Rewards and Consumption in the Credit Card Market

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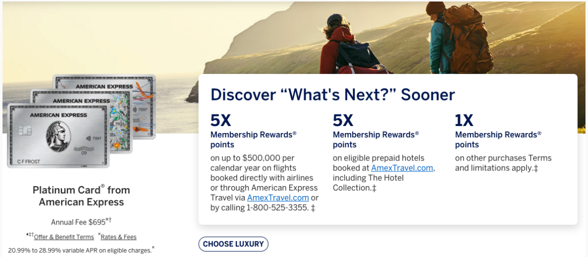
Background

Reward programs are usually the unique selling proposition of credit cards



- US: 84% adults hold credit cards, $70B reward payments by top six issuers
- Little quantitative research on the causal effect of reward programs on spending and leverage decisions

Research Questions

Main questions

1. How do credit card rewards affect consumption?
    - Reward-earning vs. non-reward-earning
2. Do consumers understand the expenditure changes induced by rewards?
3. Implications for market structure, welfare, and marketing strategies?

Empirical setup

- A large commercial bank in China: financial behavior
- Platinum card rewards + fuzzy regression discontinuity (RD)
    - Platinum vs. Gold cards
    - Platinum eligibility: assets > US$ 30,769 (CNY 200,000)
- Data: actual + perceived spending
    - Survey: subjective expectations of consumption
    - Supplemented responses with actual behavior

Preview of Results

Platinum rewards $\nearrow$ monthly spending by \$118 (10%) (118 = 64 + 54)

- Reward-earning spending $\nearrow$ \$64
- Non-reward-earning spending $\nearrow$ \$54: a positive spillover effect

Underestimate Δtotal consumption: $\nearrow$\$17 (17 = 63 – 46) (vs. $\nearrow$\$118)

- Accurately understand Δreward-earning spending: $\nearrow$\$63 (vs. $\nearrow$\$64)
- Underestimate Δnon-reward-earning spending: $\searrow$\$46 (vs. $\nearrow$\$54)

Complementarity ignorance: consumers ignore add-on complementary purchases

- Misperception $\nearrow$ excess spending + spending underestimation
- Cross-subsidy: naive $\longrightarrow$ sophisticated
- Misperception $\nearrow$ reward offerings
- Efficiency loss: 2.5% of consumption

Related Literature

Reward programs and their impacts

- Agarwal, Chakravorti, and Lunn (2010); Agarwal, Presbitero, Silva, and Wix (2022); Ching and Hayashi (2010); Hayashi (2009); Liu and Ansari (2020); Orhun, Guo, and Hagemann (2022); Rossi and Chintagunta (2023)

"Behavioral industrial organization" (Heidhues & Kőszegi, 2018)

- Consumption of "behavioral agents:" Augenblick, Jack, Kaur, Masiye, and Swanson (2022); Di Maggio, Williams, and Katz (2022); Thaler (1985)
- Naivete and sophistication: Gabaix and Laibson (2006)
- Exploiting naivete in contract design: DellaVigna and Malmendier (2004, 2006); Ellison (2005); Heidhues and Kőszegi (2010, 2017)

Role of beliefs in decision-making processes

- Allcott, Kim, Taubinsky, and Zinman (2022); Armona, Fuster, and Zafar (2019); Han and Yin (2022); Jindal and Aribarg (2021); Morrison and Taubinsky (2021)

Data: Sample Construction

A top-10 commercial bank in China

- Credit card users nationwide
- Sample gives good coverage of the whole demographic distribution

Ensure a reliable observation of consumption

- Transactions outside of the bank, e.g., switches from other banks?
  - Include only active consumers, e.g., Ganong and Noel (2019)
    - At least 15 outflow transactions during the sampling period
    - Monthly income is paid as a direct deposit to the bank
- Changes in payment methods, e.g., debit to credit?
  - Total consumption = credit + checking + saving accounts
- Goal: transactions are mostly observable

▸ Discussion

Data: Survey + Actual Behavior

4,564 credit card users nationwide surveyed in July 2022

Perceived total and reward-earning consumption

- Average monthly spending in the past six months (excluding spending on fixed assets, rents, or loans)?
- Average monthly spending that can earn cashback and rewards?

Merge with actual consumption, savings, earned rewards, etc.

