Marketplace Lending: A New Banking Paradigm?

Boris Vallée

Yao Zeng

Harvard Business School University of Washington

April 5th, 2019 Conseil Scientifique de l'AMF

Marketplace Lending: A New Banking Paradigm? (1/2)

 Marketplace lending is growing rapidly (20%+ annually) and already represents 1/3 of the unsecured consumer loans in the US in 2016.

LendingClub PR05PER

Innovation: does not invest but offers a two-sided platform:

On borrower side Collects standardized information to pre-screen individual borrowers, list some loans, and the information is subsequently distributed to investors

On investor side Relies on investors to screen and finance listed borrowers directly

Marketplace Lending: A New Banking Paradigm? (2/2)

- Investors on the platforms are increasingly sophisticated.
 - 55% institutional investors, 29% managed accounts, and 13% self-directed retail investors in 2017
 - They internalize large-scale loan screening on the platforms.
 - Heterogeneity of sophistication in each segment as well
- This banking model thus significantly differs from the traditional banking paradigm where depositors are isolated from the borrowers.
 - Both the platform and investors produce information.
 - Challenges the traditional roles of banks of information production and screening on behalf of investors (Diamond and Dybvig, 1983, Gorton and Pennacchi, 1990)

Lending Marketplaces in a Nutshell

- Borrower side:
 - Information collection
 - Pre-screening: extensive and intensive margin
- Investor side:
 - Funding
 - Information distribution
- Pricing in Equilibrium

▶ More institutional details



A Puzzle

- While built using transparency as a substitute for skin in the game, on November 7th, 2014, Lending Club removed 50 out of the 100+ variables on borrowers' characteristics they were sharing to investors.
- The move was unanticipated and puzzled many market participants as it was the only investor-unfriendly move in Lending Club history.



Research Questions

 How do platform and investor information production relate to and interact with each other in this new lending paradigm?

Investors Are more sophisticated investors on platforms consistently more efficient at screening borrowers and outperforming?

Platform→Investors If so, how does their out-performance relate to changing designs of the platforms?

Platform←Investors Given the heterogeneity of investors, what is the optimal design of a platform in terms of platform pre-screening and information provision to investors?

 Many interesting questions are left for future research: Welfare, competition to traditional banking, financial stability, etc...



Literature and Contribution

- The literature of marketplace lending has so far mainly focused on borrowers, in particular on their soft information (Morse 2015).
 - e.g., Duarte, Siegel, Young (2012), Iyer, Khwaja, Luttmer, Shue (2015)
 - or tackle banking/household finance questions: Paravisini, Rappoport, and Ravina (2016), Hertzberg, Liberman and Paravisini (2018)
- Recent papers study the motivation behind the platforms' switch from an auction mechanism to posted prices, and the removal of fees to lender group leaders
 - Franks, Serrano-Velarde, Sussman (2017), Liskovich and Shaton (2017), Hildebrand, Puri and Rocholl (2017)

and the interaction between traditional banking and FinTech/online lending

- e.g., Tang (2018), De Roure, Pelizzon and Thakor (2018), Fuster, Plosser, Schnabl and Vickery (2018), Buchak, Matvos, Piskorski and Seru (2017)
- 3. Endogenous adverse selection in production settings
 - Fishman and Parker (2015), Bolton, Santos, Scheinkman (2016), Yang and Zeng (2017)
- First study to focus on investors' screening and its interaction with platform actions, exploring the investor side of this new banking model



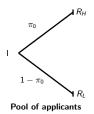
Preview of Results

- We rely on a model and novel data to establish that:
 - Informationally sophisticated investors are more efficient at screening-in good loans, helping boost the volume of loans.
 - But create endogenous adverse selection and hurt volume.
 - The platform trades off these two forces in designing its optimal policies, which leads to intermediate levels of pre-screening and information provision.
- First study to focus on investor screening and its interaction with platform design, exploring the investor side of this banking model

Theoretical Framework

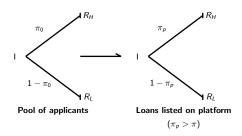
Model Setting (1/3)

- One platform pre-screens and lists loans; maximizes volume.
- Investors: Ω sophisticated and many competitive unsophisticated; each can finance one loan but only sophisticated can acquire information
- Loan applicant composition: π_0 good $(R_H > I)$ and $1 \pi_0$ bad $(R_L < I)$
- Endogenous supply of applications: $x_0(p) \ge 1$ with $x_0'(p) > 0$
- Platform price *p* determined by marginal investor's offer price (later)



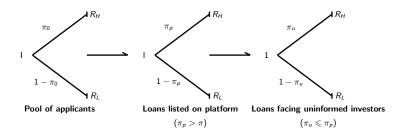
Model Setting (2/3)

- Platform pre-screens and lists $x_p = \frac{\pi_0}{\pi_p} x_0$ loans (interim posterior π_p).
- Pre-screening cost $C(\pi_p) = \frac{1}{2}\kappa(\pi_p \pi_0)^2$
- Platform provides information to sophisticated investors, determining their information acquisition cost μ.
- Changing μ is costless to the platform.



