Online Appendix: Can Facing the Truth Improve Outcomes? Effects of Information in Consumer Finance

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A Additional Evidence for Information Avoidance

Another way to measure the impact of credit score trends on whether the user avoids information is to utilize the panel structure of the data, through which individual-level differences can be controlled for. We estimate the following linear regression for a user i when she checks her report at year-month t, for users in the sample who have checked their reports at least twice.[1] The regression is:

$$\begin{aligned}\mathbb{1}\{CheckNextMonth\}_{it} &= \alpha_m + \alpha_w + \alpha_i + \delta_1 \mathbb{1}\{\Delta CS_{it} < 0\} + \delta_2 |\Delta CS_{it}| \\ &+ \delta_3 (\mathbb{1}\{\Delta CS_{it} < 0\} \times |\Delta CS_{it}|) + \delta_4 NChecks_{it} + \delta_5 AccountAge_{it} + \delta_6 CS_{it} + \epsilon_{it},\end{aligned} \tag{1}$$

where $\mathbb{1}\{CheckNextMonth\}_{it}$ is an indicator for whether the user checks her score in the following calendar month. CS_{it} is i's credit score at time t, and ΔCS_{it} is the change in i's credit score between t and $t-1$ ($CS_{i,t} - CS_{i,t-1}$).[2] $\mathbb{1}\{\Delta CS_{it} < 0\}$ is an indicator for whether the user is currently on a declining credit score trend. $|\Delta CS_{it}|$ is the absolute value of ΔCS_{it}, and $NChecks_{it}$ is how many times the user

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[1] The user needs to have checked at least twice in order to construct the current credit score trend

[2] Note that $t-1$ may not always be the previous calendar month.

has previously checked her score. Since there is selection bias in who checks their report, we include individual-level fixed effects α_i. We also control for the user's current credit-score level, account age (in months), and seasonality with α_m and α_w, which are fixed effects for month and day of week, respectively, for when the user checks her report.

Table 11 displays the OLS estimates of Equation 1. Column (3) contains the main specification and columns (1) and (2) show that the results are robust to various specifications. The coefficient for $\mathbb{1}\{\Delta CS_{it} < 0\}$ is negative and statistically significant across all columns, indicating that if a user checks her report and sees that her score has decreased since her last credit report, she is less likely to check her score in the following calendar month. The negative coefficient of $\mathbb{1}\{\Delta CS_{it} < 0\} \times |\Delta CS_{it}|$ in column (3) shows that the greater the decrease in score, the less likely the user is to check her updated report next month. Table 12, which displays estimates for Equation 1 for each tercile of credit score, shows that this effect exists for users in each credit score tercile, indicating that even if the overall credit score is high, the trend in score is relevant for whether a user checks. Tables 28 and 29 in Appendix G.1 include robustness checks with various random and fixed effects removed and for different time intervals for the pre-trend (difference between t and $t-1$). In all specifications, the coefficient for $\mathbb{1}\{\Delta CS < 0\}$ remains negative and statistically significant.

B Email Randomization Check

This paper's identification strategy requires: 1) exogenous variation introduced through A/B tested email copies within each campaign, and 2) that the variation in click rates across campaigns is not correlated with pre-treatment variables, conditional on campaign target rules. This section presents evidence that these conditions are fulfilled.

First, we test the randomization of the email copies/variants within a single campaign. Specifically, we test whether the credit scores and the trends in credit score are significantly different for users who receive different email variants within the same campaign. Figure 9 displays a histogram of the p-values from ANOVA tests, in which the null hypothesis is that there is no significant difference in means across email variants within campaigns. Each observation is at the campaign level. Two campaigns had significantly different rates of $\mathbb{1}\{\Delta CS < 0\}$ (p-values of 0.024 0.074) and two had significantly different credit scores prior to receiving the email (p-values of 0.066

Table 11: OLS Estimates of Equation 1

	Dependent variable:		
	$\mathbb{1}\{CheckNextMonth\}$		
	(1)	(2)	(3)
$\mathbb{1}\{\Delta CS < 0\}$	-0.019^{***}	-0.017^{***}	-0.013^{***}
	(0.0004)	(0.0004)	(0.001)
$\mathbb{1}\{\Delta CS < 0\} \times \lvert\Delta CS\rvert$			-0.0003^{***}
			(0.00002)
AccountAge	-0.004^{***}	0.006^{***}	0.006^{***}
	(0.00004)	(0.0001)	(0.0001)
CS	0.001^{***}	0.001^{***}	0.001^{***}
	(0.00001)	(0.00001)	(0.00001)
$NCheck$		-0.014^{***}	-0.014^{***}
		(0.0001)	(0.0001)
|CSChange|			0.0002^{***}
			(0.00001)
Person FE	Y	Y	Y
Day of Week FE	Y	Y	Y
Month FE	Y	Y	Y
Observations	4,339,410	4,339,410	4,339,410
R^2	0.343	0.346	0.347
Note:			*p<0.1; **p<0.05; ***p<0.01

Notes: Each observation is at the user-credit (it) report level. The sample consists of 561,864 users who have checked their credit report at least twice before May 1, 2018. Users who check their reports in May 2018 are dropped because the data is truncated at June 12, 2018, thus we do not observe whether a user returns. Standard errors are clustered at the individual level. Column (1) omits controls for NCheck and the $|\Delta CS_{it}|$. Column (2) includes the control for NCheck, and Column (3) reports the full specification in Equation 1.

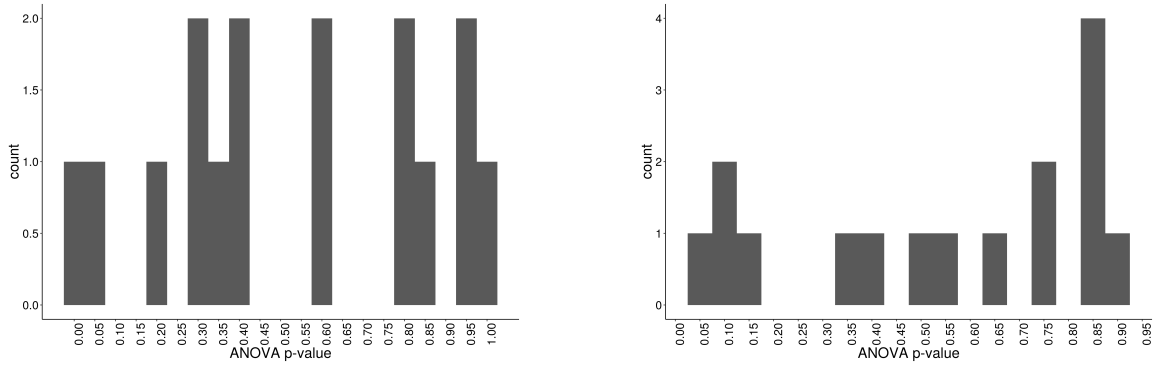
and 0.083). However with 16 campaigns we would expect a few to have differences by chance. This suggests that within campaigns, the variants are randomized across relevant observables.

Table 12: OLS Estimates of Equation 1 by Credit Score Tercile

	Dependent variable:		
	$\mathbb{1}\{CheckNextMonth\}$		
	(1)	(2)	(3)
$\mathbb{1}\{\Delta CS < 0\}$	-0.014^{***}	-0.013^{***}	-0.009^{***}
	(0.001)	(0.001)	(0.001)
$\mathbb{1}\{\Delta CS < 0\} \times \lvert\Delta CS\rvert$	0.0002^{***}	-0.0004^{***}	-0.001^{***}
	(0.00004)	(0.00004)	(0.00004)
AccountAge	0.013^{***}	0.009^{***}	0.001^{***}
	(0.0002)	(0.0002)	(0.0002)
CS	0.001^{***}	0.0004^{***}	-0.00001
	(0.00002)	(0.00002)	(0.00002)
NCheck	-0.023^{***}	-0.017^{***}	-0.008^{***}
	(0.0003)	(0.0003)	(0.0002)
|CSChange|	0.0002^{***}	0.001^{***}	0.001^{***}
	(0.00003)	(0.00002)	(0.00002)
CS Tercile	1	2	3
Person FE	Y	Y	Y
Day of Week FE	Y	Y	Y
Month FE	Y	Y	Y
Observations	1,298,633	1,469,684	1,571,093
R^2	0.423	0.404	0.364
Note:			*p<0.1; **p<0.05; ***p<0.01

Notes: This table shows the OLS estimates of Equation 1 for users with credit scores in each tercile. The tercile cutoffs are 571 (33^{rd} percentile) and 654 (66^{th} percentile). The sample in the first column is comprised of users with credit scores in the bottom tercile (less than 571), the sample in the second column is users with credit scores in the middle tercile (between 571 and 654), and the third column is users with credit scores in the top tercile (above 654). Standard errors are clustered at the individual level.

Figure 9: Histogram of the P-Values Checking Covariate Balance for Randomization



Notes: This is a histogram of p-values from ANOVA tests to detect if the user has a negative trend in their credit score (left plot) and credit score (right plot) are significantly different across email variants within each campaign. Each observation is one campaign.

To measure whether these campaigns affect the main IV estimates, we removed the campaigns that had p-values of less than 0.1. The results were very similar as seen in Tables 13 and 14. At the monthly level, for negative-pre-trend users, the change is no longer statistically significant due to a drop in sample size, however the direction and magnitude remain similar.