- Misperception: Under-reporting = True spending - reported spending

Data: Example Reward Benefits

Rewards: equivalent USD value of the earned benefits

	Gold	Platinum
5% off JD.com purchases	Y	Y
50% Starbucks/KFC	Y	Y
5% off gas/groceries	Y	Y
$10 off movie tickets	Y	Y
Cashback on international flights		Y
Foreign airport pickup		Y
Travel insurance		Y
Hotel free buffet		Y
Travel medical insurance		Y

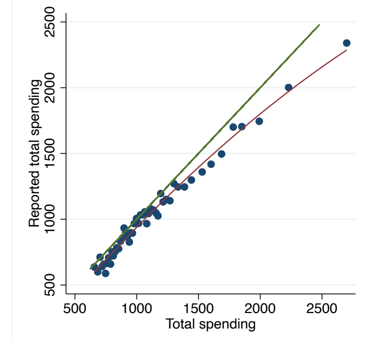
Categories change over time per seasonal business goals

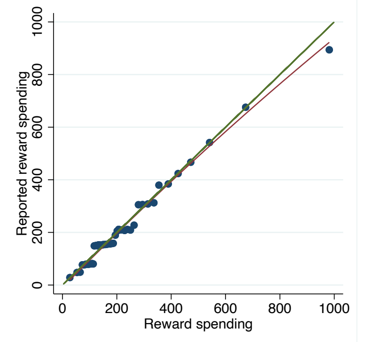
Data: Summary Statistics

	mean	sd	p25	p50	p75	count
Total spending	1133.6	419.0	838.8	1024.3	1268.0	4564
Reward spending	213.1	171.7	109.0	163.2	249.8	4564
Non-reward spending	920.6	273.8	715.4	861.1	1037.0	4564
Rewards	43.40	30.14	29.46	34.35	42.80	4564
Platinum	0.378	0.485	0	0	1	4564
Holding period	282.8	66.18	232	283	334	4564
Debt	852.6	2549.1	0	0	422.3	4564
Asset	32364.6	21617.0	18462.3	26157.2	40337.5	4564
Income	1690.6	1088.9	964.5	1331.4	2200.4	4564
Female	0.585	0.493	0	1	1	4564
Age	37.32	10.60	28	36	46	4564
Education	2.878	0.859	2	3	3	4564
Credit score	55.11	5.403	51.39	54.57	58.11	4564

Data: Spending Under-Report

	mean	sd	p25	p50	p75	count
Total spend under-report	85.71	550.9	-248.5	89.47	399.1	4564
Reward spend under-report	6.560	30.06	-11.08	3.714	20.59	4564
Total spend under-report rate	0.0719	0.452	-0.237	0.0878	0.379	4564
Reward spend under-report rate	0.0354	0.157	-0.0598	0.0213	0.134	4564





Identification Strategy: Fuzzy RD

Causal effect of reward availability on spending, reward redemption, and the corresponding beliefs

Mutually exclusive card offerings: Gold (13 benefits) and Platinum (13 Gold benefits + 14 Platinum benefits)

- Only difference is the available benefits (except for the color) ▸ Discussion
- Eligible for a Platinum card only if total assets > 200,000 CNY ($30,769)

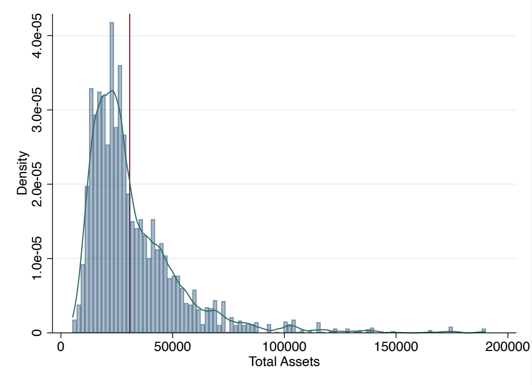
Fuzzy RD

- Local average treatment effect (LATE) of Platinum reward availability around the asset threshold
  - Compliers who opt for the Platinum card as narrowly passing the asset threshold

Fuzzy RD: Assumptions

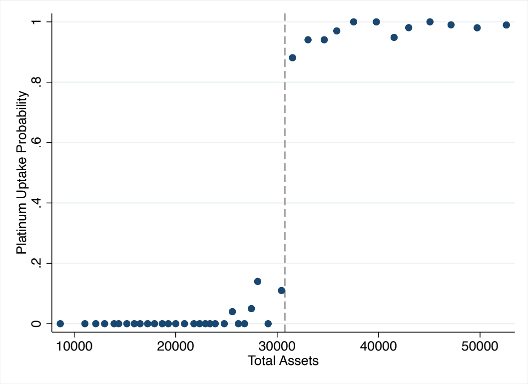
Independence: threshold passage is as good as randomly assigned

- Consumers don't manipulate asset values
- No bunching: McCrary (2008) diff: -0.131 (0.109)



Fuzzy RD: Assumptions (cont.)

