Attention Constraints and Financial Inclusion

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Disclosure Statements

- Bo Huang has nothing to disclose.
- Jiacui Li has nothing to disclose.
- Tse-Chun Lin has nothing to disclose.
- Mingzhu Tai has nothing to disclose.
- Yiyuan Zhou has nothing to disclose.

Paper preview

- **Setting:** retail loan officer decisions in a major bank in China
- **Finding:** when loan officers are *attention constrained*, low SES applicants are more likely rejected without careful review
- **Main takeaway** is the mechanism
  - Decision maker *attention constraints* ⇒ *worse financial inclusion*

Attention-based mechanism

- Suppose you are a loan officer. You make two decisions:
  1. How much time to spend reading an application
  2. Approval or reject

- *If you have infinite time*, you can carefully read all applications

- *If you are busy*, you will have to ration your attention... which has *differential* impact on high vs. low SES applicants
  - Low SES applicants are more likely *"rashly rejected"*
  - Under extreme conditions, some ultra-high SES applicants may even be *"blindly approved"*

- To be clear, this could be *entirely rational* for you (the loan officer)
  - But this *negatively impacts financial inclusion*
  - Mechanism formalized in a model

details

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Policy implications

- Here, *attention constraint* is the main impediment to inclusion
- Therefore, technologies that *relax decision-maker attention constraints* may promote inclusion
  - e.g. Better algorithms for summarizing applicant information
- Broader implications: we suspect that attention constraints matter in other settings too
  - *Recruiters* spend less than a minute on each resume
  - *College admission officers* spend minutes on each application
  - *Judges* and *patent officers* often have years of backlog

Related literature

- The attention-based mechanism: Bartoš, Bauer, Chytilová, and Matějka (2016)
  - **Our contribution:** micro-level field evidence for the effect of attention constraints
- Literature on *attention constraints* and *decision making*:
  - e.g., Müller (2022); Shu, Tian, and Zhan (2022); Hirshleifer, Levi, Lourie, and Teoh (2019); Huang, Huang, and Lin (2019); Liao, Wang, Xiang, Yan, and Yang (2021); etc.
- *Inclusion issues* in finance:
  - e.g., Bayer, Ferreira, and Ross (2018); Bartlett, Morse, Stanton, and Wallace (2022); Giacoletti, Heimer, and Yu (2021); Ambrose, Conklin, and Lopez (2021); Montoya, Parrado, Solís, and Undurraga (2020); Dobbie, Liberman, Paravisini, and Pathania (2021); Fisman, Paravisini, and Vig (2017); Fisman, Sarkar, Skrastins, and Vig (2020); Charles, Hurst, and Stephens (2008); Butler, Mayer, and Weston (2022); Lanning (2021); Ongena and Popov (2016); Brock and De Haas (2021); Beck, Behr, and Madestam (2018); Hebert (2020); Ewens and Townsend (2020); Hu and Ma (2021); Zhang (2020); etc.

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OUTLINE

1. Setting and preliminary findings

2. Main results

Retail loan screening data

- **Setting**: retail loan applications from a large Chinese bank
  - $\approx$ 146,000 applications (April 2013 - April 2014)
  - Decisions by 92 loan officers. Approval rate 34%
  - Workload dispatched to officers via an *external* algorithm
- **Detailed administrative data**:
  - Attention measure: time spent reviewing each application
  - All credit-relevant information that loan officers see
- Loan officers are attention constrained
  - Even though each application has hundreds of pages, median review time per application is only 18 minutes

Social-economic status (SES) labels

- **Social status labels:**
  - Local resident: not a migrant worker
  - Public Employee: employed by government or state-owned firms
- **Economic status labels:**
  - Homeowner: whether one owns property
  - Employment certificate: a verifiable certificate provided by large employers, indicating stable long-term employment
  - Income certificate: a verifiable certificate for stable income
  - Regular pay: a complementary measure for stable income

Theory and anecdotal evidence suggests that loan officers may use these simple SES labels to *guide attention allocation.*