Table 13: IV Removing Campaigns that Failed the Randomization Check

	ΔCS^{post}	
	(1)	(2)
$\mathbb{1}\{Check\}$	-18.244**	8.386***
	(8.783)	(2.563)
Campaign Targeting Controls	Y	Y
ΔCS^{pre}	< 0	≥ 0
Observations	107,588	214,568

Notes: The table presents the IV regression of Equation 5 with only the check regressor listed. Campaigns 8, 9, 15, and 17 are removed as those had significant p-values during the randomization check. $\mathbb{1}\{Check\}$ *is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email was sent to after with at least a two-month gap. Targeting controls are omitted for readability.*

Table 14: IV Removing Campaigns that Failed the Randomization Check

	ΔCS^{post}	
	(1)	(2)
$\mathbb{1}\{Check\}$	-3.936	1.315**
	(2.659)	(0.635)
Campaign Targeting Controls	Y	Y
ΔCS^{pre}	< 0	≥ 0
Observations	107,588	214,568

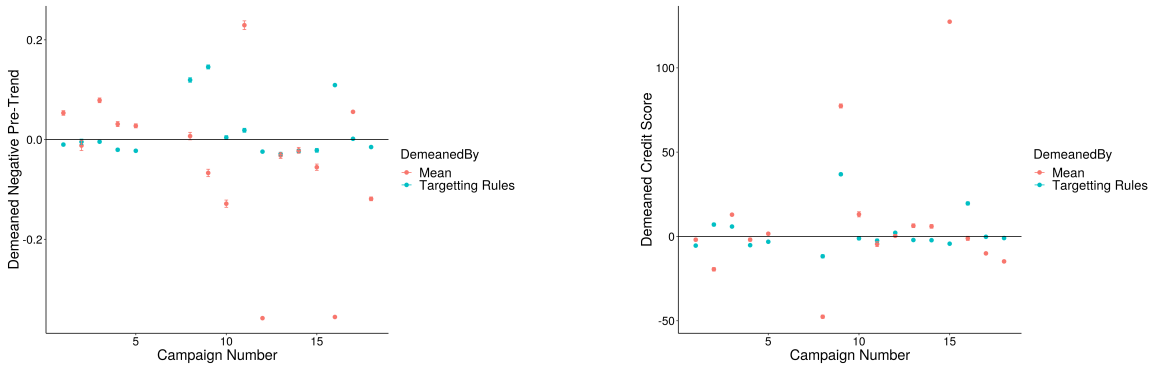
Notes: The table presents the IV regression of Equation 5 with only the check regressor listed. Campaigns 8, 9, 15, and 17 are removed as those had significant p-values during the randomization check. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email was sent to after with at least a two-month gap.

Second, we show that after controlling for the campaign targeting rules, there is no correlation between the campaign the user received and her credit score or trend in credit score. In other words, we show that the targeting rules explain the vast majority of variation in the credit score and the trend in credit score. To do this, for each campaign, we plot each outcome variable demeaned by the variables used in the targeting rules, compared to the outcome variable demeaned by the mean across all users in the sample, regardless of campaign.[3]

Figure 10 displays these plots for whether a user has a declining credit score (left plot) and her credit score (right plot) prior to receiving an email in each campaign. We can visually see that much of the variation across campaigns in negative_pre_trend and credit score is eliminated after controlling for the campaign targeting rules.

[3]We demean by the targeting rules by estimating $y_i = \alpha + \beta X_i + \epsilon_i$, where X_i is the matrix of variables used in the targeting rules. These variables are listed in the regressors in Table 36, excluding ΔCS^{pre}. The demeaned variables are then the residuals of this regression, $y_i - \hat{y}_i$.

Figure 10: Variation by Group Across Campaigns



Notes: This figure shows the variation in whether users have $\Delta CS^{pre} < 0$ (left) and credit score (right) before and after controlling for the campaign targeting rules. The red points represent the average variation in the outcome variables, in which the outcome variables are demeaned by the average value across all users. The blue points are the average outcome variables after they are demeaned by the campaign targeting rules.

To compare this more quantitatively, we measure how much the incremental variation campaign fixed effects explain. We compare the adjusted R^2 between the following regressions.

$$y_{ie} = \alpha + \beta X_{ie} + \epsilon_{ie}$$

$$y_{ie} = \alpha_c + \beta X_{ie} + \eta_{ie}$$

where α_c are campaign fixed effects and the outcomes y_i are $\Delta CS^{pre} < 0$ and credit score. We find that adding campaign fixed effects explains only 0.52% more variation in credit scores and 0.55% more variation in whether the user has a declining credit score.[4] Since these numbers are so low, we conclude that the campaign assignments are not correlated with pre-trends and absolute credit scores after controlling for the targeting rules.

B.1 Instrument Strength

We test for whether the emails serve as strong instruments by conducting an F-test on the instruments to see if they are jointly significant for each sample (users with

[4]For the regression on $\Delta CS^{pre} < 0$, adding campaign fixed effects increases the adjusted R^2 from 0.658 to 0.662, and 0.676 to 0.679 for the regression on credit score.

declining and non-declining credit scores prior to checking). The unrestricted and restricted regressions are as follows:

$$\mathbb{1}\{Check_{ie}\} = \alpha_e + \gamma X_{ie} + \eta_{ie} \tag{2}$$

$$\mathbb{1}\{Check_{ie}\} = \gamma X_{ie} + \eta_{ie}. \tag{3}$$

The regression estimates are reported in Table 15. The incremental F-statistic for the comparison between the restricted and unrestricted regressions above is 25 for users with declining credit scores and 187 for users with non-declining credit scores, indicating that the emails are not weak instruments for whether the user checks her credit information.[5] An alternative measure is the change in the R^2. The inclusion of email fixed effects increases the R^2 by 3% (0.222 to 0.228) for users with declining scores, and by 27% (0.182 compared to 0.231) for users with non-declining scores.

[5]The F-statistics were computed using a Wald test which compared the unrestricted versus restricted regressions (Equations 2 versus Equation 3) for both groups.

Table 15: OLS Results for the Restricted (First Column) and Unrestricted (Second Column) First-Stage Regression

	Dependent variable:			
	$1\{Check\}$			
	(1)	(2)	(3)	(4)
Homeowner	0.016^{***}	0.015^{***}	0.011^{***}	0.008^{***}
	(0.002)	(0.002)	(0.002)	(0.001)
ccclicks	0.042^{***}	0.029^{***}	0.028^{***}	0.023^{***}
	(0.002)	(0.002)	(0.001)	(0.001)
active	0.012^{***}	0.009^{***}	0.046^{***}	0.029^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
refreshSameMonth	0.173^{***}	0.104^{***}	0.288^{***}	0.164^{***}
	(0.002)	(0.005)	(0.001)	(0.003)
CreditUtilizationGradeAB	-0.011	-0.009	-0.023^{***}	-0.002
	(0.011)	(0.011)	(0.006)	(0.005)
CreditUtilizationGradeDF	0.014	0.017^{**}	-0.064^{***}	-0.006
	(0.008)	(0.008)	(0.005)	(0.005)
CSgreater700	0.033^{***}	0.027^{***}	0.002	0.007^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
ChangeinDebt	0.067^{***}	0.074^{***}	0.050^{***}	0.074^{***}
	(0.003)	(0.004)	(0.002)	(0.002)
Collections	-0.022^{***}	-0.023^{***}	-0.040^{***}	-0.028^{***}
	(0.002)	(0.002)	(0.002)	(0.001)
PaymentHistoryGradeCDF	0.032^{***}	0.029^{***}	0.044^{***}	0.038^{***}
	(0.006)	(0.006)	(0.004)	(0.004)
CreditAgeGradeAB	-0.559^{***}	-0.559^{***}	-0.353^{***}	-0.566^{***}
	(0.013)	(0.013)	(0.007)	(0.007)
CreditAgeGradeCDF	-0.552^{***}	-0.553^{***}	-0.368^{***}	-0.552^{***}
	(0.014)	(0.014)	(0.007)	(0.007)
CreditUtilizationNotA	-0.006	-0.007	0.050^{***}	0.005
	(0.010)	(0.010)	(0.005)	(0.005)
ChangeinCreditUtilizationGrade	0.807^{***}	0.264^{**}	0.273^{***}	0.062^{***}
	(0.126)	(0.134)	(0.005)	(0.005)
DebtIncrease	-0.006^{***}	-0.004^{**}	-0.025^{***}	-0.018^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
CSIncrease			0.062^{***}	-0.020^{***}
			(0.002)	(0.002)
CSIncrease2016	0.103^{***}	0.104^{***}	-0.050^{***}	0.042^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Email FE	N	Y	N	Y
ΔCS^{pre}	< 0	< 0	≥ 0	≥ 0
Observations	254,223	254,223	451,594	451,594
R^2	0.222	0.228	0.182	0.231
Adjusted R^2	0.222	0.227	0.182	0.231
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: This table tests the strength of the instruments by estimating the restricted and unrestricted (adding in email fixed effects) regressions. The outcome variable is whether a user checks her score within 31 days of receiving the email.

C Addressing Selection

C.1 Differential Attrition

While we cannot extend the results to users who do not return after receiving an email or users who opt out of all emails, we can check if users who receive positive or negative information have different retention rates, regardless of whether they check their information. Although users with declining and non-declining trends may be inherently different, we do not find that users in one group are disproportionately more likely to drop out than the other. The drop-out rates for these two groups are similar, with the positive information group having a 23.2% drop out rate and the negative information group having a 21.5% drop out rate.[6]

C.2 Retention

Another source of selection bias comes from unobserved credit scores of those who do not return, in combination with the potential for email to impact retention. To illustrate, consider the case that compliers have persistent downward trends in credit scores, regardless of whether they check their score. If more effective emails are sent, then more compliers will remain on the platform. More compliers will then lead to a higher retention of users with declining scores, and therefore lend to the interpretation that more effective emails lead to a decrease in credit score. Through simulations, we find that this form of bias exists when the instruments impact retention. To measure whether this is the case in this setting, we estimate the following regression:

$$\mathbb{1}\{\text{Return}\}_{ie} = \beta ClickRate_e + \gamma X_{ie} + \epsilon_{ie}. \tag{4}$$

The dependent variable $\mathbb{1}\{\text{Return}\}_{ie}$ is an indicator variable for whether i has an observed post-trend credit score change (returns to the platform). $ClickRate_e$ is email e's click rate, or effectiveness. The click rates range from 0 to 1, with 1 meaning that all users who receive e click on the email. X_{ie} are the campaign controls. Table 16 displays the OLS estimates of Equation 4. We find that for users on a declining

[6]Note that these drop out rates are statistically significantly different, but not meaningfully so. The 95% confidence interval of the difference between the two proportions is (0.016, 0.19) which is not very economically meaningful. In addition, since the positive pre-trend group has a larger drop-out rate than the negative pre-trend group, we are not concerned that we are losing a disproportionate number of users due to traditional information avoidance.

trend, a 100% increase in the email's click rate increases the probability that the user has an observed post-trend by 0.6 percentage points. This effect is significant at the 10% level. For users with a non-declining trend, the effect is close to zero and not statistically significant. The measured effect sizes are similar when the email's open rate, instead of click rate, is used as a measure of effectiveness. Therefore, in this setting, the instruments do not impact whether the outcome is observed.

A potential reason that we do not see any effect on retention is that because the metric is whether the user returns in two or more months, and that variation in the emails' effectiveness are not enough to induce retention over this period. Receiving an email compared to not receiving an email may be a stronger nudge to increase retention, but the variation in this regression comes from receiving a more effective email compared to receiving a less effective email, which may not enough to create long-term retention. Additionally, due to the randomization of the email copy in this month, users may receive another email in two months with an uncorrelated effectiveness to the focal email, which would have a stronger impact on whether the user checks in that month.

This, with the effects from imputing the missing outcomes in Appendix Section C.3, create more confidence that the effects of information are not entirely driven by selection bias resulting from unobserved outcomes.