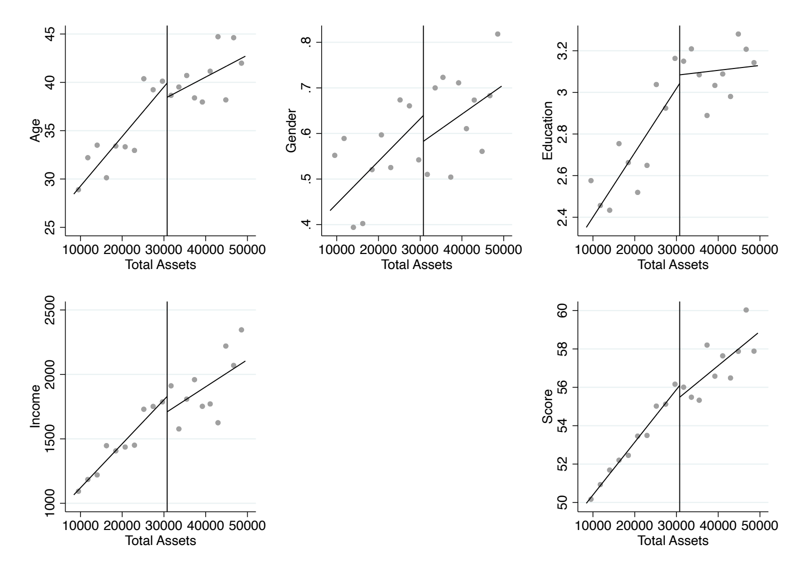
First stage: threshold passage increases Platinum uptake probability



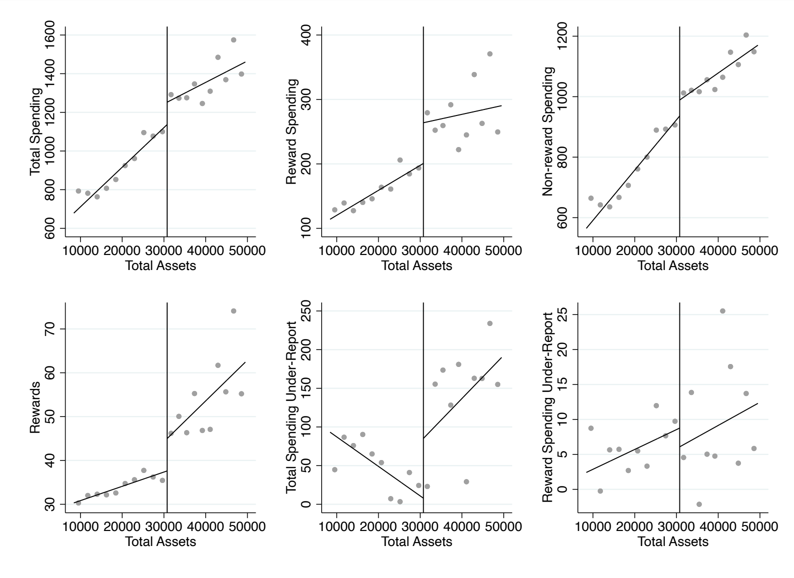
Exclusion restriction: effect is only through Platinum card takeup