HIGH SES APPLICANTS ARE APPROVED MORE

Dependent variable:	Approval									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PublicEmployee	0.246***						0.098***		0.020***	0.023***
	(17.062)						(12.828)		(2.956)	(3.312)
LocalResident		0.467***					0.452***		0.161***	0.145***
		(28.719)					(28.729)		(7.524)	(5.961)
EmploymentCert			0.527***					0.399***	0.286***	0.278***
			(30.703)					(22.789)	(12.942)	(10.824)
IncomeCert				0.395***				0.088***	0.042**	0.034**
				(23.722)				(5.712)	(2.516)	(2.123)
RegularPay					0.419***			0.113***	0.159***	0.163***
					(22.675)			(9.521)	(12.228)	(10.936)
HomeOwner						0.460***		0.179***	0.217***	0.222***
						(27.833)		(17.394)	(17.502)	(14.873)
Application Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
Week FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
Branch FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
Loan type FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.140	0.265	0.354	0.222	0.170	0.217	0.268	0.369	0.372	0.342

Takeaway: after controlling for a comprehensive list of credit quality controls, applicants with SES labels are much more likely approved

Attractive vs. Unattractive groups

- **Summarize SES labels** using their implied approval rates:

$$\text{SocialStatus}_i \equiv \widehat{\text{Approval}}_i | \{\text{PublicEmployee}_i, \text{LocalResident}_i\}$$

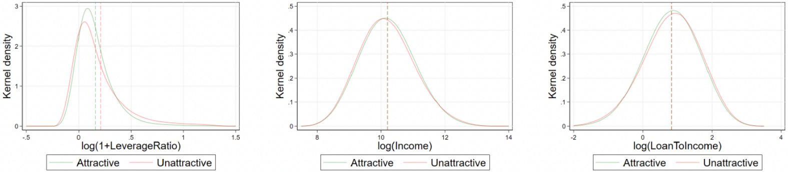
$$\text{EconomicStatus}_i \equiv \widehat{\text{Approval}}_i | \{\text{EmploymentCert}_i, \text{RegularPay}_i, \text{IncomeCert}_i, \text{HomeOwner}_i\}$$

- **Group definition**: attractive group = *above median* applicants according to social or economic status labels:
  - $Corr(\text{Socially Attractive}_i, \text{Economically Attractive}_i) = -0.13$

- **Large gaps** in approval rates
  - Socially attractive vs. unattractive: 51.9% vs. 18.1%
  - Economically attractive vs. unattractive: 65.5% vs. 25.4%

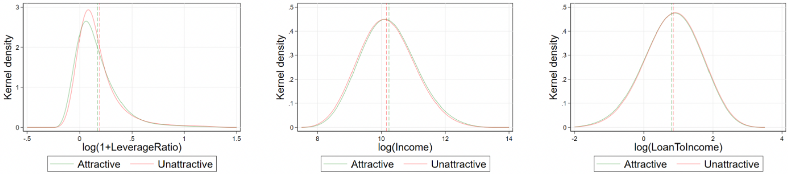
PUZZLE: THE TWO GROUPS HAVE LARGELY *similar* CREDIT QUALITY METRICS

Panel A. Distribution of credit quality by applicant *social status*



(a) log(1+LeverageRatio) **(b)** log(Income) **(c)** log(LoanToIncome)

Panel B. Distribution of credit quality by applicant *economic status*

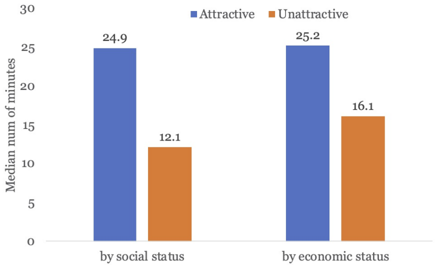


(d) log(1+LeverageRatio) **(e)** log(Income) **(f)** log(LoanToIncome)

What might be going on?

