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

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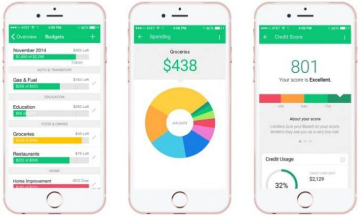
Motivation

Information tracking services are gaining in popularity.



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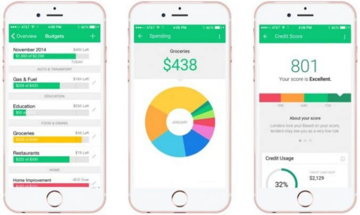
  - "All you need is a well-built plan, a strong willpower, and the right fitness app to help you stay on track."



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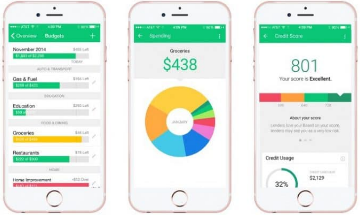

Is this true? Are consumers benefiting from more information?

Drop Out Rates of Information Tracking Services Are High

- 42% of people who buy fitness trackers stop using them within 6 months.
- On our consumer finance platform, 38% of users do not return to the tracking platform after receiving their first credit report.
  - These users tend to have the lowest credit scores.

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Individuals with poor standing have the largest room for improvement, yet they are the most likely to stop seeking information.

Research Questions

Context: Financial health - credit scores

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1. **Do individuals change their demand for information (or engage in information avoidance), and under what circumstances?**

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Context: Financial health - credit scores

1. **Do individuals change their demand for information (or engage in information avoidance), and under what circumstances?**

2. **What is the effect of information on outcomes? (credit scores)**
   - When should consumers seek/avoid information?
   - How does it change for:
     - Individuals who are likely to avoid the information to begin with?
     - Individuals with low vs. high credit scores?

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There are heterogenous effects of:

- Seeking/avoiding information.
- Checking information on future outcomes.

Literature Review

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- Information Avoidance
  - **Information avoidance:** any behavior intended to prevent or delay the acquisition of available but *potentially* unwanted information (Sweeney (2010))
  - Individuals avoid information when they feel uncertain about the outcome
    - Koszegi (2003); Masatlioglu et al., (2017); Karlsson et al., (2009).
  - Health
    - CDC, (1997); Lyter et al., (1987); Thornton, (2008)
  - Stock market
    - Sicherman, Lowenstein, Seppi, Utkus (2015)
  - Social information
    - Huang (2018); Huck, Szech, Wenner (2018); Goulas and Megalokonomou (2021)

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  - Social information
    - Huang (2018); Huck, Szech, Wenner (2018); Goulas and Megalokonomou (2021)
- Financial Attention and Nudges
  - Medina (2016); Beshears (2015); Stango and Zinman (2009); Karlan et. al (2016), Liu, Montgomery, Srinivasan (2018)

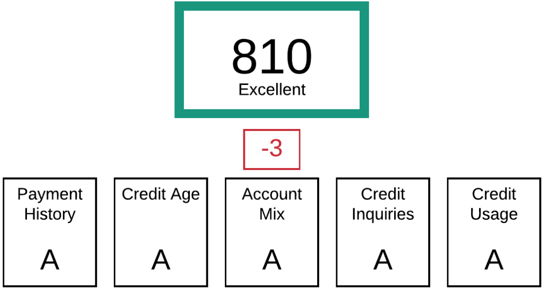
Data Context

- Credit score monitoring platform.
  - Provides free credit score reports, financial health grades, fraud monitoring.
- Over 15 million users.
- Credit score reports are pulled the first time the user logs in in the calendar month.
  - If a user does not log in, we do not observe their credit score.

