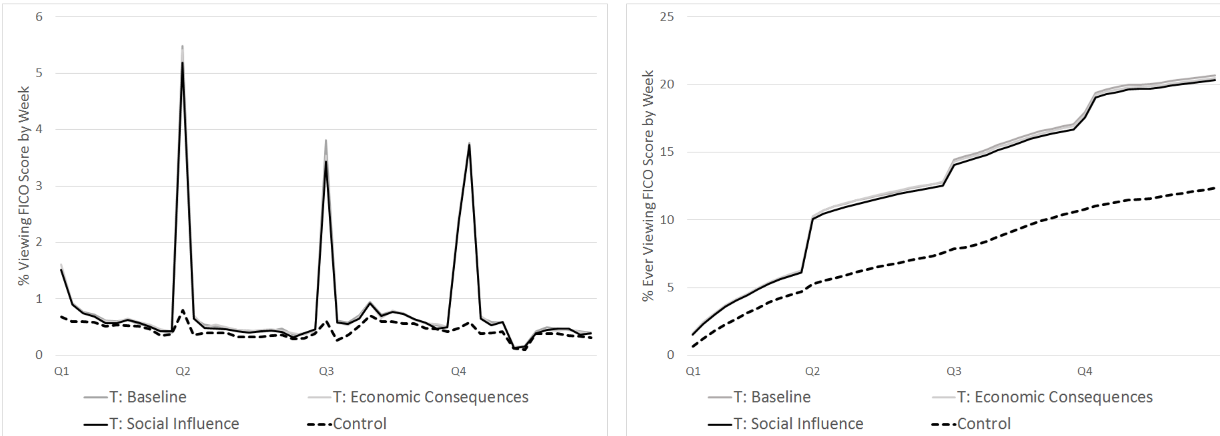
(c) FICO Score



Source: Sallie Mae and TransUnion, June 2015 to June 2017.
Timeline labels correspond to release dates of quarterly communications.

Figure 8: FICO Score Views by Message Type

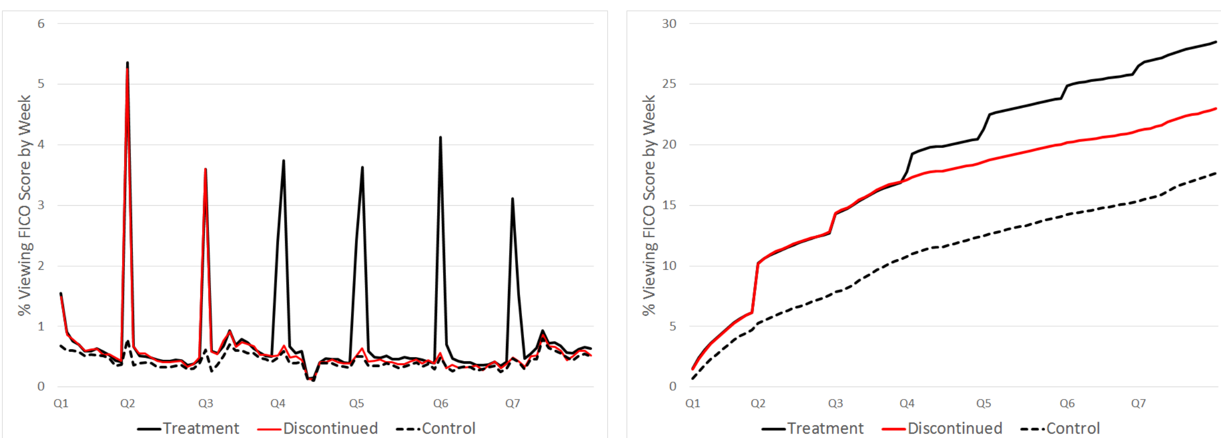
(a) Weekly View Rate (b) Ever Viewed by Week



Source: Sallie Mae, June 2015 to June 2017.
Timeline labels correspond to release dates of quarterly communications.
Treatment group includes all borrowers who received messages for eight quarters.

Figure 9: FICO Score Views – Main versus Discontinued Sample

(a) Weekly View Rate (b) Ever Viewed by Week



Source: Sallie Mae, June 2015 to March 2017.
Timeline labels correspond to release dates of quarterly communications.
Treatment group members in the main sample received messages for eight quarters;
treatment group members in the discontinued sample received messages for three quarters.

Appendix A: FICO Financial Literacy Survey Questionnaire

A. FICO Score Views

Q: How many times have you viewed your FICO Score within the past 12 months?

(1) I did not review my FICO® Score within the past 12 months

(2) 1 time

(3) 2 times

(4) 3 times

(5) 4 times

(6) 5 or more times

(7) Not sure

B. Personal FICO Score Knowledge

Q: Do you know what your FICO Score is?