- **Conjecture:** unattractive applicants are *not paid adequate attention*

Median num of minutes spent per application



- **Suggestive evidence 1:**

  low SES applicants receive *less review time*

- **Suggestive evidence 2:** low SES applicants are more likely rejected with boilerplate reasons

- **Next step:** explore *orthogonal* variation in attention constraints

Outline

Attention constraint variation

- **Busyness measure:** # of applications processed/day
  - Distribution: (10%, 25%, 50%, 75%, 90%) = (10, 15, 19, 24, 27)

- **Concern**: *realized* busyness can be endogenous

- **Instrument:** workload assignments
  - **Relevance:** can explain ≈ 40% variation

$$\widehat{\text{Busyness}}_{j,d} = \sum_{\tau=0}^{3} \hat{b}_\tau \cdot \text{Assignment}_{j,d-\tau}$$

  - **External:** assignments made by an algorithm that loan officers have *no control over* details
  - **Orthogonal:** num of assignments uncorrelated with observable credit metrics and applicant characteristics details

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Illustration: varying attention constraint

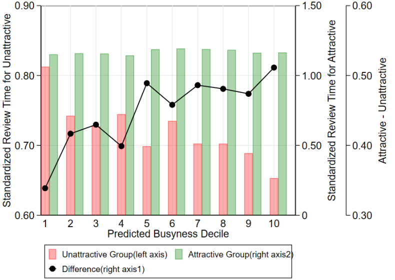
- Sort the sample into deciles by assignment-predicted busyness

- **Takeaway:** when officers are busier, they pay less attention to low SES applicants and reject them more frequently
  - Some evidence *higher* approval rate for high SES applicants

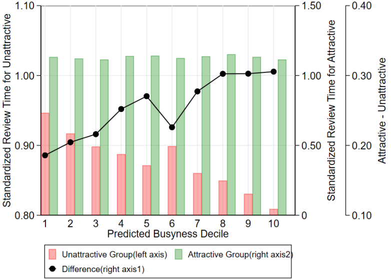
ILLUSTRATION: VARYING ATTENTION CONSTRAINT

- Sort the sample into deciles by assignment-predicted busyness
  - **Plots of officer attention** (log num of minutes review time):

By social status:



By economic status:



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  - **Plots of approval rate:**

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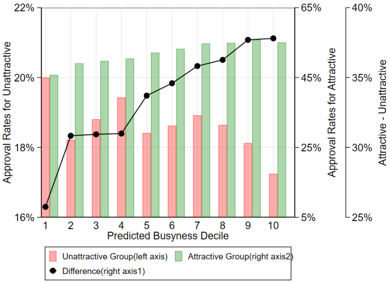

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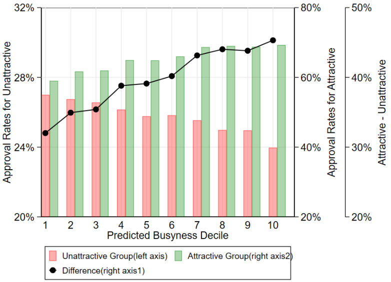

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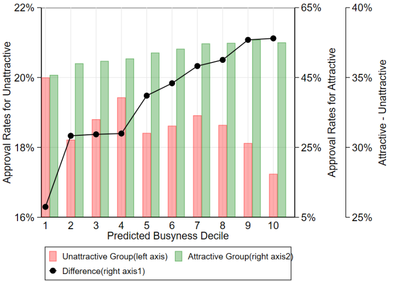

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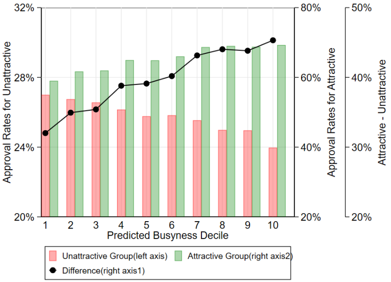

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RESULT 1: ATTENTION ALLOCATION