Monotonicity: no defiers

Fuzzy RD: Covariate Balance Check



Fuzzy RD: Plots

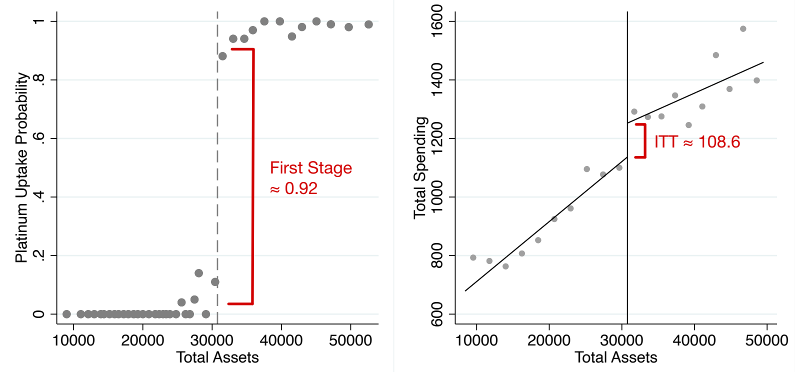


Fuzzy RD: Econometric Specification

Fuzzy RD as IV: $T_i \equiv$ Platinum takeup; $S \equiv$ asset threshold; $\mathbf{X_i} \equiv$ covariates

- Reduced form: $y_i = \alpha + \beta \widehat{T_i} + \sum_{k=1}^{K} \gamma_k s_i^k + \mathbf{X_i'}\lambda + \varepsilon_i$
- First stage: $T_i = a + b\, \mathbb{1}\{s_i > S\} + \sum_{k=1}^{K} c_k s_i^k + \mathbf{X_i'}\mathbf{d} + e_i$

Wald Estimator ($118 = 108.6/.92$)



Fuzzy RD Result: Global 2SLS with Quadratic Polynomial

	(1) Reward spending	(2) Non-reward spending	(3) Rewards	(4) Tot-spend under-repo	(5) Rew-spend under-repo
Platinum	64.153**	53.872**	14.853***	101.052***	0.982
	(27.725)	(22.195)	(4.354)	(29.903)	(4.392)
Asset (thousand $)	0.542	13.180***	-0.154	0.853	-0.109
	(1.256)	(1.116)	(0.234)	(1.610)	(0.176)
Asset (thousand $)^2	0.004	-0.038***	0.004***	0.000	0.000
	(0.006)	(0.007)	(0.001)	(0.010)	(0.001)
Observations	4564	4564	4564	4564	4564
R^2	0.268	0.812	0.256	0.012	0.008

Omitted control variables include age, income, gender, education, and credit score

City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

▸ Alt. specifications ▸ Covariates ▸ Total spending ▸ Debt

Rewards $\nearrow$ perception bias in total spending

$$\Delta Under\_Reporting = \Delta Spending - \Delta \widehat{Spending}$$

$$\implies \Delta \widehat{Spending} = \underbrace{\Delta Spending}_{=118} - \underbrace{\Delta Under\_Reporting}_{=101}$$

$$= 17$$

For a spending increase of \$118, consumers think the increase is only \$17

	Truth	Belief
Reward spending increase	64	63
Non-reward spending increase	54	$\implies$ -46
Total spending increase	118	17

Unplanned spending in the non-reward-earning category

Interpretation: Complementarity Ignorance

Platinum rewards: upfront payment, e.g., flight tickets

- Cannot resist due to high reward values $\longrightarrow$ intend to save money
- May overlook add-on demand for complementary consumption later on, e.g., hotel rooms $\longrightarrow$ non-reward spending rises eventually

▸ Discussion

External validity

- Spillover effect on other consumption: Di Maggio et al. (2022)
- Shrouded attributes: Gabaix and Laibson (2006)
- Upfront vs. backend fees: Blake, Moshary, Sweeney, and Tadelis (2021)
- Mental accounting: Thaler (1985)
- Budget negligence: Augenblick et al. (2022)

Fuzzy RD Result: Heterogeneous Effect

	(1) Reward spending	(2) Non-reward spending	(3) Rewards	(4) Tot-spend under-repo	(5) Rew-spend under-repo
Holding-period: long	49.230^{**}	42.476^{**}	12.306^{***}	82.239	1.769
	(23.661)	(19.730)	(3.985)	(51.097)	(4.033)
Holding-period: short	78.780^{**}	66.163^{**}	17.374^{***}	126.571^{***}	0.186
	(36.742)	(28.677)	(5.511)	(45.924)	(5.413)
Debt-to-income: high	113.191^{***}	83.491^{**}	21.914^{***}	151.193^{***}	-10.995
	(41.316)	(33.642)	(7.229)	(51.759)	(6.813)
Debt-to-income: low	-2.813	3.479	4.622	52.966	1.829
	(16.827)	(14.257)	(3.479)	(37.613)	(3.412)

City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

More

Model

Quasi-linear utility

$$\max_{CR,CN,S} \alpha \log(CR) + \beta \log(CN - mCR) + S \quad \text{subject to} \quad pCR + CN + S \leq y$$