Table 16: Impact of Email Effectiveness on Retention

	Dependent variable:	
	1{Return}	
	(1)	(2)
Click Rate	0.006*	−0.002
	(0.003)	(0.003)
DV Mean	0.88	0.86
ΔCS^{pre}	< 0	≥ 0
Campaign Targeting Controls	Y	Y
Observations	254,223	451,594
R^2	0.509	0.418
Note:	*p<0.1; **p<0.05; ***p<0.01	

Notes: OLS estimates of Equation 4. Sample consists of all users who viewed their report within three months of receiving a campaign email. Each observation is at the user-email level. Standard errors clustered at the email level.

C.3 Imputation

Due to the way the data provider pulls credit reports only when a user logs on, we have missing outcomes. For users in the IV sample (who have a non-missing pre-trend and logged onto the platform within the last three months before they received the focal email), 13.5% having missing outcomes. In general, it is not advisable to impute missing outcomes since they are not likely to be missing at random. Users who do not return to the platform after receiving one of the focal emails might be inherently different than users who remain, or at least a sample of them are. However, to measure how sensitive the results are and to provide some bounds, we impute these missing credit scores using two different imputation strategies.

First, we impute data as if the credit scores were missing at random. Second, since the data is not likely to be not missing at random, we impute under the assumption that users with lower credit scores are less likely to return. We match only on users whose post-trend is below the median, in which the median is a one-point increase

in credit score. Given that we find users are less likely to return if they are doing badly, this seems like a reasonable counterfactual. The results are not sensitive to the missing data.

The imputation algorithm matches two users who are similar on the following list of covariates. One user has a missing outcome while the other does not. The missing outcome will then be imputed by the user who is similar on the covariates but has an observed outcome. We use the following covariates (as defined before the email was sent) to match users:

- Most recent credit score
- Number of times the user has checked her score
- First credit score pulled by the website
- Year and month
- Number of months the user has been on the website
- Pre_trend
- Indicator for whether the user has a negative_pre_trend
- Number of open accounts
- Total balances
- Total monthly payments
- Number of public records
- Number of delinquent accounts
- Number of derogatory accounts
- Number of inquiries that affect credit score
- Length of time since user last logged on
- The campaign that the user is assigned to
- Number of emails the user has received from the website since she signed up
- Click rate of the emails for that user
- Average rate at which the user clicks through on emails that she has opened
- Homeowner indicator*
- Whether the credit score increased in 2016*
- Whether the score increased in the past year*
- Whether the credit score changed since last report*
- Collections*
- Indicator for a credit score of greater than 700*
- Indicator for active on the website*
- Indicator for whether the debt has changed*
- Indicator for whether the debt has increased*

The * denotes the targeting rules used for email campaigns.[7]

Both imputation methods are done using predictive mean matching with the MICE (Multivariate Imputation via Chained Equations) package in R. For both strategies, five sets of imputed data are created. We estimate the IV regression five

[7]We do not use all the targeting rules in these covariates because the imputation method is not able to handle a large number of covariates. Therefore, we also select the campaign the user was assigned to as a covariate to control for all the targeting rules.

times, once on each set of imputed data. The coefficient shown is the average of the five coefficients. The standard errors are pooled across the five regressions accounting for imputation variance.

Table 17 displays the summary statistics for the observed post-trends, and the imputed values using each imputation method. The imputed values are similar to the overall distribution of original values, and the values imputed with below median values are lower than the observed, as expected. Table 18 displays the 2SLS estimates of Equation 5 and Equation 6 for this sample in which the missing values are imputed at random. Table 19 displays the estimates for those assuming the missing values are below the median. The estimated coefficients are robust to imputation strategies and are similar to the estimates on the non-imputed data in Table 8.

Table 17: Summary Statistics for Observed and Imputed ΔCS_{ie}^{post}

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Original ΔCS_{ie}^{post}	-405.00	-20.00	1.00	-2.63	17.00	349.00
Imputed ΔCS_{ie}^{post}	-405.00	-19.00	1.00	-2.302	18.00	349.00
Imputed with Below Median Values	-405.00	-47.00	-21.00	-32.86	-6.00	0.00
Original and Imputed Combined	-405.00	-19.00	1.00	-2.309	18.00	409.00
Imputing All	-405.00	-19.00	1.00	-2.38	18.00	349.00

Notes: The sample used for this table is the same as that used in the main IV specification. The first row are the observed, non-missing ΔCS_{ie}^{post} summary statistics for users who have checked their credit score within three months of receiving the email, as is the sample in the main IV specification. The second row are the summary statistics just for the imputed values. The third row is for imputed values based on users who have below median outcomes. The fourth row are the summary statistics combining rows one and two for one of the five imputed data sets. The "imputing all" row imputes the outcome variable for all users based on the non-missing data. In all, the imputations are repeated five times and the summary statistics reflect an average of these five imputations.

Table 18: Two-Stage Least Squares IV Imputed Outcomes

	ΔCS^{post}		$\overline{\Delta CS^{post}}$ monthly	
	(1)	(2)	(3)	(4)
$\mathbb{1}\{Check\}$	-25.40***	10.25***	-5.28**	2.64***
	(7.557)	(2.045)	(2.284)	(0.517)
Campaign Targeting Controls	Y	Y	Y	Y
ΔCS^{pre}	< 0	≥ 0	< 0	≥ 0
Observations	254,196	451,54	254,196	451,545

Notes: This table presents the 2SLS estimates of Equation 5 and Equation 6. Targeting rules omitted for readability. Standard errors are clustered at the email level. Missing outcome values are imputed by matching on the targeting covariates. In this analysis we assume that the data is missing at random.

Table 19: Two-Stage Least Squares IV Imputed Outcomes using Users with Below Median Outcomes

	ΔCS^{post}		$\overline{\Delta CS^{post}} monthly$	
	(1)	(2)	(3)	(4)
$\mathbb{1}\{Check\}$	-22.84***	28.78***	-4.90**	2.18***
	(7.479)	(3.587)	(2.301)	(0.479)
Campaign Targeting Controls	Y	Y	Y	Y
ΔCS^{pre}	< 0	≥ 0	< 0	≥ 0
Observations	247,003	438,587	247,003	438,587

Notes: This table presents the 2SLS estimates of Equation 5 and Equation 6. Targeting rules omitted for readability. Standard errors are clustered at the email level. Missing outcome values are imputed with matching on email targeting covariates and only on users with below median outcomes.

In order to check the accuracy of the imputation, we also impute credit scores for all users, regardless of whether their actual credit score is observed. To do this, we replicate all users who do not have missing outcomes and remove their outcomes for both the total change in credit score, and the average monthly change in credit score. Imputation is done assuming outcomes are missing at random. The results, shown in Table 20, show that the estimates are similar when using this imputation strategy as well.

Table 20: Two-Stage Least Squares IV Imputed Outcomes For All Observations

	ΔCS^{post}		$\overline{\Delta CS^{post}} monthly$	
	(1)	(2)	(3)	(5)
$\mathbb{1}\{Check\}$	-27.92***	9.79***	-5.49***	2.48***
	(8.577)	(2.473)	(2.302)	(0.110)
Campaign Targeting Controls	Y	Y	Y	Y
ΔCS^{pre}	< 0	≥ 0	< 0	≥ 0
Observations	254,196	451,545	254,196	451,545

Notes: This table presents the 2SLS estimates of Equation 5 and Equation 6. Targeting rules omitted for readability. Standard errors are clustered at the email level. Outcome values are imputed with matching on email targeting covariates even on the observations that are not missing.

D Compliers

In order to understand what population the LATE results hold for, we estimate the percentage of compliers in the sample. To calculate this, we follow steps first modeled by Imbens and Angrist (1994) and adapted by Maestas et al. (2013). This method has been used before with non-binary instruments. According to Bernstein et al. (2019),

> As pointed out by Maestas et al. (2013), when the treatment variable is binary and the instrument varies between zero to one, the size of the population that is on the margin and sensitive to the instrument is equal to the first-stage coefficient.

Furthermore, from Maestas et al. (2013), "More precisely, in the case of a binary treatment... the size of the marginal population is the first-stage coefficient times the range of [instruments]."

The treatment variable is whether or not a user checked her credit score, which is binary. To make the instrument vary between zero and one, rather than using the email copy, we use the average rate of checking one's credit score upon receiving a given email e. The average rate of checking for each email will be the new instrument, Z. Again, we split the sample into those with declining and those with non-declining pre-trends. Z is also calculated separately for each sub-sample. In other words, we calculate the mean of $\mathbb{1}\{Check\}$ for each email copy within users with declining pre-trends and again for those with non-declining pre-trends.

We then estimate the following OLS regression:

$$\mathbb{1}\{Check_{ie}\} = \beta_0 + \beta_1 Z_i + \nu_i. \tag{5}$$

The estimates of Equation 5 are in Table 21. Next, we take the coefficient from this regression and multiply it by the range of values of Z within each subsample. Within this range, there are some emails where the user would have checked their score and some where they would not have. In other words, there is some email that would have changed their treatment outcome.

Table 21: Estimates of Equation 5: First Stage Using Average Rate of Checking

	Dependent variable:	
	$1\{Check\}$	
	(1)	(2)
Average Check Rate By Email	0.545^{***}	0.710^{***}
	(0.016)	(0.011)
ΔCS^{pre}	< 0	≥ 0
Campaign Targeting Controls	Y	Y
Observations	223,913	386,570
R^2	0.126	0.110
Note:	*p<0.1; **p<0.05; ***p<0.01	

Notes: This table is based on the sample of users that we use in the IV estimation. Targeting rules are omitted for better readability.

Therefore, the percentage of compliers for each declining and non-declining sample is the following:

$$\mathbb{1}\{\Delta CS_{ie}^{pre} < 0\} : (max(Z_{\mathbb{1}\{\Delta CS_{ie}^{pre}<0\}}) - min(Z_{\mathbb{1}\{\Delta CS_{ie}^{pre}<0\}})) * 0.545 = 28.7\%$$

$$\mathbb{1}\{\Delta CS_{ie}^{pre} >= 0\} : (max(Z_{\mathbb{1}\{\Delta CS_{ie}^{pre}\geq 0\}}) - min(Z_{\mathbb{1}\{\Delta CS_{ie}^{pre}\geq 0\}})) * 0.710 = 30.0\%.$$

Other work has been done to characterize compliers in more detail, but, to our knowledge (as well as according to Marbach and Hangartner (2020)), these methods have not been extended to include a non-binary instrument. Still, similar to Bernstein et al. (2019), we can conduct some characterization of the compliers by splitting the sample into different groups based on other covariates of interest, reconstructing Z, and re-estimating the first stage. We further split the samples into users who had pre-trend credit score changes of ten points or fewer or more than ten points in magnitude (in each pre-trend subsample). The percentage of compliers in each group is Table 22.

