

# To Pay or Autopay? Fintech Innovation and Credit Card Payments

by Jialan Wang

Discussion by Taha Choukhmane  
MIT Sloan & NBER

**Great paper!**

**Rich administrative data +  
quasi-experimental variation**

**An important contribution to both  
Nudge & Fintech literatures!**

# Part I

# The Policy Variation

# Policy variation

## Pre-event applicants

Cashflow-based  
underwriting  
(majority)

Traditional credit  
metrics  
(minority)

# Policy variation

## Pre-event applicants

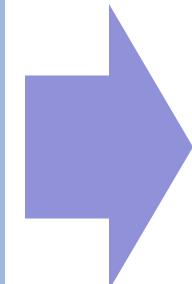
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## 1<sup>st</sup> change

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- ↘ auto-pay & min payment
- ↗ charge-offs
- ≈ avg. payment

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## 1<sup>st</sup> change

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Traditional credit  
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## 2<sup>nd</sup> change (a few months later)

Cashflow-based  
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Traditional credit  
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# Part II

# The Mechanism

# 4 Types of Applicants

High Trad  
High CF

⇒ Always  
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⇒ Never  
approved

Low Trad  
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# Channel 1: Change in selection ?

High Trad  
High CF

Low Trad  
High CF

High Trad  
Low CF

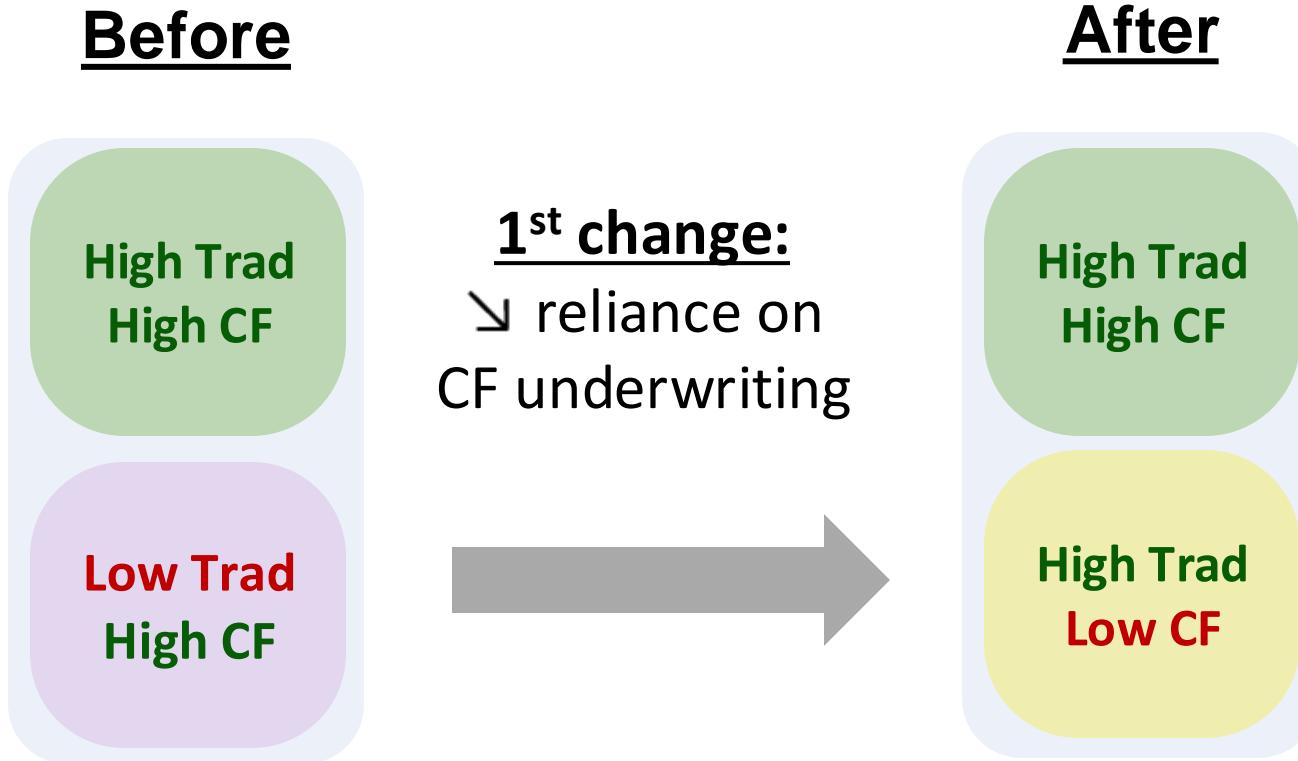
Low Trad  
Low CF

**Before:** most applicants subject to CF underwriting

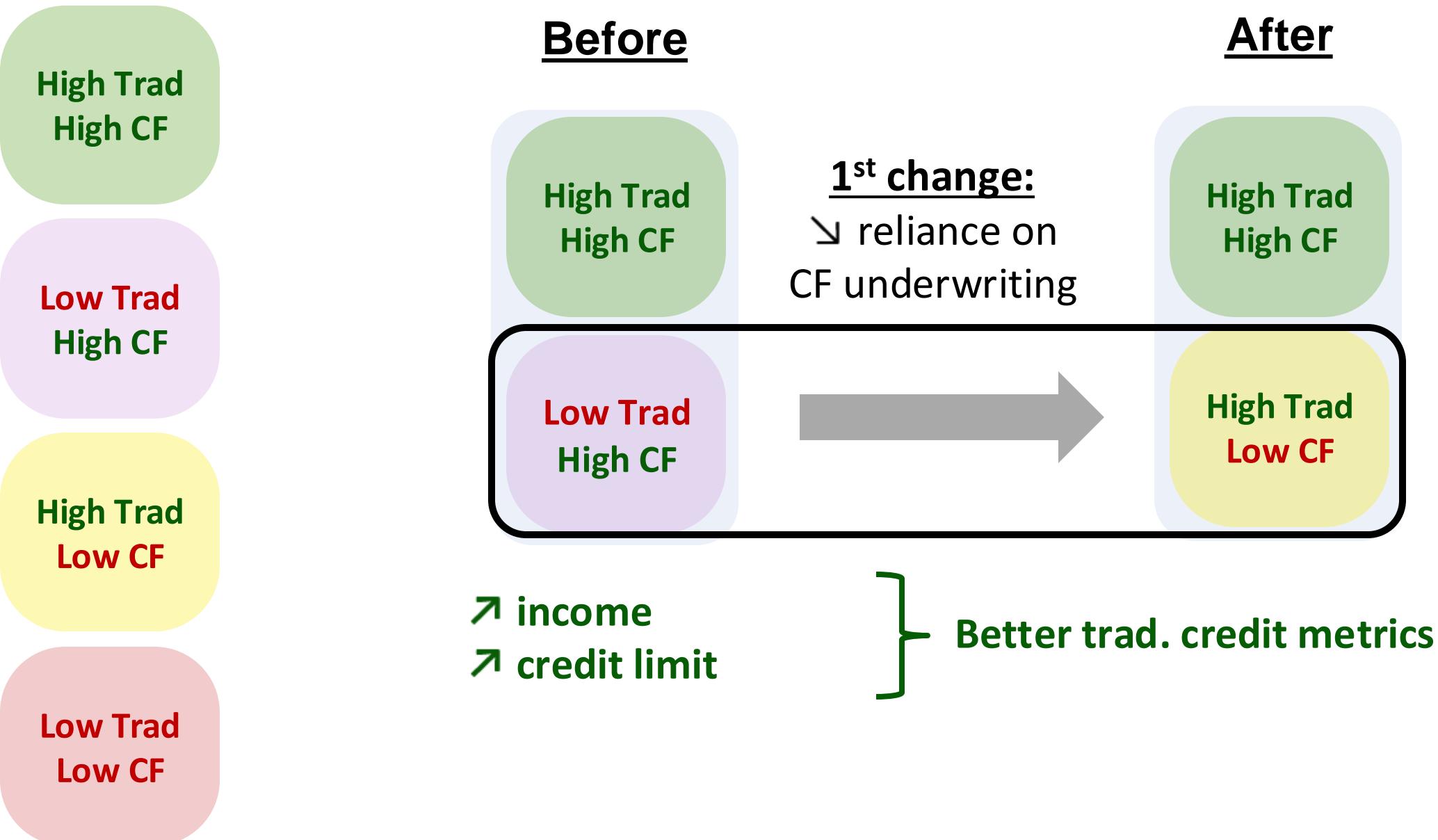
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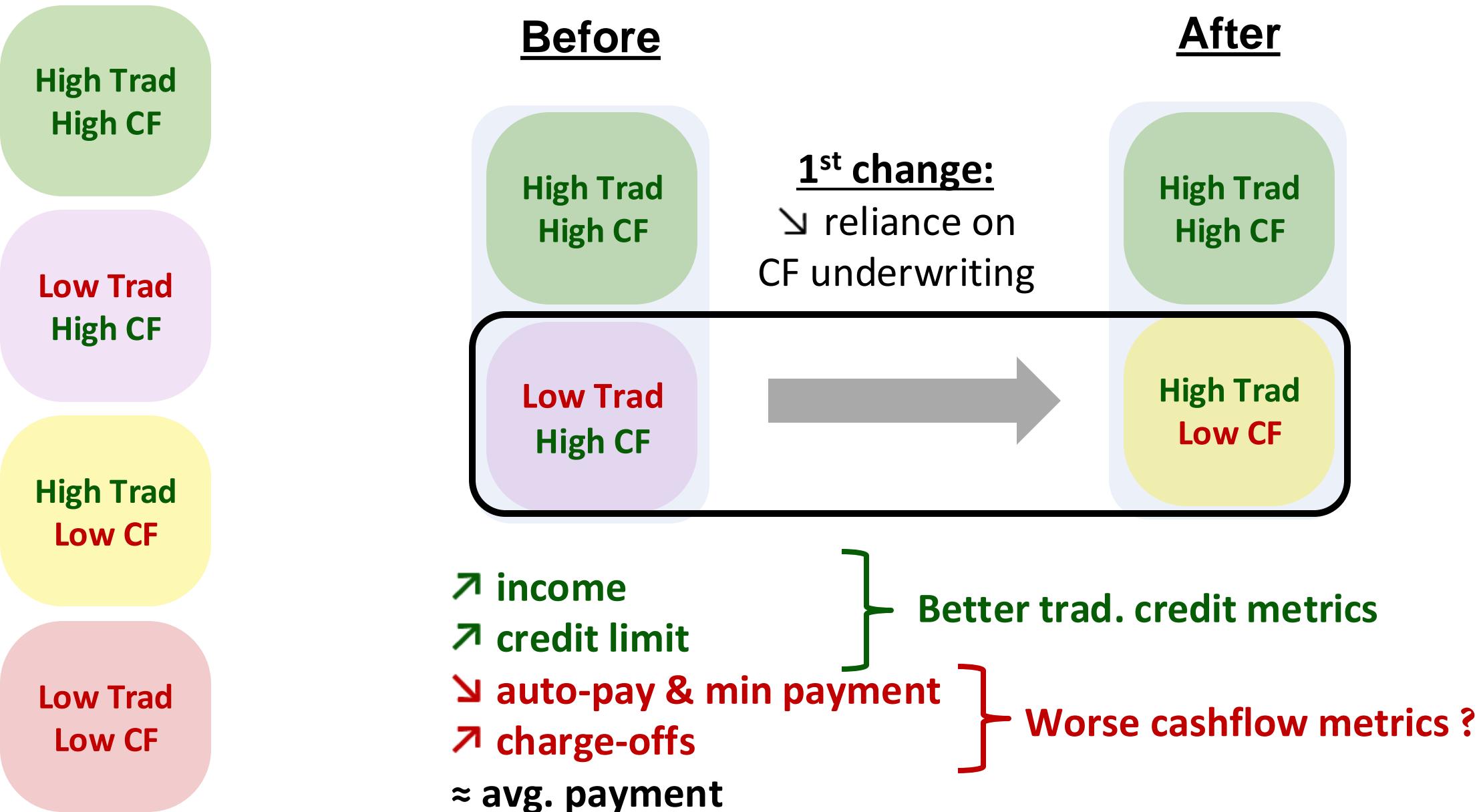
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# Is it all selection?