Summary Statistics

Data Context

Figure: Mock Design of Credit Information on the Homepage



Notes: This figure displays the credit report information that the user sees immediately upon logging on to her account. Her credit score is displayed along with her credit tier (Excellent, Good, Fair, Poor, Very Poor) and associated color. The "-3" is how much her credit score has changed since her last observed credit report. The bottom five panels are the letter grades for each credit grade.

Summary Statistics

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Table: Summary Statistics for Changes in Credit Score and Frequency of Checking Between Consecutive Reports

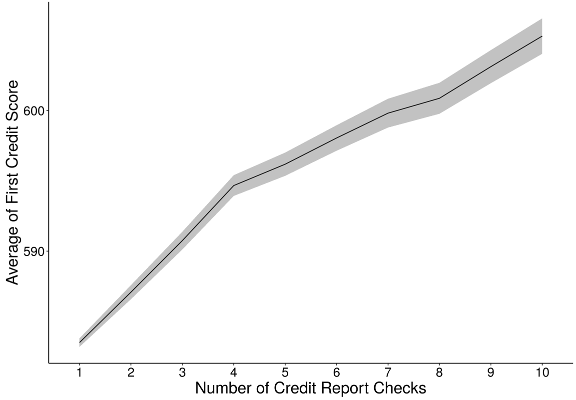
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Change in CS	-386.00	-6.00	1.00	0.93	10.00	326.00
Months Between Checking CS	0.00	0.90	1.07	1.73	1.57	36.53

Notes: The sample is 561,864 users who have checked their score at least twice. "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.

- Who is viewing their credit score and when?

- Who is viewing their credit score and when?
  - Checking information is costly
  - When consumers are doing well, information is not as valuable.
  - When consumers are doing poorly, information causes psychological disutility.

Figure: First Observed Credit Score by Number of Credit Score Checks



Notes: Each observation is a user's credit score from the first credit report she checked through this platform. The horizontal axis is the number of times the user has checked her updated credit report ending at 10 checks. Shaded areas depict 95% confidence intervals.

Left-Digit Bias - Check for Change in Demand for Information

- Perceived difference between 99 and 100 much greater than 97 and 98
  - Thomas and Morwitz (2005)

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- Users with credit score of 599 perceive their score to be much lower than those with 600.
  - Users should be similar on other aspects (unobservables).

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- Users with credit score of 599 perceive their score to be much lower than those with 600.
  - Users should be similar on other aspects (unobservables).
- A user is less likely to check her credit report next month if her score drops from 600 to 599 than if it drops from 601 to 600.

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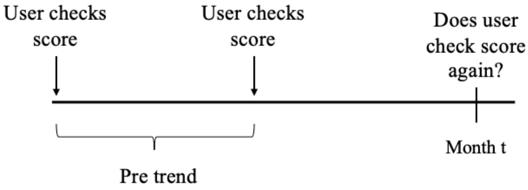

$$\mathbb{1}\{CheckNextMonth\}_{it} = \alpha_m + \alpha_w + \beta_1 \mathbb{1}\{LeftDigitChanged\}_{it} + \beta_2 \mathbb{1}\{Pre\_trend_{it} < 0\}$$
$$+ \beta_3(\mathbb{1}\{LeftDigitChanged\}_{it} \times \mathbb{1}\{Pre\_trend_{it} < 0\})$$
$$+ \beta_4 RoundedCS_{it} + \beta_5 |Pre\_trend_{it}| + \beta_6 AccountAge_{it} + \epsilon_{it} \quad (1)$$

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- If a user's credit score decreases, her rate of checking declines by 3%*** of the average.
- If a user's credit score decreases and her score crosses the hundred threshold, she is 5.6%*** less likely to check her score.
- **Evidence that consumers who perceive that they are doing worse, lower their demand for information**.

The Effect of Information

- Consumers who have poor and declining scores are less likely to log in.
- **How does learning their information affect their credit score?**

Identification Challenge

How to get a causal effect?