Table 22: Percentage of Compliers by Pre-Trend Direction and Magnitude

	$\Delta CS^{pre} < 0$	$\Delta CS^{pre} \geq 0$
Change > |10|	24.7%	26.4%
Change <= |10	30.2%	32.1%

In both the compliance rates by pre-trend, and by the magnitude of the change in credit score within pre-trend samples, we find that there are slightly more compliers in the positive/flat pre-trend group, which makes sense given the initial evidence of users who are on increasing trends are more likely to return. It is interesting to note that the percentage of compliers does not vary drastically across groups.

E Comparing Across Different Samples of Users

E.1 Users Who Opt Out of Emails

We selected a random sample of 100,000 users who opt out of emails entirely. After removing users with data errors, we have 83,857 users.[8] Users who opt out of emails have slightly higher credit scores than the random sample of users, with an average score of 626 when they first log on and a standard deviation of 96.6 (compared to 599 and 91 for the random sample). The average score across all observed credit reports is 655 and the standard deviation is 93.1. 75% of these users (62,934) return to the website at least once past their initial sign up. Table 23 displays summary statistics for these users. Changes in credit score and the rate at which users check their score are similar to the random sample.

[8]We removed users with credit scores < 300 or >850.

Table 23: For Users Who Opt Out of Emails - Summary Statistics for Changes in Credit Score and How Often Users Check Updated Credit Reports

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Change in CS	-376.00	-6.00	1.00	1.07	10.00	309.00
Months Between Checking CS	0.00	0.87	1.07	1.68	1.57	47.20

Notes: The table is based on a random sample of 83,857 users who opt out of email communication. An observation is a user and credit report check. "Change in CS" is the difference in credit score between the consecutive reports, and "Months Between" is the number of months between when the user checks her updated reports.

E.2 IV vs. Random Sample

Next we compare users in the IV sample with those in our random sample. Table 24 shows that users in the IV sample check their credit score more often on average and have higher credit scores upon signing up for the platform compared to the general population.

We also looked at email engagement in Table 25. The first row is the number of emails that a user receives a month over the course of our data window. To be in the IV analysis, users have to at least receive the focal instrument emails. However, in the random sample, users can opt-out of email communication. Therefore, we see that users in the IV sample receive more 3 emails per month. Additionally, they have a 6% higher open rate for emails. Both groups have similar rates of clicking on the emails, conditional on opening.

We also measure whether users in the IV sample engage in information avoidance after receiving negative feedback. We estimate Equation 1 on the IV sample, using all observed credit scores from these users.[9]

[9]We do not estimate the left-digit-bias regression, as this is a drastically smaller sample than the random sample, and are not able to get enough observations close to the 00 cutoff.

Table 24: Summary Statistics for Users in IV and Random Sample

Variable	Group	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Change in CS	IV Sample	-148	-1.95	0.68	0.54	3.38	131.5
	Random Sample	-386	-6	1	1.01	10	409
Months Between Checking CS	IV Sample	0.39	1.17	1.53	2.07	2.33	18.78
	Random Sample	0	0.87	1.07	1.72	1.53	37.93
Number of CS Checks	IV Sample	3	10	17	18.22	25	81
	Random Sample	1	1	2	5.91	7	81
First CS	IV Sample	300	551	613	618.05	680	839
	Random Sample	300	524	581	594.21	653	839
Average CS	IV Sample	300	499	558	568.91	635	839
	Random Sample	300	512	560	575.91	635	839

Notes: This table consists of the sample of users who are in the IV analysis as well as the random sample of 969,254 users from Section 3. "Change in CS" is the difference in credit score between the consecutive reports, and "Months Between Checking CS" is the number of months between when the user checks her updated reports. "Number of CS Checks" is the number of times the user has ever checked her score. "First CS" is the user's credit score the first time she logs onto the platform. "Average CS" is the user's average credit score across the data set.

Table 25: Email Engagement Summary Statistics for Users in IV and Random Sample

Variable	Group	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Emails Per Month	IV Sample	0.15	9.22	21.15	30.64	39.28	431.65
	Random Sample	0	11.31	25.07	26.45	41.87	84
Percent Opened	IV Sample	0.18	12.07	24.66	31.42	45.48	100
	Random Sample	0.18	6.52	16.76	25.29	36.98	100
Percent Clicked	IV Sample	0	6.71	15.35	21.81	30.51	100
	Random Sample	0	3.11	12.5	21.06	30.56	100

Notes: This table consists of the sample of users who are in the IV analysis as well as the random sample of 969,254 users from Section 3. Emails Per Month is the average number of emails a user receives in our data window. Percent opened is the percentage of those emails received that the user opened. Percent clicked is the percent of those emails that the user clicked on, conditional on opening.

Table 26: OLS Estimates of Equation 1 for Users who Receive IV Emails

	Dependent variable:		
	$\mathbb{1}\{\text{Check Next Month}\}$		
	(1)	(2)	(3)
$\mathbb{1}\{\Delta CS < 0\}$	-0.136^{***}	-0.148^{***}	-0.065^{***}
	(0.002)	(0.002)	(0.002)
$\mathbb{1}\{\Delta CS < 0\} \times \lvert\Delta CS\rvert$			-0.005^{***}
			(0.0001)
Account Age	-0.003^{***}	-0.047^{***}	-0.048^{***}
	(0.0001)	(0.0003)	(0.0003)
CS	0.002^{***}	0.001^{***}	0.001^{***}
	(0.00002)	(0.00002)	(0.00002)
NCheck		0.064^{***}	0.066^{***}
		(0.0003)	(0.0003)
$\lvert\Delta CS\rvert$			0.002^{***}
			(0.0001)
Person RE	Y	Y	Y
Day of Week FE	Y	Y	Y
Month FE	Y	Y	Y
Observations	7,539,647	7,539,647	7,539,647
Note:			*p<0.1; **p<0.05; ***p<0.01

Notes: This table replicates Table 11 for the final sample of users who are in our main IV specification.

E.3 Users with Missing Outcomes

Lastly, in Table 27, we compare users in the IV sample with users who would have been in the IV sample, except they did not return to the website two months after receiving the email. Users who have a missing outcome tend to check their reports less frequently, and a more positive change in credit scores prior to receiving the email.

Table 27: Summary Statistics of Users in IV and Users With Missing Outcome Variable

Variable	Sample	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Pre Trend Change	Missing Outcome	-318	-4	1	2.31	14	271
	IV Sample	-352	-6	1	1.44	10	315
# of Months Between	Missing Outcome	0	0.88	1.34	2.73	3.3	20.95
Pre Trend Checks	IV Sample	0	0.9	1.08	1.68	1.66	20.85

Notes: The "IV sample" are the 464,752 users who are in the main IV analysis (received an email from one of the selected campaigns, checked their report at least twice before receiving the email, and checked their credit report within three months of receiving the email, and have an observed credit score at least two months after receiving the email). The "missing outcome" sample are the 90,565 users who fulfill the first three criteria to be in the IV sample but do not have an observed credit score at least two months after receiving the email.

F Simulating Credit Scores and Retention

In this section, we simulate the evolution of user retention and the credit scores of these users over time, given the estimated effects of checking and avoiding information. The intuition of these effects is the following. The estimated effect of checking credit reports on credit score is negative for users with declining scores, but positive for those with increasing scores. Additionally, users with declining scores are less likely to check their report in the next month. These two effects lead to the following cycle: for users who start off with declining scores, if they receive an email, their score further decreases, causing them to be less likely to return to the platform. Upon receiving an email, of those that do return, their score further declines. On the other hand, those with increasing scores have a further increase their credit score after receiving the email, and are more likely to return to the platform. The goal of these simulations is to combine these effects and isolate their impact on user retention and credit scores.

To be comparable to the random sample of users' data in this paper, we generate a sample of one million users, and simulate their credit scores for two consecutive time periods. In the first period, their credit scores are drawn from empirical distribution of credit scores of the random sample, as shown in Figure 2. We then generate the credit score transition matrix ρ using the observed transitions in consecutive months of the random sample. The two credit scores allow us to observe the users' initial credit score trend. Thus, the entire sample consists of users who have checked their credit score at least twice. We then simulate their activity for the next six time periods (months).

We simulate four email targeting policies: no emails (baseline), emails sent to everyone, emails sent to only people with increasing credit scores, and emails sent only to people with decreasing credit scores. We follow a similar timeline as in Figure 6. In the simulations, t is analogous to t_2^e, $t-1$ to t_1^e, and $t+1$ to t_{post}^e. In all these simulations, except the baseline, emails are sent out between t and $t+1$. Note that t_{check}^e in Figure 6 is not a time period in the simulations because not everyone checks their score after receiving the email. Additionally, another difference is that in the simulations, t denotes a calendar month, where in t in Figure 6 is an instance when a user checks their report.

We generate the users' decisions to view their report and their subsequent credit score evolutions with the following steps. For each user,

1. Given the user's trend in credit score between $t-1$ and t, estimate the probability π the user will check her report at $t+1$ using regression estimates from Table 3.

2. Randomly draw whether the user checks her report at $t+1$, given π.

3. If she checks her report at $t+1$, generate the user's credit score at $t+1$, given her score at t, using the transition matrix ρ and whether she received an email between t and $t+1$. If she receives an email, then her score at $t+1$ is adjusted by the intent to treat effects estimated in Table 7.

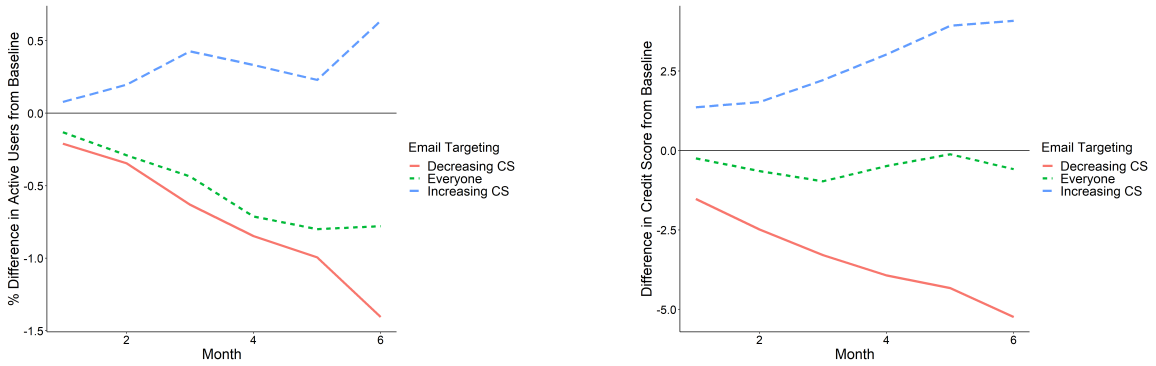
4. Repeat steps 1-3 until the user chooses not to check her score in the next period.