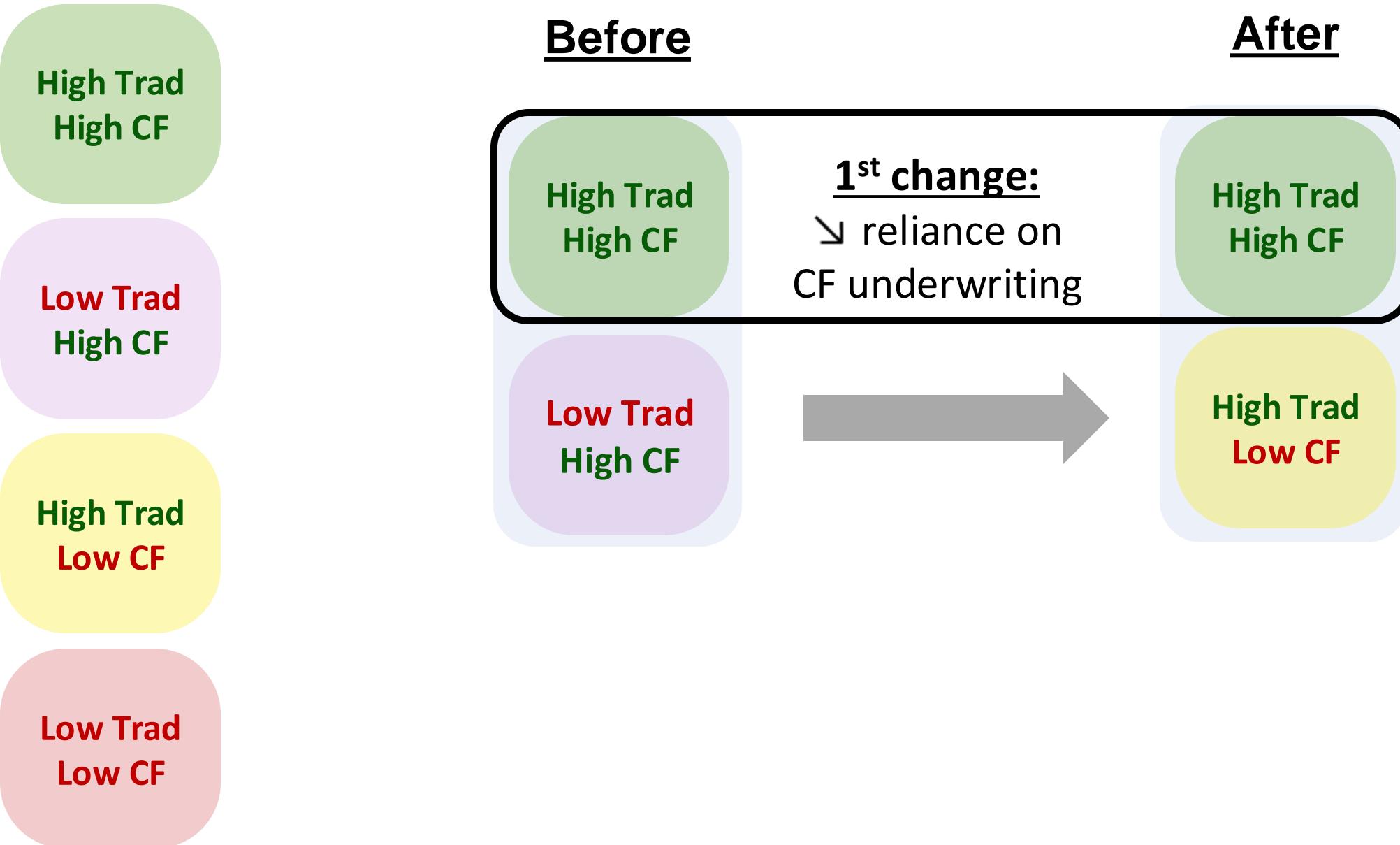
Careful (and convincing) discussion of selection in the paper!