- CR: reward-earning consumption
  - $p < 1$: price index for reward-earning goods; i.e., $1 - p$: reward rate
- CN: non-reward-earning consumption
- S: savings (numeraire)
- y: wealth
- α, β: preferences over consumption categories
- m: complementarity between consumption categories

Timeline

Quasi-linear utility

$$\max_{CR,CN,S} \alpha \log(CR) + \beta \log(CN - mCR) + S \quad \text{subject to} \quad pCR + CN + S \leq y$$

Similar to Gabaix and Laibson (2006)

- Period 0: bank decides on reward offerings p
- Period 1: consumers decide upfront CR; form expectations of $\widehat{CN}$ and $\widehat{S}$
  - Naifs: $\widehat{m}_{naif} = 0$
  - Sophisticates: $\widehat{m}_{soph} = m$
- Period 2: true m realizes; readjust CN according to m

Demand Side: Overspending and Underestimation

Proposition 1

Relative to the first best, for naive consumers

- Consumption is scaled up by $\frac{p+m}{p}$
- Unplanned spending is $\frac{m(\alpha+\beta)}{p}$

$$CR_{naif} = \frac{\alpha}{p} = \underbrace{\frac{p+m}{p}}_{\text{overspending}} CR_{soph}$$

$$CN_{naif} = \underbrace{\beta}_{=\widehat{CN}_{naif}} + \underbrace{\frac{m(\alpha+\beta)}{p}}_{\text{under-reporting}} = \underbrace{\frac{p+m}{p}}_{\text{overspending}} CN_{soph}$$

Supply Side: Tradeooff between Interchange Fee and Reward Payback

Supply: tradeoff between interchange fee and reward disbursement ▸ In Practice

- r: interchange fee rate (through consumption)
- c: constant cost of operation

$$\pi_{naif} = r(CR_{naif} + CN_{naif}) - (1 - p)CR_{naif} - c$$
$$\pi_{soph} = r(CR_{soph} + CN_{soph}) - (1 - p)CR_{soph} - c$$

- $0 \leq q \leq 1$: fraction of naive consumers

$$\pi = q\pi_{naif} + (1 - q)\pi_{soph}$$

Perfectly Competitive Equilibrium Profit: Cross-Subsidy

Proposition 2

- Non-negative profit from naifs: $\pi_{naif} = \frac{cm(1-q)}{p+mq} \geq 0$
- Non-positive profit from sophisticates: $\pi_{soph} = -\frac{cmq}{p+mq} \leq 0$

Cross-subsidy in equilibrium

- $-\pi_{soph}$ is the welfare gain of sophisticates
- The benefits come at the cost of naifs π_{naif}

Comparative Statics: Equilibrium Reward Offerings

Propositions 3 and 4

Assume a reasonable interchange fee rate r

- Naif fraction $\nearrow$ rewards: $\partial p / \partial q < 0$
- Complementarity $\nearrow$ rewards: $\partial p / \partial m < 0$

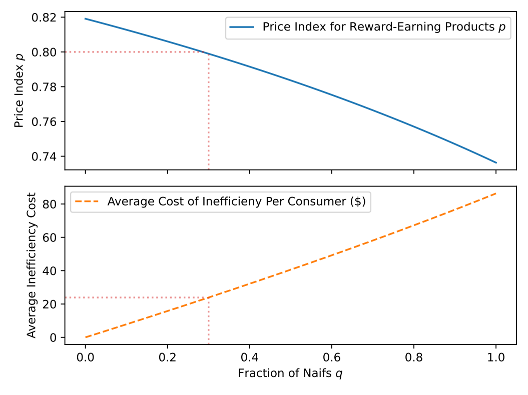
Rationales behind reward offerings

- Naivete exploitation incentivizes reward offerings
- Complementarity helps with naivete exploitation

Calibration: Implications for Welfare

Moments: average level consumption and spending perception errors

- Benchmark utility u^*: no naive consumers
- $inefficiency = q\left[u^* - u_{naif}(p)\right] + (1-q)\left[u^* - u_{soph}(p)\right]$