Note that this simulation makes the following simplifications. First, it includes only users who check *consecutively*. Once a user chooses to not check her score in the next month, she drops out of the sample for the remaining time periods. This simplification allows us to not model a user's belief about her credit score if she does not check in a given month. Second, we assume that all emails are "effective" emails, meaning they have a click rate of 100%. This allows us to simplify the data generating process by ignoring modeling emails of varying click rates, and assuming that each email received decreases future credit scores by 1.6, or increases future credit scores by 1.2, depending on the prior credit score trend. Note that receiving an effective email between t and $t+1$ does not guarantee the user checks her report at $t+1$. Rather, a 100% click rate means that the user checks her report at the time of the email.

Below, we report the results from two sets of simulations. In the first set of simulation results (which we refer to as "Information effects only"), emails do not have any impact on the probability that the user checks her report in the next time period. This allows us to isolate the effects from checking information and information avoidance only. The second set of results (referred to as "Information and email effects") assumes that emails increase the probability that users check their reports, which is closer to reality, but by itself is more difficult to parse the effects of information from receiving an email. Since we do not observe the causal effect of receiving an email on whether the user checks her report, as there is no exogenous variation in whether a user receives an email, we assume that receiving an email this month increases the probability that a user checks her report next month by 8%. This estimate is derived

from Table 32, which shows that users are 8% more likely to click on an "Update" email rather than a "Non-Update" email.

Figure 11: Simulation Results: Information Effects Only



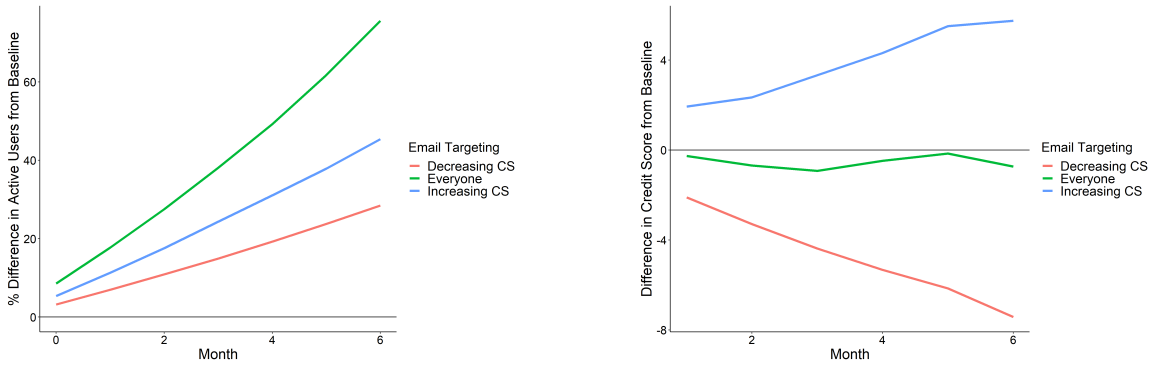
(a) Retention (b) Credit Scores

Notes: Results from 1 million simulated users. Receiving an email does not boost the probability the user checks her report. Panel (a) displays the retention metric, which is the percentage difference in the number of users who check their report in a given month compared to the baseline policy where no emails are sent. Panel (b) displays the difference in the average credit scores of users who check their scores in a given month, relative to the baseline policy.

Figure 11 displays the simulation results, relative to the baseline of the firm not sending any emails. Figure 11a displays the percentage difference in the number of users who are checking their credit report in a given month, relative to the the baseline. At month six, if the email was sent to only those with increasing credit scores each month, there would be 0.5% more active users on the platform compared to the baseline. This illustrates that the targeting rule of sending emails to only those with increasing scores leads to a 2% higher retention rate, or 20,000 more active users on the platform, compared to if the platform sent emails only to those with decreasing scores. Figure 11b displays the difference in the average credit scores across the different policies. Similarly, sending emails only to users with decreasing trends leads to an average of eight points lower than if the emails were sent only to users with increasing trends.[10]

[10]Comparing the distance between the red and blue lines.

Figure 12: Simulation Results: Information and Email Effects



(a) Retention

(b) Credit Scores

Notes: Simulation results from 1 million simulated users. Receiving an email increases the probability the user checks her report by 8%. Panel (a) displays the retention metric, which is the percentage difference in the number of users who check their report in a given month compared to the baseline policy where no emails are sent. Panel (b) displays the difference in the average credit scores of users who check their scores in a given month, relative to the baseline policy.

Figure 12 displays the simulation results when emails boost the probability that users check their report in the next time period. Since receiving an email boosts retention, the retention rate increases for all targeting policies compared to the baseline, with the smallest increase in retention for the policy of sending emails only to users with decreasing trends. However, in Panel (b), the credit score disparity between the increasing-only policy and decreasing-only policy is larger: the average credit score for active users under the decreasing trend email policy is 12 points lower than that of the increasing trend email policy.[11] This disparity is caused by the email's effect on retention. If a user's credit score was decreasing (increasing), she is more (less) likely to stop checking her report. However, if she receives an email, she is more (less) likely to check her report, causing her score to drop (increase) further. Due to the differences in retention and credit scores across policies, these simulations suggest that the credit score trend is an important piece of information to take into consideration for email targeting.

[11] Comparing the distance between the red and blue lines.

G Additional Tables and Figures

G.1 Evidence of Information Avoidance

Table 28: Robustness Checks: OLS Estimates of Equation 1

	Dependent variable:			
	$\mathbb{1}\{CheckNextMonth_t\}$			
	(1)	(2)	(3)	(4)
$\mathbb{1}\{\Delta CS < 0\}$	-0.029^{***}	-0.030^{***}	-0.030^{***}	-0.003^{***}
	(0.0005)	(0.0004)	(0.0004)	(0.001)
$\mathbb{1}\{\Delta CS < 0\} \times \lvert\Delta CS\rvert$				-0.001^{***}
				(0.00002)
$AccountAge$				-0.013^{***}
				(0.0001)
CS				0.0001^{***}
				(0.00000)
$NCheck$				0.021^{***}
				(0.0001)
|CSChange|				0.001^{***}
				(0.00001)
$\mathbb{1}\{CheckNextMonth_{t-1}\}$				0.214^{***}
				(0.001)
Person FE	N	Y	Y	N
Day of Week FE	N	N	Y	Y
Month FE	N	N	Y	Y
Observations	4,339,410	4,339,410	4,339,410	4,339,410
R^2	0.001	0.338	0.338	0.115
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents alternative specifications of Equation 1 by iteratively removing person fixed effects and controls for seasonality. The last column displays the estimates when the lagged dependent variable is used, instead of individual fixed effects. Standard errors clustered at the individual level.

Table 29: Robustness Checks: OLS Estimates of Equation 1 by Time Interval

	Dependent variable:			
	$\mathbb{1}\{CheckNextMonth\}$			
	(1)	(2)	(3)	(4)
$\mathbb{1}\{\Delta CS < 0\}$	-0.011^{***}	-0.013^{***}	-0.018^{***}	-0.013^{***}
	(0.001)	(0.001)	(0.004)	(0.003)
$\mathbb{1}\{\Delta CS < 0\} \times \lvert\Delta CS\rvert$	-0.00001	-0.0002^{***}	-0.001^{***}	-0.0005^{***}
	(0.00003)	(0.00004)	(0.0001)	(0.0001)
AccountAge	0.014^{***}	0.015^{***}	0.024^{***}	0.016^{***}
	(0.0002)	(0.0002)	(0.001)	(0.0003)
CS	0.0004^{***}	0.001^{***}	0.001^{***}	0.0004^{***}
	(0.00001)	(0.00001)	(0.0001)	(0.00004)
NCheck	-0.020^{***}	-0.023^{***}	-0.047^{***}	-0.053^{***}
	(0.0003)	(0.0003)	(0.001)	(0.001)
|CSChange|	0.0002^{***}	0.0003^{***}	0.001^{***}	0.0003^{***}
	(0.00002)	(0.00002)	(0.0001)	(0.0001)
t - $(t-1)$ (Months)	1	2	3	4+
Person FE	Y	Y	Y	Y
Day of Week FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Observations	2,072,852	1,534,876	300,412	430,824
R^2	0.411	0.430	0.704	0.691
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: This table displays results of Equation 1 for different sample based on the time interval of the pre-trend. Observations in the first column are users in which t - $(t-1)$ is 1 month, second column is 2 months, etc. Standard errors clustered at the individual level.

Table 30: Robustness Checks: OLS Estimates of Equation 1

	Dependent variable:		
	$\mathbb{1}\{CheckNextMonth\}$		
	(1)	(2)	(3)
$\mathbb{1}\{LeftDigitChanged\}$	-0.002	-0.008^{***}	0.019^{***}
	(0.001)	(0.001)	(0.001)
$\mathbb{1}\{LeftDigitChanged\} \times \mathbb{1}\{\Delta CS < 0\}$	-0.020^{***}	-0.009^{***}	-0.014^{***}
	(0.002)	(0.002)	(0.002)
$\mathbb{1}\{\Delta CS < 0\}$	-0.025^{***}	-0.020^{***}	-0.001
	(0.001)	(0.001)	(0.001)
$\lvert\Delta CS_{it}\rvert$		0.0001^{***}	0.0003^{***}
		(0.00002)	(0.00003)
$AccountAge$		0.001^{***}	-0.004^{***}
		(0.0001)	(0.0001)
Person FE	N	N	Y
Day of Week FE	N	Y	Y
Month FE	N	Y	Y
Rounded CS FE	N	Y	Y
Observations	854,329	854,329	854,329
R^2	0.001	0.024	0.528
Adjusted R^2	0.001	0.024	0.289
Note:			*p<0.1; **p<0.05; ***p<0.01

Notes: This sample consists of users with credit scores within 10 points to the nearest hundred (scores between X90 and Y09). Both specifications include controls for the rounded credit score to the nearest hundred, month, and day of week. Second column has individual fixed effects.