**My read:** the lender changed screening thinking it would not adversely affect credit outcomes and was surprised by the  $\uparrow$  in charge-offs!

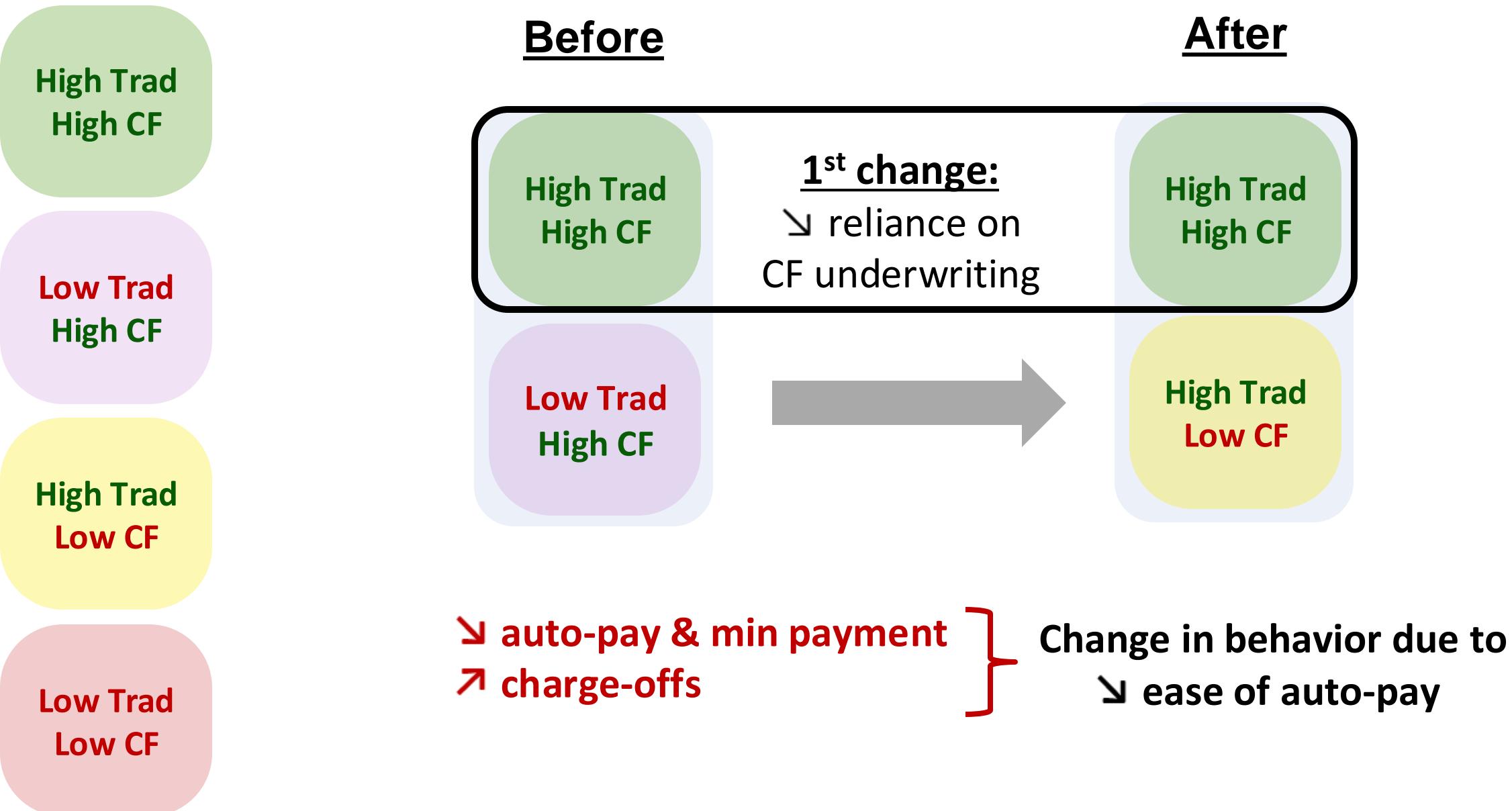
Consistent with this: reversed change after few months!