(1) Between 0 and 299

(2) 300 - 449

(3) 450 – 549

(4) 550 – 649

(5) 650 – 749

(6) 750 – 850

(7) More than 850

(8) No – I don't know what my FICO Score is

(9) No – I don't have a FICO Score

(10) No – I don't know what a FICO Score is

C. Knowledge of Creditworthy Actions

Q: Which of the following do you think are considered positive credit behaviors - that is actions that may improve your credit? (Select all that apply)

(1) Paying your bills on time

(2) Having no credit cards

(3) Having a lot of credit cards

(4) Keeping a high balance on your credit card

(5) Keeping a low balance on your credit card

(6) Using as much of your credit limit as possible

(7) None of the above

D. FICO Familiarity

Q: How familiar are you with the concept of a FICO Score or another credit score?

(1) Very familiar – I'm confident that I can explain what a credit score is to a friend

(2) Somewhat familiar – I could explain what a credit score is in very general terms

(3) Somewhat unfamiliar – I have heard about credit scores, but I don't exactly know what a credit score is

(4) Not at all familiar – I have never heard of credit scores

E. Financial Literacy

Q1. If a student takes out a $5,000 student loan at 7% interest, will he have to pay back...?

(1) Less than $5,000

(2) Exactly $5,000

(3) More than $5,000

(4) I'm not sure

Q2. Imagine that there are two options when it comes to paying back your student loan and both come with the same interest rate. Provided you have the needed funds, which option would you select to minimize your out-of-pocket costs over the life of the loan?

(1) Option 1 allows you to take 10 years to pay back the loan

(2) Option 2 allows you to take 20 years to pay back the loan

(3) Both options have the same out-of-pocket cost over the life of the loan

(4) I'm not sure

Q3. When a private student loan, such as the Smart Option Student Loan from Sallie Mae, is deferred, that is, no payment is required while the student is enrolled in college, what happens to the interest on this loan?

(1) Interest doesn't start accruing until the student has graduated and starts repaying the loan

(2) Interest is capitalized, that is, the interest that accrues during the deferment period is added to the principal amount of the loan

(3) Interest accrues, but nobody has to pay for it

(4) Other, please specify

(5) I don't know

Appendix B: FICO Score Views by Source

As mentioned in Section IV.A, one concern with our administrative data is that it only contains information on FICO Score views through the lender's website, not through other sources. Therefore, the effects we observe in the previous section may suggest that the intervention causes borrowers to shift to the lender's website to view their score rather than through a different source, but does not increase the likelihood of viewing her score overall. To address this concern, we use data from the FICO financial literacy survey to estimate the effects of the intervention on FICO Score views from various sources.

Appendix Table B.1 presents the effects of treatment status on FICO Score views during the first year of the intervention through the lender's website as well as measures of FICO Score viewing patterns from any source. Column 1 shows that responses to the self-reported survey questions regarding FICO Score viewing behavior through any source, not only the provider's website, were consistent with behavior we observed by tracking FICO Score views in our administrative data. Treatment group members were 7.1 percentage points more likely to have viewed their score in the first year of the intervention than control group members and the average number of views for this group was 0.3 views higher.

It is important to note that while these treatment effects are similar in magnitude to those estimated using administrative data on views at only the provider's website in Table 3 (an increase of 8.1 percentage points in the likelihood of viewing and an increase in the average number of views of 0.2), the control group means are quite different. Twelve percent of control group members viewed their score through the provider's website according to our administrative data (and 28 percent of control group members in the survey sample), while 73 percent of control group members in the survey reported viewing their score through any source. It is also important to note that the survey sample exhibited larger treatment effects on viewing through the provider's website – and increase of 20 percentage points in the first year of the intervention. So while these survey results suggest that the treatment was effective at increasing overall FICO Score views and not simply shifting where individuals viewed their score, the intervention may have only increased the number of overall FICO views or shifted the source of viewing for others.