Table 31: Robustness Checks: RD Results with Different Bandwidths

	Dependent variable:			
	$\mathbb{1}\{CheckNextMonth\}$			
	(1)	(2)	(3)	(4)
$\mathbb{1}\{LeftDigitChanged\}$	0.001	-0.005^{***}	-0.008^{***}	-0.009^{***}
	(0.002)	(0.002)	(0.001)	(0.001)
$\mathbb{1}\{LeftDigitChanged\} \times \mathbb{1}\{\Delta CS < 0\}$	-0.011^{***}	-0.010^{***}	-0.009^{***}	-0.010^{***}
	(0.004)	(0.003)	(0.002)	(0.002)
$\mathbb{1}\{\Delta CS < 0\}$	-0.020^{***}	-0.021^{***}	-0.020^{***}	-0.018^{***}
	(0.003)	(0.002)	(0.001)	(0.001)
$\lvert\Delta CS_{it}\rvert$	0.0001^{***}	0.0001^{***}	0.0001^{***}	0.0001^{***}
	(0.00004)	(0.00003)	(0.00002)	(0.00002)
$AccountAge$	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.00004)
Bandwidth	3	5	10	15
Person FE	N	N	N	N
Day of Week FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Rounded CS FE	Y	Y	Y	Y
Observations	256,903	425,520	854,329	1,284,648
R^2	0.024	0.023	0.024	0.023
Adjusted R^2	0.024	0.023	0.024	0.023
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: This table presents the OLS estimates of Equation 1 with different bandwidths. For example, a bandwidth of 3 in the first column means that only credit scores that are within 3 of the hundred threshold are included (497 to 502, 597 to 602, 697 to 702, 797 to 802).

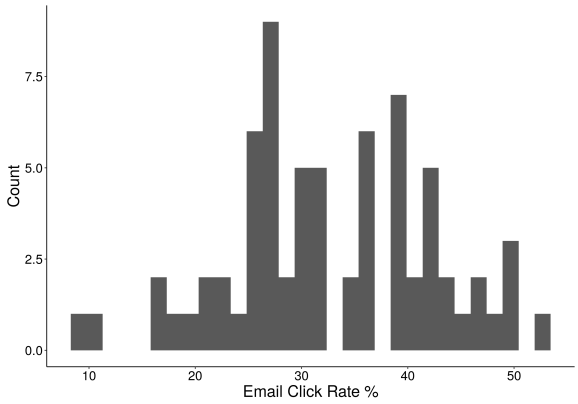
Table 32: OLS Results of Whether the Email is an "Update" Email on Open and Click Rates.

	Dependent variable:	
	Open Rate (%)	Click Rate (%)
	(1)	(2)
$\mathbb{1}\{\text{Update Email}\}$	4.905***	1.116***
	(0.245)	(0.151)
Constant	34.298***	13.120***
	(0.102)	(0.063)
Observations	26,240	26,240
R^2	0.015	0.002
Adjusted R^2	0.015	0.002
Note:	*p<0.1; **p<0.05; ***p<0.01	

Notes: This table presents the OLS results of $y_e = \alpha + \beta \mathbb{1}\{\textit{Update Email}\}_e + \epsilon_e$, where y_e is the open rate (Column 1) and click rate conditional on opening (Column 2). Each observation is at the email (e) level. Sample consists of all emails sent by the firm to at least 1000 users before June 1, 2018. An "update" email is an email in which the subject line contains "update" or "changed".

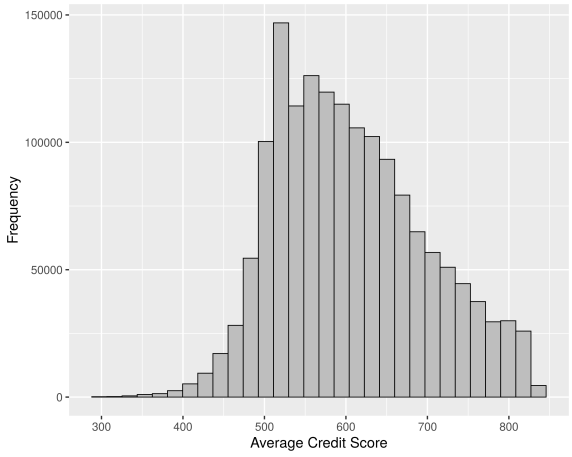
G.2 IV Validity

Figure 13: Histogram of Click Rates for the IV Email Copies



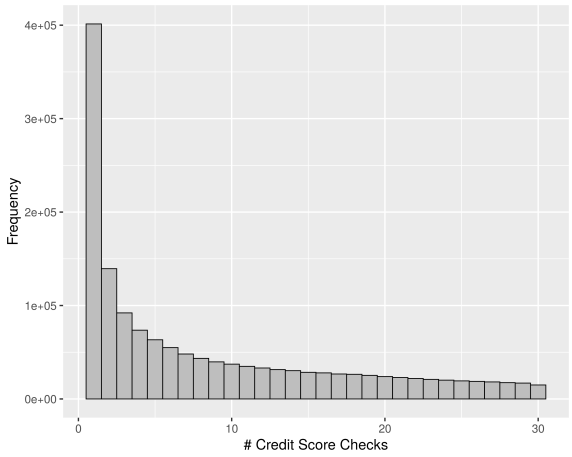
Notes: In this table, each observation is an email copy in the IV analysis. For each email, we calculated the percentage of users who receive the email who click on the email, conditional on opening, which is on the x-axis. The y-axis is how many of the emails are in that click rate bucket. The click rates range from 10-53%.

Figure 14: Average Credit Score for Users in the IV Analysis



Notes: This table is based on the sample of users who are in the IV analysis. Each observation is at the individual level. A user's average credit score is averaged over all her observed credit reports.

Figure 15: Histogram of the Number of Times a User in the IV Analysis Sample Checks her Score



Notes: This histogram consists of the sample of users who are in the IV analysis. Number of times a user checks her credit score, truncated at 30 checks.

Table 33: Summary Statistics of Time Before and After Receiving the Email

Pre-Trend	Variable	Min	Median	Mean	Max	SD
Declining	$t^e - t_2^e$ (Months)	0.0	0.7	0.9	3.0	0.7
	$t_{post}^2 - t^e$ (Months)	2.1	2.9	4.2	27.3	3.3
Non-declining	$t^e - t_2^e$ (Months)	0.0	0.5	0.8	3.0	0.7
	$t_{post}^2 - t^e$ (Months)	2.1	2.8	3.9	27.4	3.1

Notes: Each observation is at the user-email level. The first row is the number of months the user last checks her credit report before receiving her email ($t^e - t_2^e$) and the second row is the difference in time between her credit report for the post period and receiving the email ($t_{post}^e - t^e$).

Table 34: Subject Lines for Each of the Emails Sent Out over All 16 Campaigns

subject_line
##[F][S][P][\first]##, Your Score Has Been Updated For August.
Don't forget to check your score change before changing your clocks this weekend
Your Year in Review
##[F][S][P][\first]##, get all 3 scores today!
##[F][S][P][\first]##, find out how to get all 3 scores today!
Do you know your credit age?
##[F][S][P][\first]##, we've organized your recommendations based on your great credit!
Your debt has changed.
Congrats! Your credit improved in 2016.
Find the right card for the holidays!
Start off 2017 with a free extra score update.
##[F][S][P][\first]##, we updated your Credit History Grade.
Your credit profile has changed since last month.
##[F][S][P][\first]##, find out how your credit usage affects your score.
##[F][S][P][\first]##, we made it easier for you to compare cards!
##[F][S][P][\first]##, we've customized your recommended actions to your amazing credit.
##[F][S][P][\first]##, we've updated your credit usage grade.
##[F][S][P][\first]##, get all 3 scores and your full credit profile today!
See your new score!
##[F][S][P][\first]##, have you seen your updated approval odds?
##[F][S][P][\first]##, your credit usage grade is ready for review.
Congrats! We're giving you an extra free score update this month.
Need a credit card? We got you.
##[F][S][P][\first]##, your updated credit usage grade is ready for review.
##[F][S][P][\first]##, have you seen your updated payment history grade?
##[F][S][P][\first]##, take advantage of your great credit usage grade today!
##[F][S][P][\first]##, find out if your other 2 scores are as awesome as your TransUnion score.
##[F][S][P][\first]##, are you spending too much? See your updated credit usage grade.
We've calculated how much you need to pay off to get an A.

Notes: Each campaign has at least 2 email variants. "##[F][S][P][first]##" is the user's first name.

G.3 Additional IV Robustness Checks

Table 35: Heterogeneity in Intent-to-Treat Effects by Credit Score

	Dependent variable:					
	ΔCS^{post}					
	(1)	(2)	(3)	(4)	(5)	(6)
Click Rate	-3.665^{***}	1.125	-0.681	1.165	1.895^{**}	1.097
	(1.234)	(1.320)	(0.692)	(1.120)	(0.753)	(0.838)
ΔCS^{pre}	< 0	< 0	< 0	≥ 0	≥ 0	≥ 0
CS Tercile	Bottom	Middle	Upper	Bottom	Middle	Upper
Campaign Targeting Controls	Y	Y	Y	Y	Y	Y
Observations	75,187	75,126	73,600	109,938	128,951	147,681
R^2	0.013	0.029	0.014	0.014	0.033	0.019
Note:						*p<0.1; **p<0.05; ***p<0.01

Notes: This table replicates Table 7, but instead further separates samples by the user's credit score tercile before receiving the email. The tercile cutoffs are 578 and 661.

Table 36: OLS Results for the First Stage in the IV Estimation

	Dependent variable:	
	$1\{Check\}$	
	(1)	(2)
Homeowner	0.016***	0.011***
	(0.002)	(0.002)
ccclicks	0.042***	0.028***
	(0.002)	(0.001)
active	0.012***	0.046***
	(0.003)	(0.003)
refreshSameMonth	0.173***	0.288***
	(0.002)	(0.001)
CreditUtilizationGradeAB	−0.011	−0.023***
	(0.011)	(0.006)
CreditUtilizationGradeDF	0.014	−0.064***
	(0.008)	(0.005)
CSgreater700	0.033***	0.002
	(0.002)	(0.002)
ChangeinDebt	0.067***	0.050***
	(0.003)	(0.002)
Collections	−0.022***	−0.040***
	(0.002)	(0.002)
PaymentHistoryGradeCDF	0.032***	0.044***
	(0.006)	(0.004)
CreditAgeGradeAB	−0.559***	−0.353***
	(0.013)	(0.007)
CreditAgeGradeCDF	−0.552***	−0.368***
	(0.014)	(0.007)
CreditUtilizationNotA	−0.006	0.050***
	(0.010)	(0.005)
ChangeinCreditUtilizationGrade	0.807***	0.273***
	(0.126)	(0.005)
DebtIncrease	−0.006***	−0.025***
	(0.002)	(0.002)
CSIncrease		0.062***
		(0.002)
CSIncrease2016	0.103***	−0.050***
	(0.002)	(0.002)
Constant	0.430***	0.421***
	(0.004)	(0.004)
ΔCS^{pre}	< 0	≥ 0
Observations	254,223	451,594
R^2	0.222	0.182
Note:	*p<0.1; **p<0.05; ***p<0.01	

Notes: This table is the regression of Equation 4. The outcome variable is whether or not a user checks her score within 31 days of receiving the email. The independent variables in this regression are the targeting rules, which are all indicator variables. We describe the targeting rules with unclear names: ccclicks (whether the user has clicked on a credit card application in the same month), active (user has created an account, or opened or clicked on an email in the last three months), refreshSameMonth (viewed their credit report more than once in that month), CSIncrease (an indicator for whether the user's last observed credit score has increased since their previous score), CSIncrease2016 (whether the user's credit score has increased in 2016).