Dependent variable:	StandardizedReviewTime					
Busyness measure:	Predicted Busyness			LOO-Predicted Busyness		
	(1)	(2)	(3)	(4)	(5)	(6)
β_1BusynessDecile	-0.025^{***}	-0.024^{***}	-0.029^{***}	-0.019^{***}	-0.016^{***}	-0.022^{***}
	(−8.297)	(−9.248)	(−8.999)	(−6.393)	(−6.134)	(−6.397)
β_2Attractive(Social)	0.461^{***}		0.434^{***}	0.470^{***}		0.445^{***}
	(23.833)		(21.608)	(23.819)		(21.431)
β_3Attractive(Social) × BusynessDecile	0.013^{***}		0.015^{***}	0.013^{***}		0.013^{***}
	(4.722)		(5.152)	(4.668)		(4.334)
β_4Attractive(Economic)		0.285^{***}	0.215^{***}		0.289^{***}	0.220^{***}
		(13.311)	(10.031)		(13.975)	(11.090)
β_5Attractive(Economic)× BusynessDecile		0.013^{***}	0.012^{***}		0.012^{***}	0.011^{***}
		(4.139)	(3.645)		(3.980)	(4.022)
Application Controls	Y	Y	Y	Y	Y	Y
Local Busyness Controls	N	N	N	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.074	0.044	0.082	0.075	0.045	0.082
$\beta_1 + \beta_3$	-0.011^{***}		-0.014^{***}	-0.006^{***}		-0.009^{***}
P-value of ($\beta_1 + \beta_3$)	(0.000)		(0.000)	(0.001)		(0.000)
$\beta_1 + \beta_5$		-0.011^{***}	-0.017^{***}		-0.004^{*}	-0.011^{***}
P-value of ($\beta_1 + \beta_5$)		(0.000)	(0.000)		(0.070)	(0.000)

(standard errors clustered by week and officer)

Takeaway: when loan officers are busier, they spend less time reviewing low SES applicants

RESULT 2: APPROVAL RATE

Dependent variable:	Approval					
Busyness measure:	Predicted Busyness			LOO-Predicted Busyness		
	(1)	(2)	(3)	(4)	(5)	(6)
β_1BusynessDecile	-0.004^{***}	-0.003^{***}	-0.006^{***}	-0.004^{***}	-0.003^{***}	-0.006^{***}
	(-4.380)	(-4.046)	(-8.048)	(-5.087)	(-4.382)	(-9.354)
β_2Attractive(Social)	0.399^{***}		0.367^{***}	0.403^{***}		0.370^{***}
	(56.706)		(50.568)	(58.399)		(53.776)
β_3Attractive(Social) $\times$ BusynessDecile	0.009^{***}		0.008^{***}	0.008^{***}		0.008^{***}
	(7.241)		(7.018)	(6.683)		(7.171)
β_4Attractive(Economic)		0.383^{***}	0.331^{***}		0.384^{***}	0.331^{***}
		(36.447)	(31.948)		(36.992)	(35.311)
β_5Attractive(Economic)$\times$ BusynessDecile		0.013^{***}	0.012^{***}		0.013^{***}	0.012^{***}
		(8.564)	(7.725)		(8.553)	(8.111)
Application Controls	Y	Y	Y	Y	Y	Y
Local Busyness Controls	N	N	N	Y	Y	Y
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.272	0.219	0.342	0.272	0.219	0.342
$\beta_1 + \beta_3$	0.005^{***}		0.002^{***}	0.004^{***}		0.001^{**}
P-value of $(\beta_1 + \beta_3)$	(0.000)		(0.000)	(0.000)		(0.039)
$\beta_1 + \beta_5$		0.010^{***}	0.006^{***}		0.009^{***}	0.005^{***}
P-value of $(\beta_1 + \beta_5)$		(0.000)	(0.000)		(0.000)	(0.000)

(standard errors clustered by week and officer)

Takeaway: when loan officers are busier, they are more likely to reject low SES applicants

Summary

- **Finding:** why busy, loan officers are more likely to reject low SES applicants

- **Mechanism:** attention rationing $\Rightarrow$ worse inclusion

- **Takeaway:** *attention constraints* of decision makers can *hinder financial inclusion*

- THANK YOU FOR YOUR ATTENTION.

Summary

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- **Mechanism:** attention rationing $\Rightarrow$ worse inclusion
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Ambrose, Brent W, James N Conklin, and Luis A Lopez, 2021, Does borrower and broker race affect the cost of mortgage credit?, *Review of Financial Studies* 34, 790–826.

Bartlett, Robert, Adair Morse, Richard Stanton, and Nancy Wallace, 2022, Consumer-lending discrimination in the fintech era, *Journal of Financial Economics* 143, 30–56.