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- Simultaneity: Are consumers logging in because they are taking actions that they think are changing their credit score, and that is why we see credit score change?
- Selection bias: Individuals with decreasing credit score might be less financially responsible and less likely to check information.
- Unobserved shocks: That affect financial status and likelihood of checking information.

Identification Challenge - Solution

How to get a causal effect?

- Need an **exogenous shock** that affects the rate at which users log in and **view their score.**

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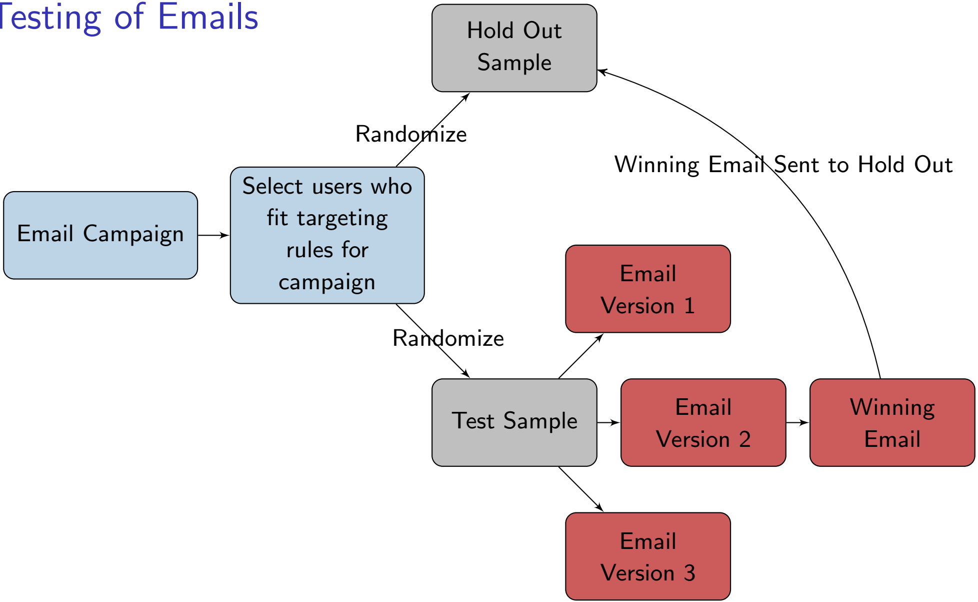
How to get a causal effect?

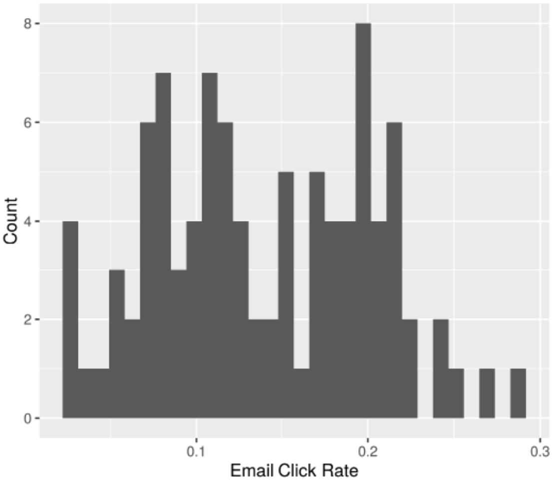
- Need an **exogenous shock** that affects the rate at which users log in and **view their score.**
- Use **randomized emails that affect log in rate.**
  - We cannot directly manipulate whether a user logs in and views her score.
  - We use the emails as an instrument.

A/B Testing of Emails



Email Data

- 16 email campaigns
- Targeting rules for each campaign
- 70 email copies (instrument)
- $\sim$500,000 users
- 25% average open rate
- 19% average click rate, conditional on opening



Identification for Casual Effect

- Given a certain email campaign, users are randomized to different email copies.
- Emails have different rates of getting users to log in and check their credit score.
- We use email copies the firm sends as instruments for checking their information.
- Negative pre-trend versus positive or flat pre-trend.