Table 37: IV with All Regressors Displayed

	ΔCS^{post}	
	(1)	(2)
$\mathbb{1}\{Check\}$	-23.247***	9.084***
	(6.928)	(2.094)
active	-1.393***	-0.439
	(0.354)	(0.352)
Homeowner	2.540***	1.949***
	(0.199)	(0.184)
ccclicks	-3.043***	-3.848***
	(0.539)	(0.255)
refreshSameMonth	6.714***	1.092
	(1.655)	(0.688)
CreditUtilizationGradeAB	0.762	-2.492**
	(2.963)	(1.068)
CreditUtilizationGradeDF	12.702***	4.621***
	(3.852)	(1.476)
CSgreater700	-3.892***	-5.429***
	(0.556)	(0.480)
ChangeinDebt	-0.746	-4.026***
	(0.960)	(0.484)
Collections	3.406***	2.908***
	(0.544)	(0.465)
PaymentHistoryGradeCDF	14.106***	0.333
	(2.668)	(1.003)
CreditAgeGradeAB	-19.203***	4.694***
	(5.564)	(1.670)
CreditAgeGradeCDF	-26.049***	-0.636
	(5.466)	(2.149)
CreditUtilizationNotA	-7.125***	0.779
	(2.350)	(1.590)
ChangeinCreditUtilizationGrade	7.031	-3.060***
	(9.629)	(1.025)
DebtIncrease	-5.759***	-5.852***
	(0.232)	(0.201)
CSIncrease	0.000	-2.834***
	(.)	(0.271)
CSIncrease2016	3.993***	-2.230***
	(0.987)	(0.327)
Constant	14.152***	-2.292**
	(2.638)	(1.115)
Campaign Targeting Controls	Y	Y
ΔCS^{pre}	< 0	≥ 0
Observations	223,913	386,570

Notes: This table presents the IV regression of Equation 5 with all regressors. $\mathbb{1}\{Check\}$ *is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent.*

Table 38: Number of Emails Users Receive and Open Each Month

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Emails Per Month	0.15	9.22	21.15	30.63	39.26	431.65
Percent Opened	0.18	6.84	16.73	24.53	35.56	100.00
Percent Clicked	0.00	3.79	11.85	19.53	27.38	100.00

Notes: The sample is users who are in the IV analysis, i.e., any user who received at least one of the 16 campaigns. The statistics presented are the same as in Table 2 to compare these to a random sample of users. Each observation is the user-month level.

Table 39: IV with Different Samples of when a User Last Logged On Before the Email

	ΔCS^{post}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}\{Check\}$	-14.923**	4.911**	-25.536***	9.814***	-24.784***	12.607***
	(6.403)	(2.345)	(6.879)	(2.365)	(6.777)	(2.620)
Campaign Targeting Controls	Y	Y	Y	Y	Y	Y
ΔCS^{pre}	< 0	≥ 0	< 0	≥ 0	< 0	≥ 0
Prev Login Window	1 Month	1 Month	6 Months	6 Months	No Cutoff	No Cutoff
Observations	143,836	267,934	259,867	441,246	283,461	474,492

Notes: This table presents the IV regression of Equation 5 with only the check regressor listed. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for the email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent. "Prev Login Window" refers to the last time a user checked her score before the email was sent. For one month, this means that a user last checked her score within a month before the email was sent. The main specification allows a user to have checked her score within the last three months. The last columns do not restrict the sample.

Table 40: IV with Different Samples of when a User Last Logged On Before the Email

	ΔCS^{post}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}\{Check\}$	-3.051	0.785	-4.282**	1.727***	-3.616*	2.348***
	(2.009)	(0.608)	(2.029)	(0.505)	(2.005)	(0.505)
Campaign Targeting Controls	Y	Y	Y	Y	Y	Y
ΔCS^{pre}	< 0	≥ 0	< 0	≥ 0	< 0	≥ 0
Prev Login Window	1 Month	1 Month	6 Months	6 Months	No Cutoff	No Cutoff
Observations	143,836	267,934	259,867	441,246	283,461	474,492

Notes: This table presents the IV regression of Equation 6 with only the check regressor listed. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for the email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent divided by the number of months between the credit scores. "Prev Log on Window" refers to the last time a user checked her score before the email was sent. For one month, this means that a user last checked her score within a month before the email was sent. The main specification allows a user to have checked her score within the last three months. The last columns do not restrict the sample.

Table 41: Two-Stage Least Squares IV With Sample of Users Who Received One Focal Email

	ΔCS^{post}	
	(1)	(2)
$\mathbb{1}\{Check\}$	-5.373	6.007***
	(5.909)	(1.847)
Campaign Targeting Controls	Y	Y
ΔCS^{pre}	< 0	≥ 0
Observations	77,736	138,904

Notes: This table presents the IV regression of Equation 5 with only the check regressor listed. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent. This analysis restricts the sample to users who received one of the focal emails which is 84% of the users in the sample.

Table 42: Two-Stage Least Squares IV With Sample of Users Who Received One Focal Email Within a Month

	ΔCS^{post}	
	(1)	(2)
$\mathbb{1}\{Check\}$	-19.478***	9.490***
	(6.090)	(2.065)
Campaign Targeting Controls	Y	Y
ΔCS^{pre}	< 0	≥ 0
Observations	183,938	318,288

Notes: This table presents the IV regression of Equation 5 with only the check regressor listed. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent. This analysis restricts the sample to users who received at most one of the focal emails within a month which is 97.3% of the users in the sample.

Table 43: Two-Stage Least Squares IV With Sample of Users Who Received One Focal Email - Monthly Change Outcome

	ΔCS^{post}	
	(1)	(2)
$\mathbb{1}\{Check\}$	0.213	0.421
	(1.528)	(0.469)
Campaign Targeting Controls	Y	Y
ΔCS^{pre}	< 0	≥ 0
Observations	77,736	138,904

Notes: This table presents the IV regression of Equation 6 with only the check regressor listed. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent divided by the number of months between the credit scores. This analysis restricts the sample to users who received one of the focal emails which is 84% of the users in the sample.

Table 44: Two-Stage Least Squares IV With Sample of Users Who Received One Focal Email Within a Month - Monthly Change Outcome

	ΔCS^{post}	
	(1)	(2)
$\mathbb{1}\{Check\}$	-3.649**	1.615***
	(1.808)	(0.446)
Campaign Targeting Controls	Y	Y
ΔCS^{pre}	< 0	≥ 0
Observations	183,938	318,288

Notes: This table presents the IV regression of Equation 6 with only the check regressor listed. $\mathbb{1}\{Check\}$ *is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent divided by the number of months between the credit scores. This analysis restricts the sample to users who received at most one of the focal emails within a month which is 97.3% of the users in the sample.*

Table 45: Two-Stage Least Squares IV By Tercile - Full Regression

	ΔCS^{post}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}\{Check\}$	-21.521***	-0.504	-11.610*	-4.223**	19.629***	21.511***
	(6.618)	(7.584)	(6.232)	(2.118)	(2.839)	(2.537)
active	-4.387***	-3.712***	-0.448	-1.896**	-2.014***	-1.575***
	(0.978)	(0.734)	(0.487)	(0.846)	(0.731)	(0.346)
Homeowner	3.231***	5.033***	3.545***	2.174***	3.812***	3.292***
	(0.629)	(0.458)	(0.297)	(0.529)	(0.452)	(0.222)
ccclicks	-0.967	-3.758***	-4.725***	-1.957***	-3.840***	-5.043***
	(0.724)	(0.768)	(0.608)	(0.314)	(0.362)	(0.504)
refreshSameMonth	3.980***	7.753***	5.452***	3.082***	2.450**	-0.170
	(1.360)	(1.823)	(1.405)	(0.661)	(0.990)	(0.710)
CreditUtilizationGradeAB	1.563	2.420	3.298	0.257	-1.389	-1.797
	(5.500)	(6.181)	(4.652)	(3.720)	(1.312)	(1.298)
CreditUtilizationGradeDF	-9.204	-2.396	-7.477*	0.011	-1.533**	-2.753***
	(5.642)	(4.479)	(4.366)	(2.972)	(0.755)	(1.036)
ChangeinDebt	1.715**	-0.741	0.483	-1.852***	-1.986***	-0.582
	(0.803)	(1.182)	(1.366)	(0.419)	(0.633)	(0.610)
Collections	-0.569	-3.173***	-2.266***	-3.085***	-2.900***	-1.335***
	(0.480)	(0.365)	(0.507)	(0.667)	(0.269)	(0.368)
PaymentHistoryGradeCDF	13.701***	1.294	-2.736	-6.390**	-2.767***	-3.003***
	(3.948)	(4.534)	(2.915)	(2.777)	(0.759)	(0.858)
CreditAgeGradeAB	0.757	-1.219	-8.945	16.438***	11.677***	9.459***
	(11.050)	(10.654)	(6.437)	(5.669)	(2.634)	(2.098)
CreditAgeGradeCDF	-4.294	-15.228*	-19.194***	8.704	6.314***	3.203
	(10.212)	(8.018)	(7.400)	(5.456)	(2.070)	(1.991)
CreditUtilizationNotA	5.864	-0.948	-5.138*	2.703	1.003	0.971
	(7.552)	(6.948)	(3.013)	(3.355)	(2.062)	(1.368)
ChangeinCreditUtilizationGrade	-18.596**	0.090	36.626***	0.163	-5.040***	-4.146***
	(7.673)	(10.331)	(8.070)	(2.582)	(0.530)	(1.066)
DebtIncrease	-6.874***	-7.102***	-2.738***	-3.610***	-7.126***	-5.354***
	(0.647)	(0.338)	(0.284)	(0.447)	(0.285)	(0.274)
CSIncrease	0.000	0.000	0.000	1.041	-3.534***	-3.620***
	(.)	(.)	(.)	(0.730)	(0.432)	(0.246)
CSIncrease2016	4.262***	3.052***	2.853***	-0.909	-2.718***	-1.097**
	(1.394)	(1.102)	(0.828)	(0.769)	(0.388)	(0.428)
Constant	30.307***	0.611	-0.532	17.429***	-9.875***	-17.801***
	(2.174)	(3.008)	(2.642)	(1.505)	(1.548)	(1.513)
Campaign Targeting Controls	Y	Y	Y	Y	Y	Y
Tercile	Bottom	Middle	Upper	Bottom	Middle	Upper
ΔCS^{pre}	< 0	< 0	< 0	≥ 0	≥ 0	≥ 0
Observations	51,185	81,078	91,650	71,803	134,781	179,986