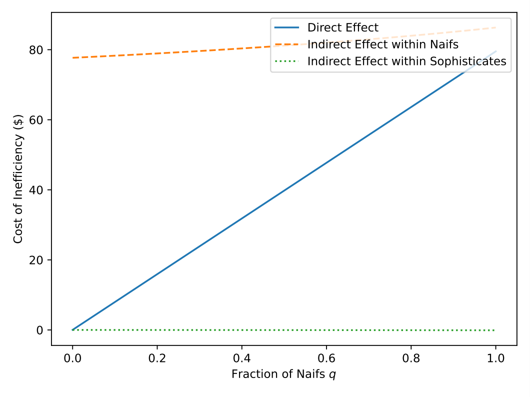
- Average efficiency cost: 2.5% of consumption

Calibration: Welfare Decomposition

Direct effect: $q \nearrow$ *inefficiency*

Indirect effect: p within $u_{naif}(p)$ and $u_{soph}(p)$

- Naivete itself costs \$80, $q \searrow p \nearrow$ *inefficiency*
- Sophisticates benefits from $q \searrow p$ but marginally



Concluding Remarks

Summary

- Field data + survey $\leftarrow$ quasi-experiment
- Reward programs work effectively: positive spillover effect
- Consumers are not fully aware of $\nearrow$ non-reward spending
  - Ignorance of add-on non-reward purchases when deciding on reward redemption upfront
- Naivete exploitation incentivizes reward offerings

Contributions

- Identification of the causal effect of rewards on consumer behavior
- Complementarity ignorance, a behavioral bias in field data
  - Revealed by the combination of quasi-experiment and survey responses
- Theory with calibration to formalize the economics of this bias
- Findings apply to other settings with rewards and promotions
  - New insights into product designs and pricing strategies

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Sample Construction: Discussion

Focus on active consumers due to inability to observe consumption elsewhere

- Spending within the bank is close to the total spending on credit reports
- Most consumers only use a “primary” card for consumption
- Cash transactions are rare

The New York Times

ON TECH

Don’t Even Try Paying Cash in China

How two apps created new kinds of commerce in China, and what a cashless future might look like.

- Reported spending is close to the true spending recorded by the bank

Spending within the bank is a good measure of total consumption

Back

Descriptive Analysis: Rewards

	(1) Rewards	(2) Rewards	(3) Rewards	(4) Rewards	(5) Rewards	(6) Rewards	(7) Rewards	(8) Rewards
Total spending	0.069***							
	(0.005)							
Reward spending		0.159***						
		(0.009)						
Non-reward spending			0.091***					
			(0.008)					
Asset (thousand $)				0.570***				
				(0.071)				
Debt					0.005***			
					(0.001)			
Platinum						20.189***		
						(2.483)		
Tot-spend under-repo							0.004***	
							(0.001)	
Rew-spend under-repo								0.192***
								(0.067)
Constant	-23.892***	12.684***	-31.274***	20.266***	27.818***	28.993***	28.722***	28.660***
	(3.537)	(1.313)	(5.209)	(1.721)	(1.183)	(1.314)	(1.317)	(1.366)
Observations	4564	4564	4564	4564	4564	4564	4564	4564
R^2	0.729	0.768	0.566	0.300	0.363	0.256	0.189	0.218

Omitted control variables include age, income, gender, education, and credit score

City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Descriptive Analysis: Consumption

	(1) Total spending	(2) Total spending	(3) Total spending	(4) Total spending	(5) Total spending
Asset (thousand $)	10.992***				
	(0.784)				
Debt		0.065***			
		(0.007)			
Platinum			409.934***		
			(28.207)		
Tot-spend under-repo				0.067***	
				(0.014)	
Rew-spend under-repo					1.742***
					(0.624)
Constant	594.693***	749.673***	762.961***	759.335***	761.279***
	(18.801)	(15.611)	(15.620)	(17.941)	(18.340)
Observations	4564	4564	4564	4564	4564
R^2	0.636	0.548	0.567	0.418	0.426

Omitted control variables include age, income, gender, education, and credit score

City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Descriptive Analysis: Total Spending Under-report

	Total spending under-reporting			Reward spending under-reporting		
	(1)	(2)	(3)	(4)	(5)	(6)
Asset (thousand $)	2.432***			-0.039		
	(0.609)			(0.049)		
Debt		0.004			0.002**	
		(0.006)			(0.001)	
Platinum			120.399***			-0.767
			(20.821)			(2.245)
Constant	53.263***	89.983***	90.321***	2.961**	1.825	2.367*
	(18.144)	(14.811)	(15.021)	(1.328)	(1.294)	(1.274)
Observations	4564	4564	4564	4564	4564	4564
R^2	0.024	0.018	0.026	0.051	0.082	0.051