Email Data

Instrument Validity

- Relevance
  - The email copy is correlated with whether a user logs in.
  - Strong F-statistic for each group (decreasing and constant/increasing credit score pre-trends).

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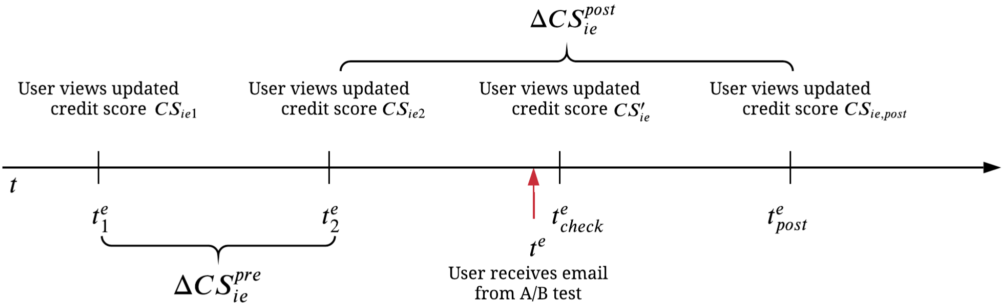
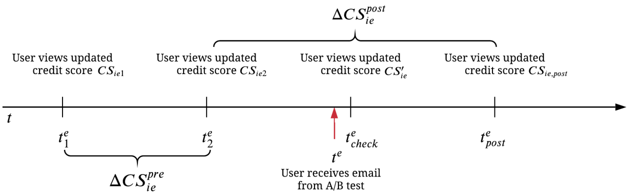
- Relevance
  - The email copy is correlated with whether a user logs in.
  - Strong F-statistic for each group (decreasing and constant/increasing credit score pre-trends).
- Exclusion restriction
  - The email copy affects credit score only through increasing the likelihood the user logs in.

IV Regression



- Each observation is a user-email (*ie*) combination. Time periods are relative to the time that email *e* is received.
- CS_post is the first credit score observed at least two months after the email, to allow users time to make changes.

IV Regression



First stage

$$\mathbf{1}\{Check\} = \alpha_e + \gamma_1 X_{ie} + \eta_{ie}$$

- For $\mathbb{1}\{\Delta CS_{ie}^{pre} < 0\}$ and $\mathbb{1}\{\Delta CS_{ie}^{pre} >= 0\}$.
- α_e: email fixed effect.
- X_{ie}: matrix of user i's characteristics at time, t.
  - Control for correlations between α_e and η_{ie}.

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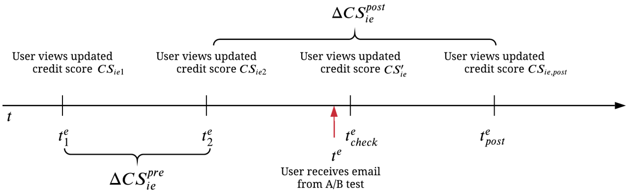

Second stage

$$CS\_post\_trend_{ie} = \beta_0 + \beta_1 \mathbf{1}\{\hat{Check}_{ie}\} + \Delta X_{ie} + \epsilon_{ie}$$

- $\mathbf{1}\{\hat{Check}_{ie}\}$ - fitted values from first stage

Results - Intent to Treat Effect

	Dependent variable:	
	ΔCS^{post}	
	(1)	(2)
Click Rate	-1.591^{**}	1.167^{*}
	(0.677)	(0.667)
ΔCS^{pre}	< 0	≥ 0
Campaign Targeting Controls	Y	Y
Observations	223,913	386,570
R^2	0.017	0.022
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

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Results

For users who are on a declining trend, when prompted to check their score, upon checking, their credit score **declines an additional 23 points.**
For users who are on a flat or increasing trend, when prompted to check their score, upon checking, their credit score **increases an additional 9 points.**