Notes: This table presents the IV regression of Equation 5. $\mathbb{1}\{Check\}$ *is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent.*

Table 46: Two-Stage Least Squares IV By Tercile - Full Regression - Monthly Change

	ΔCS^{post}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}\{Check\}$	-3.795**	1.450	-2.106	5.047***	2.190***	1.186**
	(1.853)	(2.365)	(1.925)	(0.658)	(0.584)	(0.493)
active	-0.589***	-0.584***	-0.152	-0.312*	-0.373***	-0.258***
	(0.112)	(0.174)	(0.115)	(0.165)	(0.129)	(0.076)
Homeowner	0.719***	1.029***	0.753***	0.443***	0.789***	0.724***
	(0.187)	(0.093)	(0.061)	(0.120)	(0.089)	(0.042)
ccclicks	-0.400*	-1.218***	-1.433***	-0.673***	-1.070***	-1.404***
	(0.211)	(0.222)	(0.178)	(0.092)	(0.111)	(0.153)
refreshSameMonth	2.650***	1.315**	0.700*	0.838***	0.482**	-0.229
	(0.390)	(0.575)	(0.422)	(0.210)	(0.229)	(0.163)
CreditUtilizationGradeAB	0.142	0.440	0.140	0.380	-0.173	-0.700*
	(0.415)	(0.501)	(0.301)	(0.966)	(0.304)	(0.386)
CreditUtilizationGradeDF	-0.249	-0.169	-0.568*	0.103	-0.494***	-0.717***
	(0.330)	(0.299)	(0.313)	(0.749)	(0.188)	(0.214)
ChangeinDebt	0.388	-0.432	-0.208	-0.390***	-0.419**	0.033
	(0.248)	(0.365)	(0.384)	(0.118)	(0.170)	(0.159)
Collections	-0.277*	-0.877***	-0.553***	-0.939***	-0.805***	-0.264***
	(0.145)	(0.092)	(0.108)	(0.189)	(0.078)	(0.078)
PaymentHistoryGradeCDF	0.872***	0.466	0.013	-1.146	-0.880***	-0.614***
	(0.287)	(0.303)	(0.207)	(0.823)	(0.189)	(0.199)
CreditAgeGradeAB	-3.511***	0.178	-0.703	2.038***	2.722***	2.441***
	(1.008)	(1.514)	(1.198)	(0.747)	(0.455)	(0.591)
CreditAgeGradeCDF	-3.660***	-0.275	-1.137	0.734	1.590***	1.337**
	(0.943)	(1.425)	(1.245)	(0.995)	(0.536)	(0.565)
CreditUtilizationNotA	0.108	0.394	-0.272	1.686*	1.138***	0.807***
	(0.495)	(0.548)	(0.204)	(0.942)	(0.308)	(0.297)
ChangeinCreditUtilizationGrade	2.049	-7.389**	6.311	0.137	-1.789***	-1.809***
	(1.576)	(3.629)	(4.070)	(0.705)	(0.113)	(0.156)
DebtIncrease	-1.501***	-1.574***	-0.622***	-0.808***	-1.840***	-1.351***
	(0.168)	(0.101)	(0.090)	(0.117)	(0.097)	(0.073)
CSIncrease	0.000	0.000	0.000	0.286*	-0.812***	-1.004***
	(.)	(.)	(.)	(0.164)	(0.118)	(0.064)
CSIncrease2016	1.470***	0.707**	0.679***	-0.493***	-0.566***	-0.055
	(0.370)	(0.342)	(0.236)	(0.183)	(0.129)	(0.110)
Constant	5.284***	0.044	0.379	1.130***	-0.269	-1.531***
	(0.646)	(0.917)	(0.804)	(0.364)	(0.322)	(0.283)
Campaign Targeting Controls	Y	Y	Y	Y	Y	Y
Tercile	Bottom	Middle	Upper	Bottom	Middle	Upper
ΔCS^{pre}	< 0	< 0	< 0	≥ 0	≥ 0	≥ 0
Observations	51,185	81,078	91,650	71,803	134,781	179,986

Notes: This table presents the IV regression of Equation 6. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent divided by the number of months between the credit scores.

Table 47: Two-Stage Least Squares IV Including Pre Trend As Covariate

	ΔCS^{post}	
	(1)	(2)
$\mathbb{1}\{Check\}$	-16.463**	7.697***
	(6.783)	(1.996)
Campaign Targeting Controls	Y	Y
ΔCS^{pre}	< 0	≥ 0
Observations	223,913	386,570

Notes: This table presents the IV regression of Equation 6. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent divided by the number of months between the credit scores. An additional covariate of the pre-trend credit score change is included.

Table 48: Two-Stage Least Squares IV Only Users Whose Pre-Trend Change was 10 Points Or Fewer In Magnitude

	ΔCS^{post}	
	(1)	(2)
$\mathbb{1}\{Check\}$	-11.783**	5.016**
	(5.959)	(2.247)
Campaign Targeting Controls	Y	Y
ΔCS^{pre}	< 0	≥ 0
Observations	104,693	235,417

Notes: This table presents the IV regression of Equation 6. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent divided by the number of months between the credit scores. Only users whose pre-trend is ten points or fewer in magnitude are included.

Table 49: Two-Stage Least Squares IV with Last Credit Score as Covariate

	ΔCS^{post}	
	(1)	(2)
$\mathbb{1}\{Check\}$	-13.654**	13.393***
	(6.130)	(1.675)
Campaign Targeting Controls	Y	Y
ΔCS^{pre}	< 0	≥ 0
Observations	223,913	386,570

Notes: This table presents the IV regression of Equation 6. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent divided by the number of months between the credit scores. The users last credits score observed before the email is added an additional covariate.

Table 50: Two-Stage Least Squares IV Grouped by Refresh Indicator

	ΔCS^{post}			
	(1)	(2)	(3)	(4)
$\mathbb{1}\{Check\}$	-11.747*	5.482**	-5.482	10.788
	(6.204)	(2.565)	(8.022)	(7.213)
Campaign Targeting Controls	Y	Y	Y	Y
ΔCS^{pre}	< 0	≥ 0	< 0	≥ 0
Refresh Same Month	Y	Y	N	N
Observations	118,759	235,881	105,154	150,689

Notes: This table presents the IV regression of Equation 6. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent divided by the number of months between the credit scores. Refresh Same Month is an indicator for whether the user had more than one credit score refresh that month (which was an extra credit score report). Yes indicates that the user had this and No that they did not.

Table 51: Two-Stage Least Squares IV Grouped by Active Indicator

	ΔCS^{post}			
	(1)	(2)	(3)	(4)
$\mathbb{1}\{Check\}$	-22.835***	8.881***	-12.421	7.646
	(6.862)	(2.139)	(12.023)	(7.091)
Campaign Targeting Controls	Y	Y	Y	Y
ΔCS^{pre}	< 0	≥ 0	< 0	≥ 0
Active	Y	Y	N	N
Observations	208,889	365,515	15,024	21,055

Notes: This table presents the IV regression of Equation 6. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent divided by the number of months between the credit scores. Active is a campaign control targeting covariate. It is an indicator for whether the user has created an account, opened or clicked on an email in the last three months.

Table 52: Two-Stage Least Squares IV Grouped by Credit Card Offer Click Indicator

	ΔCS^{post}			
	(1)	(2)	(3)	(4)
$\mathbb{1}\{Check\}$	-5.687	2.353	-22.227***	9.972***
	(8.778)	(4.526)	(6.763)	(2.029)
Campaign Targeting Controls	Y	Y	Y	Y
ΔCS^{pre}	< 0	≥ 0	< 0	≥ 0
Credit Card Clicks	> 0	> 0	0	0
Observations	11,518	28,422	212,395	358,148

Notes: This table presents the IV regression of Equation 6. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent divided by the number of months between the credit scores. Click is an indicator for whether the user has clicked on a credit card application in the same month.

Table 53: Two-Stage Least Squares IV Grouped by All Activity Measures

	ΔCS^{post}			
	(1)	(2)	(3)	(4)
$\mathbb{1}\{Check\}$	-22.835***	8.881***	-12.421	7.646
	(6.862)	(2.139)	(12.023)	(7.091)
Campaign Targeting Controls	Y	Y	Y	Y
ΔCS^{pre}	< 0	≥ 0	< 0	≥ 0
Activity	Y	Y	N	N
Observations	208,889	365,515	15,024	21,055

Notes: This table presents the IV regression of Equation 6. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent divided by the number of months between the credit scores. Activity is an indicator for whether the user had refresh same month, active, and click all zero or all one.

Table 54: Two-Stage Least Squares IV Grouped by Average Rate of Checking Credit Report

	ΔCS^{post}			
	(1)	(2)	(3)	(4)
$\mathbb{1}\{Check\}$	-14.478**	-15.436**	8.284***	10.416***
	(6.285)	(6.589)	(2.788)	(2.371)
Campaign Targeting Controls	Y	Y	Y	Y
ΔCS^{pre}	< 0	< 0	≥ 0	≥ 0
Rate of Checking Score	Above	Below	Above	Below
Observations	118,083	105,812	215,789	170,698

Notes: This table presents the IV regression of Equation 6. $\mathbb{1}\{Check\}$ is an indicator for whether a user checked her score within 31 days of receiving the email. This regressor is instrumented for which email version a user received. The outcome is the change in credit score from before the email to the first credit score checked at least two months after the email was sent divided by the number of months between the credit scores. The average rate number of checks per month that all users have is calculated which is, 0.89. There are many points above one as some users get extra refreshes within a month, or if a user checks on June 1 and July 1 it counts as twice in a month due to the way it is calculated. The users are then split according to whether they check more or less frequently per month than the average. Users who check their credit score often before the email is sent, are less likely to have their retention impacted by the email. Therefore, we split users into whether or not they check their credit score more or less often than average (compared to other users who receive a focal email).

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