Bartoš, Vojtěch, Michal Bauer, Julie Chytilová, and Filip Matějka, 2016, Attention discrimination: Theory and field experiments with monitoring information acquisition, *American Economic Review* 106, 1437–75.

Bayer, Patrick, Fernando Ferreira, and Stephen L Ross, 2018, What drives racial and ethnic differences in high-cost mortgages? the role of high-risk lenders, *Review of Financial Studies* 31, 175–205.

Beck, Thorsten, Patrick Behr, and Andreas Madestam, 2018, Sex and credit: Do gender interactions matter for credit market outcomes?, *Journal of Banking and Finance* 87, 280–396.

Brock, J Michelle, and Ralph De Haas, 2021, Discriminatory lending: Evidence from bankers in the lab, *American Economic Journal: Applied Economics* .

Butler, Alexander W, Erik J Mayer, and James Weston, 2022, Racial discrimination in the auto loan market, *Working paper*.

Charles, Kerwin Kofi, Erik Hurst, and Melvin Stephens, 2008, Rates for vehicle loans: Race and loan source, *American Economic Review* 98, 315–20.

Dobbie, Will, Andres Liberman, Daniel Paravisini, and Vikram Pathania, 2021, Measuring bias in consumer lending, *The Review of Economic Studies* 88, 2799–2832.

Ewens, Michael, and Richard R Townsend, 2020, Are early stage investors biased against women?, *Journal of Financial Economics* 135, 653–677.

Fisman, Raymond, Daniel Paravisini, and Vikrant Vig, 2017, Cultural proximity and loan outcomes, *American Economic Review* 107, 457–92.

Fisman, Raymond, Arkodipta Sarkar, Janis Skrastins, and Vikrant Vig, 2020, Experience of communal conflicts and intergroup lending, *Journal of Political Economy* 128, 3346–3375.

Giacoletti, Marco, Rawley Heimer, and Edison G Yu, 2021, Using high-frequency evaluations to estimate discrimination: Evidence from mortgage loan officers, *Working paper*.

Hebert, Camille, 2020, Gender stereotypes and entrepreneur financing, *Working paper*.

Hirshleifer, David, Yaron Levi, Ben Lourie, and Siew Hong Teoh, 2019, Decision fatigue and heuristic analyst forecasts, *Journal of Financial Economics* 133, 83–98.

Hu, Allen, and Song Ma, 2021, Persuading investors: A video-based study, *Working paper*.

Huang, Shiyang, Yulin Huang, and Tse-Chun Lin, 2019, Attention allocation and return co-movement: Evidence from repeated natural experiments, *Journal of Financial Economics* 132, 369–383.

Lanning, Jonathan A, 2021, Testing models of economic discrimination using the discretionary markup of indirect auto loans, *Working paper*.

Liao, Li, Zhengwei Wang, Jia Xiang, Hongjun Yan, and Jun Yang, 2021, User interface and firsthand experience in retail investing, *The Review of Financial Studies* 34, 4486–4523.

Montoya, Ana María, Eric Parrado, Alex Solís, and Raimundo Undurraga, 2020, Bad taste: Gender discrimination in the consumer credit market, *Working paper*.

Müller, Karsten, 2022, Busy bankruptcy courts and the cost of credit, *Journal of Financial Economics* 143, 824–845.

Ongena, Steven, and Alexander Popov, 2016, Gender bias and credit access, *Journal of Money, Credit and Banking* 48, 1691–1724.

Shu, Tao, Xuan Tian, and Xintong Zhan, 2022, Patent quality, firm value, and investor underreaction: Evidence from patent examiner busyness, *Journal of Financial Economics* 143, 1043–1069.

Zhang, Ye, 2020, Discrimination in the venture capital industry: Evidence from two randomized controlled trials, *Working paper*.

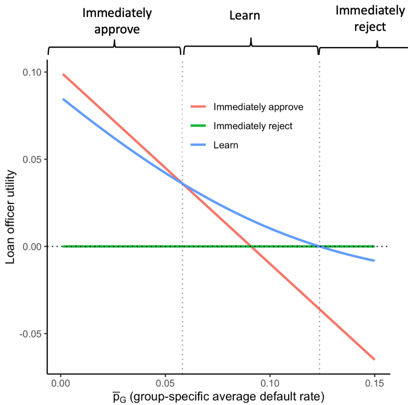
Model set up

Follows Bartoš et al. (2016)'s "attention discrimination" model.