Omitted control variables include age, income, gender, education, and credit score

City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Back

Fuzzy RD: Identification Discussion

Alternative interpretation of LATE: Platinum cards are a status good (Bursztyn, Ferman, Fiorin, Kanz, & Rao, 2018)

- Table 2 of (Bursztyn et al., 2018) shows demand for status good only if the transaction is visible

Most transactions in China are now completed through digital wallets

- A recent report shows that China's penetration rate of mobile payments is 87.6% (and rising) in 2021
- Very few physical card transactions: main cause is not status good

The majority of LATE can only be explained through the channel of rewards

Back

Fuzzy RD Result: Alternative Specifications

	(1) Reward spending	(2) Non-reward spending	(3) Rewards	(4) Tot-spend under-repo	(5) Rew-spend under-repo
Global: first-order	56.017***	129.690***	6.767*	101.009***	0.092
	(20.537)	(21.553)	(3.902)	(25.562)	(3.490)
Global: third-order	74.014***	62.345***	14.400***	114.937***	0.097
	(26.946)	(21.296)	(4.023)	(28.759)	(4.271)
Global: fourth-order	70.690**	70.851***	13.773***	110.786***	-0.152
	(29.261)	(23.002)	(4.692)	(31.630)	(4.522)
Global: fifth-order	79.316**	60.773**	10.117*	96.364***	-0.867
	(34.190)	(26.847)	(5.348)	(36.249)	(5.054)
Global observations: 4564					
Local: nonparametric	102.026***	67.108**	14.084***	67.597*	-5.675
	(39.068)	(27.163)	(4.773)	(36.114)	(5.207)
Local observations: 1112					

City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Back

Fuzzy RD Result: Covariates

	(1) Age	(2) Male	(3) Education	(4) Income	(5) Credit score
Platinum	-0.853	0.024	0.085	-135.367	-0.183
	(1.348)	(0.069)	(0.099)	(95.502)	(0.595)
Asset (thousand $)	0.460***	0.004	0.013**	17.298***	0.189***
	(0.065)	(0.003)	(0.005)	(5.042)	(0.033)
Asset (thousand $)^2	-0.002***	-0.000	-0.000**	-0.028	-0.001**
	(0.000)	(0.000)	(0.000)	(0.028)	(0.000)
Age: elder		0.018	-0.132**	-26.274	0.148
		(0.038)	(0.058)	(52.933)	(0.284)
Male	0.138		0.132**	-36.288	-0.134
	(0.727)		(0.062)	(50.184)	(0.306)
Edu: high	-1.402*	0.053		191.168***	1.263***
	(0.820)	(0.044)		(65.703)	(0.349)
Income: high	-0.340	-0.020	0.169***		2.394***
	(0.493)	(0.024)	(0.038)		(0.224)
Credit score: high	0.475	-0.006	0.398***	525.886***	
	(0.735)	(0.039)	(0.063)	(50.857)	
Observations	4564	4564	4564	4564	4564
R^2	0.159	0.023	0.143	0.162	0.374

City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Fuzzy RD Result: Total Spending

	(1) Spending	(2) Spending	(3) Spending	(4) Spending	(5) Spending
Platinum	185.423***	117.752**	136.104***	141.252***	139.782**
	(38.864)	(49.014)	(47.471)	(51.479)	(60.165)
Male	7.433	6.367	7.879	7.780	7.788
	(18.021)	(18.145)	(18.134)	(18.158)	(18.137)
Age: elder	34.038**	23.761	26.054	25.761	25.646
	(16.363)	(15.793)	(15.907)	(15.917)	(16.022)
Edu: high	28.678	24.340	27.652	27.191	27.098
	(24.621)	(23.946)	(23.823)	(23.917)	(23.640)
Income: high	79.357***	79.437***	79.303***	79.063***	79.113***
	(17.155)	(17.120)	(17.107)	(16.977)	(16.834)
Credit score: high	179.430***	168.893***	172.819***	172.341***	172.385***
	(20.586)	(21.158)	(21.527)	(21.521)	(21.454)
Asset (thousand \$)	8.448***	13.724***	8.353***	11.178**	10.524
	(0.940)	(2.284)	(2.831)	(4.461)	(8.855)
Asset (thousand \$)^2		-0.034***	0.049	-0.033	-0.005
		(0.012)	(0.036)	(0.136)	(0.379)
Asset (thousand \$)^3			-0.000**	0.000	0.000
			(0.000)	(0.001)	(0.006)
Asset (thousand \$)^4				-0.000	0.000
				(0.000)	(0.000)
Asset (thousand \$)^5					-0.000
					(0.000)
Observations	4564	4564	4564	4564	4564
R^2	0.613	0.618	0.620	0.620	0.620