	ΔCS^{post}	
	(1)	(2)
$\mathbb{1}\{Check\}$	-23.247***	9.084***
	(6.928)	(2.094)
Campaign Targeting Controls	Y	Y
ΔCS^{pre}	< 0	≥ 0
Observations	223,913	386,570

ITT More Results

Results

- 10 point credit score difference
- Mortgage rate of 4.125% versus 4%
- \$250,000, 30−year fixed−rate mortgage
- \$6,500 difference in payments

Results By Tercile

2SLS IV Splitting Users by Credit Score Tercile

	ΔCS^{post}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}\{Check\}$	-21.521***	-0.504	-12.152**	-4.223**	19.629***	21.602***
	(6.618)	(7.584)	(6.134)	(2.118)	(2.839)	(2.483)
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

More Results

Managerial Implications - Retention Simulation

- The common policy of sending retention/reminder emails to those who are least likely to return may not be the most effective at increasing retention.

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  - Sending emails to all users, sending emails to users with increasing scores only, sending emails to users with decreasing scores only

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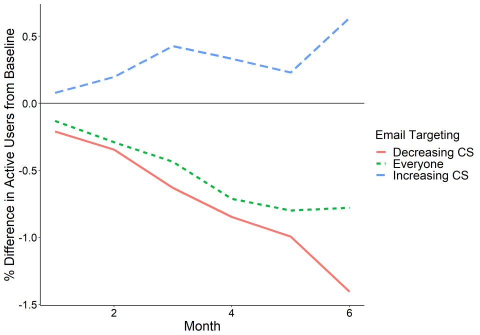
Figure: Simulation Results: Retention



Notes: Results from one million simulated users. This figure 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.

Concluding Remarks

- Documented information avoidance in financial health.
- Causal effect of checking one's credit score on future outcomes.
- Individuals who were doing worse (had a decreasing credit score prior to checking their score), experience a significant decrease in their credit score after checking.
- Important policy implications:
  - **Companies should reconsider nudging consumers with checking their information.**
  - Nudge consumers differently based on their current trends.

Thank you!

Summary Statistics

When a user logs in they see:

- Credit score, Credit grades, Debt, Monthly Payments, Scroll down to see credit card offers

Data

- Credit reports for a random sample of 1 million users
  - Active between Jan 2016 - June 2018
- Average credit score is 599
  - National average is 673
- 38% users log in only once

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	N
Change in CS	-386.00	-6.00	1.00	1.02	10.00	409	593,123
Months Between	0.03	0.87	1.07	1.72	1.53	207	593,123

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Results - Monthly

Table: Two Stage Least Squares IV - Outcome Average Monthly Credit Score Change

	ΔCS^{post} monthly	
	(1)	(2)
$\mathbb{1}\{Check\}$	-4.409**	1.436***
	(2.108)	(0.479)
Campaign Targeting Controls	Y	Y
ΔCS^{pre}	< 0	≥ 0
Observations	223,913	386,570

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Results - One Email Within 31 Days

Table: 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

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Users are less likely to log in when they are doing worse

	Dependent variable:
	$\mathbb{1}\{CheckNextMonth\}$
$\mathbb{1}\{Pre\_trend < 0\}$	$\boxed{-0.068^{***}}$
	(0.003)
$\mathbb{1}\{Pre\_trend < 0\} \times \lvert CSChange \rvert$	$\boxed{-0.004^{***}}$
	(0.0001)
$AccountAge$	-0.065^{***}
	(0.0003)
CS	0.002^{***}
	(0.00002)
$NCheck$	0.088^{***}
	(0.0004)
$\lvert CSChange \rvert$	0.001^{***}
	(0.0001)
Person RE	Y
Day of Week FE	Y
Month FE	Y
Observations	4,339,410
Note:	*p<0.1; **p<0.05; ***p<0.01

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Results - 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

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