- Loan officer receives an application. If approved:
  - Earns interest rate r if borrower does not default
  - Lose 100% otherwise
- Default probability is $p = \bar{p}_G + p_I$
  - Group-average $\bar{p}_G$ is observable at no cost
  - $p_I \sim N(0, \sigma^2)$ can be learned at cost c
- Loan officer decisions:
  - Whether to pay attention c
  - Whether to approve/reject

Model solution

- Very favorable (low $\bar{p}_G$):
  - immediately approve
- Intermediate (medium $\bar{p}_G$):
  - learn p_I before deciding
- Very unfavorable (high $\bar{p}_G$):
  - immediately reject



- **Main prediction**: If attention cost c increases, both "immediately approve" and "immediately reject" regions expand

back

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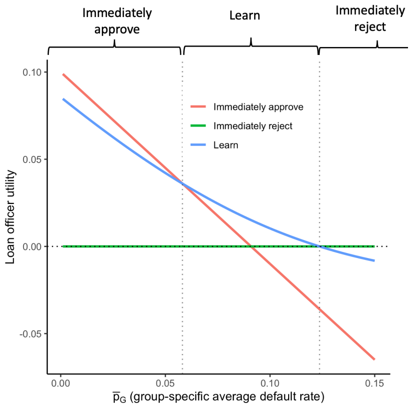

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back

Assignment does not depend on backlog

- **Concern:** if the algorithm reduces workload assignment to officers with bigger backlogs, then officers have *indirect* control

Dependent Variable:	Assignment$_{j,d}$			
	(1)	(2)	(3)	(4)
Backlog$_{j,d}$	-0.016	-0.016	-0.016	-0.016
	(-1.133)	(-1.138)	(-1.139)	(-1.136)
Backlog$_{j,d-1}$		0.005	0.005	0.005
		(1.613)	(1.627)	(1.634)
Backlog$_{j,d-2}$			0.000	0.000
			(0.123)	(0.113)
Backlog$_{j,d-3}$				0.001
				(0.407)
Officer-Month-Yr FE	Y	Y	Y	Y
Day FE	Y	Y	Y	Y
Observation	9,235	9,235	9,235	9,235
Adjusted R-squared	0.604	0.604	0.604	0.604

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Dependent variable:	StateOfficial	LocalResident	Employment Cert	IncomeCert	RegularPay	HomeOwner	log(1+Lever ageRatio)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PredictBusynessDecile	−0.402	−1.976	−2.049	−1.155	0.205	−0.431	0.666
	(−1.179)	(−1.324)	(−1.122)	(−0.901)	(0.582)	(−0.562)	(1.576)
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.045	0.345	0.090	0.317	0.392	0.387	0.042

Dependent variable:	NoCredit History	log(1+Over dueMonth)	log(1+Cred itInqury)	HasInvest mentAcc	SocialSecurity	Litigation	Peasant
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PredictBusynessDecile	−0.819	0.954	3.684***	0.042	0.396	−0.055	−0.207
	(−1.111)	(1.207)	(3.626)	(0.308)	(0.840)	(−0.640)	(−0.471)
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.061	0.031	0.114	0.010	0.082	0.011	0.459

Dependent variable:	NonCollege	Female	log(Age)	log(Income)	log(LoanTo Income)	ShortTerm	log(Interest Rate)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PredictBusynessDecile	0.479	0.522	−0.159	−0.717	0.481	0.141	−0.008
	(0.879)	(0.965)	(−0.506)	(−0.526)	(0.424)	(0.492)	(−0.728)
Officer-Month-Yr FE	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y	Y	Y
Loan type FE	Y	Y	Y	Y	Y	Y	Y
Observation	145,982	145,982	145,982	145,982	145,982	145,982	145,982
Adjusted R-squared	0.117	0.010	0.056	0.489	0.412	0.785	0.868

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