Appendix Table B.1: FICO Score Views Through Any Source

	Ever Viewed FICO	# Views
	(1)	(2)
Treatment (T)	0.0801***	0.2976***
	(0.0236)	(0.1018)
Control Mean	0.729	2.131
N	3,511	3,511

Source: FICO and Financial Literacy Survey, June 2016.
Outcomes: indicator for ever viewed FICO Score (col 1) and number of FICO Score views (col 2) through any source in past 12 months.
Treatment group includes borrowers who received a message at any point in the intervention.
Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table C.1: Subgroup Analysis: Baseline FICO Score Quartile

		Balance Past Due			Revolving Trade Activity			
	FICO	30+ Days	60+ Days	90+ Days	Any Acct	# Accts	Cred Util	Any Bal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T x FICO Q1	0.3304	-0.0110*	-0.0090	-0.0044	0.0054	0.0301*	-0.1246	30.9208
	(0.4748)	(0.0058)	(0.0057)	(0.0054)	(0.0038)	(0.0160)	(0.4483)	(36.2886)
T x FICO Q2	0.5531	-0.0088**	-0.0063**	-0.0015	0.0050	0.0184	0.7497	87.6410**
	(0.4323)	(0.0037)	(0.0031)	(0.0026)	(0.0039)	(0.0122)	(0.4892)	(38.9589)
T x FICO Q3	1.1291**	-0.0025	-0.0009	-0.0011	0.0015	0.0013	-0.2515	-8.1124
	(0.4540)	(0.0035)	(0.0027)	(0.0023)	(0.0031)	(0.0123)	(0.3460)	(51.1871)
T x FICO Q4	0.7087*	-0.0060**	-0.0015	-0.0008	0.0003	0.0037	-0.0162	-20.5699
	(0.4154)	(0.0027)	(0.0019)	(0.0016)	(0.0017)	(0.0118)	(0.2479)	(72.4009)
FICO Q1	21.2454***	-0.1259***	-0.0618***	-0.0243***	0.0262***	-0.2477***	-12.6504***	-1497.0095***
	(0.5947)	(0.0060)	(0.0057)	(0.0053)	(0.0039)	(0.0187)	(0.4822)	(75.9965)
FICO Q2	15.4882***	0.0139***	0.0325***	0.0258***	0.1327***	0.0545***	-11.4106***	-1043.3865***
	(0.5651)	(0.0043)	(0.0034)	(0.0028)	(0.0040)	(0.0160)	(0.5159)	(77.6334)
FICO Q3	7.6327***	0.0212***	0.0292***	0.0234***	0.0661***	0.1220***	-5.1512***	-560.4311***
	(0.5788)	(0.0042)	(0.0031)	(0.0026)	(0.0033)	(0.0160)	(0.4000)	(83.6255)
Control Mean	676	0.175	0.127	0.097	0.758	2.778	39.542	3,717
N	369,601	369,601	369,601	369,601	369,601	369,601	232,503	369,601

Source: Sallie Mae and TransUnion, June 2015 to June 2016.
Outcomes: FICO score (col 1), indicator for 30, 60, 90 days or more past due in past six months (col 2-4), indicator for having any revolving trade accounts (col 5), number of revolving accounts (col 6), credit utilization (col 7), and balance amount (col 8).
All outcomes are first-differences between June 2015 and June 2016.
Treatment group (T) includes all borrowers who received messages for eight quarters.
Q1 indicates borrowers in the bottom quartile of FICO Scores, Q4 indicates the top quartile.
Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table D.1: Subgroup Analysis: Baseline Delinquency Reason Code

			Balance Past Due			Revolving Trade Activity		
	FICO	30+ Days	60+ Days	90+ Days	Any Acct	# Accts	Cred Util	Any Bal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (T)	0.6599**	-0.0056***	-0.0034**	-0.0009	0.0010	0.0041	0.0554	-7.7215
	(0.2748)	(0.0019)	(0.0015)	(0.0013)	(0.0020)	(0.0071)	(0.2209)	(26.5285)
T x Delinquency Code	0.0453	-0.0052	-0.0039	-0.0036	0.0055	0.0262*	-0.0319	89.5880
	(0.4821)	(0.0052)	(0.0049)	(0.0045)	(0.0035)	(0.0156)	(0.3816)	(62.1596)
Delinquency Code	6.8513***	-0.1111***	-0.0812***	-0.0407***	-0.0669***	-0.2384***	-1.2872***	-358.1205***
	(0.4542)	(0.0049)	(0.0046)	(0.0042)	(0.0033)	(0.0146)	(0.3586)	(58.5605)
Control Mean	675.901	0.175	0.127	0.097	0.758	2.778	39.542	3717.136
N	369,601	369,601	369,601	369,601	369,601	369,601	232,503	369,601

Source: Sallie Mae and TransUnion, June 2015 to June 2016.

Outcomes: FICO score (col 1), indicator for 30, 60, 90 days or more past due in past six months (col 2-4), indicator for having any revolving trade accounts (col 5), number of revolving accounts (col 6), credit utilization (col 7), and balance amount (col 8).

Delinquency Code is an indicator for having a reason code in June 2015 (the pre-period quarter) that mentions a delinquent account.

All outcomes are first-differences between June 2015 and June 2016.

Treatment group (T) includes all borrowers who received messages for eight quarters.

Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$