=> **Something else is happening!**

# Channel 2: Change in behavior ?



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# Unintended consequences of nudging

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We generally think of cashflow underwriting as a superior screening technology

BUT can have unintended behavioral response:

Bank account linking for underwriting reduces frictions for auto-pay adoption!

**As much a contribution to nudging literature as to the  
growing literature in fintech:**

Berg, Fustter, Puri '24 ; Bickle, He, Huang adn Parlatore '24

Screening technology can change choice architecture & behavior!

=> we might over-estimate the improvement in selection from fintech

# Part III

# Welfare Impact

# Nudging in credit market

Growing literature has considerably improved understanding of the **direct & indirect treatment effect** of nudges in credit markets ...

Guttman-Kenney et al '24: no long-term impact on CC debt

Medina 2012: credit repayment text  overdraft fees

Medina Grodzicki 2023: credit card nudge  student loans

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... yet more outcomes relevant for **welfare** than we can (ever?) measure  
(e.g., pawn shops, late bills, informal credit, ret. saving, labor productivity etc.)

# Behavioral welfare analysis

- Apply the behavioral welfare framework of Choukhmane Palmer '24 (adapted from Bernheim, Taubinsky '18; Alcott, Taubinsky '24 ; Reck Seibold '24):

$$\max_{c_i, ret_i, liq_i} \quad u(c_i) + v_i(cc_i, r) + \beta_i V_i(-cc_i, a_i)$$

$$s.t. \quad c_i = c_i = y_i + cc_i - a_i - R^{cc}(cc_i) + R^a(a_i)$$

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- Planner thinks each individual  $p_i\%$  too impatient & gives no normative weight to anchoring utility

$$W(r) = \sum_i \omega_i [u(c_i(r)) + \cancel{v_i(cc_i, r)} + \beta_i (1 + p_i) V_i(-cc_i(r), a_i(r))] di + \mu \sum_i (R^{cc}(cc_i(r)) - R^a(a_i(r))) di$$

where  $\omega_i$  are welfare weights,  $\mu$  is marginal social value of financial profits and  $\gamma_i = \frac{v_{cc}}{u'}$  captures the strength of anchoring

# Behavioral welfare analysis

Abstracting from redistribution ( $g_i = 1$ ):

$$\frac{dW(r)/dr}{\mu} = \int_i \left\{ p_i \underbrace{\left( -\frac{dc_i}{dr} \right)}_{\text{cons. resp.}} + (1 + p_i) \gamma_i \underbrace{\left( -\frac{dcc_i}{dr} \right)}_{\text{CC repayment resp.}} + \underbrace{\frac{dR^{cc}}{dr} - \frac{dR^a}{d}}_{\text{interest resp.}} \right\} di$$

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- **Net interest payments:** did the policy reduce net interest payments?  
 $\mathbb{E} \left( \frac{dR^{cc}}{dr} - \frac{dR^a}{d} \right) < 0$