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

◂ Back

Fuzzy RD Result: Debt

	(1) Debt	(2) Debt	(3) Debt	(4) Debt	(5) Debt
Platinum	505.866	713.709	794.904	777.651	906.107
	(403.836)	(584.566)	(600.875)	(634.370)	(756.874)
Male	102.729	106.004	112.693	113.028	112.314
	(159.061)	(160.093)	(159.983)	(159.632)	(159.249)
Age: elder	262.162*	293.728*	303.874*	304.855*	314.893*
	(151.547)	(159.070)	(160.218)	(160.336)	(163.509)
Edu: high	96.652	109.977	124.630	126.175	134.244
	(248.056)	(242.242)	(240.199)	(242.088)	(239.134)
Income: high	-117.244	-117.490	-118.084	-117.278	-121.670
	(150.165)	(149.682)	(149.533)	(148.368)	(146.106)
Credit score: high	778.472***	810.836***	828.206***	829.808***	825.958***
	(216.978)	(227.365)	(230.972)	(230.855)	(229.929)
Asset (thousand \$)	-7.061	-23.267	-47.028	-56.493	0.642
	(7.004)	(24.157)	(34.113)	(41.373)	(79.310)
Asset (thousand \$)^2		0.103	0.470	0.744	-1.644
		(0.117)	(0.351)	(1.076)	(3.616)
Asset (thousand \$)^3			-0.001	-0.004	0.034
			(0.001)	(0.010)	(0.056)
Asset (thousand \$)^4				0.000	-0.000
				(0.000)	(0.000)
Asset (thousand \$)^5					0.000
					(0.000)
Observations	4564	4564	4564	4564	4564
R^2	0.039	0.040	0.040	0.040	0.040

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Back

Fuzzy RD Result: Additional Heterogeneous Effects

	(1) Reward spending	(2) Non-reward spending	(3) Rewards	(4) Tot-spend under-repo	(5) Rew-spend under-repo
Credit score: high	111.582**	71.803**	23.892***	102.109**	0.812
	(44.748)	(34.197)	(6.741)	(44.580)	(6.683)
Credit score: low	15.164	43.683**	2.573	130.177***	0.814
	(23.743)	(21.698)	(4.089)	(46.670)	(3.433)
Education: high	46.475	21.543	12.876**	120.221	-2.187
	(32.602)	(22.407)	(5.409)	(82.654)	(7.735)
Education: low	69.053*	64.601**	15.352***	89.716***	-0.232
	(37.631)	(29.342)	(5.715)	(33.808)	(5.645)
Gender: Male	55.199	45.294	12.209**	94.156**	-0.197
	(35.725)	(29.066)	(5.847)	(40.191)	(6.230)
Gender: Female	27.327	42.990*	10.720**	36.886	-0.058
	(29.250)	(25.100)	(4.903)	(56.345)	(4.789)
Age: elder	97.569**	88.465***	19.889***	60.929	0.431
	(40.515)	(32.175)	(6.547)	(43.779)	(6.884)
Age: young	20.824	23.480	5.554	113.261**	0.317
	(25.510)	(22.485)	(4.403)	(51.405)	(4.909)

City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Back

Forecast vs. Backcast?

Ideal setup: RCT

- Random Platinum assignment, elicit predictions, calculate diff-in-diffs

Alternative when an RCT is infeasible

- Focus on the equilibrium spending: i.e., past $\approx$ future
- Plausible if no learning: suggested by HTE results
  - Also see Han and Yin (2022); Huffman, Raymond, and Shvets (2022)

Backcast and forecast bias are strongly correlated

- Sial, Sydnor, and Taubinsky (2023): backcast bias is a lower bound on forecast bias

Back

Supply Side: In the Field

Top Credit Card Issuers Dole Out $67.9 Billion in Reward Payments in 2022, But Interchange Fees More Than Make Up for Them

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Back