Model Setting (3/3)

- Each sophisticated investor may first acquires an information technology at cost μ, becomes informed of a listed loan for sure.
 - If informed, invests in good loan and passes on bad; enjoys rents.
 - Passed loans still listed for potential financing
- Uninformed investors look at remaining listed loans based on updated π_u
 - They are competitive and thus enjoy zero profits.



Model Intuition

Main intuition (detailed derivations in paper):

- 1. Sophisticated investors, when informed, identify and finance good loans, helping boost volume.
 - They endogenously become informed if benefit exceeds cost
- But they adversely select bad loans into the uninformed pool, lowering the loan price offered in equilibrium and thus hurting volume.
 - Lower platform price lowers initial supply of loan application.
 - Uninformed investors, if cannot break even, exit the market.
 - Hence, the platform uses its two policies, π_p and μ , to trade-off these two forces.

Optimal Platform Policies

- The platform optimally chooses π_p and μ given κ , its cost of pre-screening (formal propositions in paper).
 - Four types of sub-game equilibrium depending on platform policies:

Equilibrium Volume of Loans Financed

	High μ	Low μ
Low π_p	0	$\min\{\pi_0 x_0(I), \pi_p \Omega\}$
High π_p	$\frac{\pi_0 x_0(p(0))}{\pi}$	$\frac{\pi_0 x_0(p(\Omega))}{\pi}$
	π_{p}	π_{p}

- If pre-screening cost is relatively high, pre-screens less intensively but makes information acquisition easier for sophisticated investors
 - Screening efficiency concern dominates.
- If pre-screening cost is relatively low, pre-screens more intensively but makes information acquisition harder for sophisticated investors
 - Adverse selection concern dominates.



Empirical Predictions

- 1. Sophisticated investors outperform unsophisticated ones.
- 2. When their information cost becomes higher, sophisticated investor our-performance shrinks.
- 3. The platform may increase the information cost of sophisticated investors by distributing fewer variables to investors.
- 4. The platform may increase its pre-screening intensity as it develops.

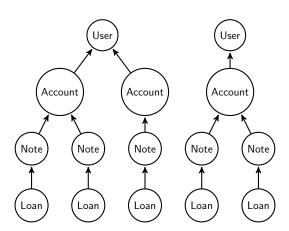
Data and Empirical Setting

Data

LendingRobot (recently merged with NSR Invest), one of the two largest robo-advisors focusing on marketplace lending, is providing us with its whole investor portfolio dataset between January 2014 and February 2017.

- Heterogeneity of investor sophistication at the account level.
- We matched it with loan-level data offered by Lending Club and Prosper.

Data Structure



Account Types

- There are three different types of accounts in our dataset:
 - Robot accounts: invest using LendingRobot screening model and automated execution
 - Advanced accounts: rely on their own screening criteria with an open API; further combine with LendingRobot screening model and automated execution in flexible ways
 - Monitor-only: do not implement LendingRobot screening model or automated execution
- These account types map into different levels of investor sophistication
 - Overall, robot and advanced accounts are more sophisticated.
 - Advanced likely even more sophisticated

Summary Statistics

	Number (1)	Total Amount Invested (2)	Median Amount Invested (3)	Mean Amount Invested (4)	Max Amount Invested (5)	Avg. Int. Rate (6)	Platform Avg. Int. Rate (7)	Risk Tolerance (8)
Lending Club							15.76%	
Total	7,368	138,633,952	3,050	18,815.7	3,712,900	18.98%		-
Robot	4,435	56,692,279	1,600	12,783.6	2,102,925	19.34%		7.96%
Advanced	2,933	81,703,628	5,925	27,936.8	3,712,900	18.83%		-
Monitor-Only	636	13,309,525	4,650	20,926.9	722,750	19.20%		-
Prosper							16.32%	
Total	1,616	21,039,794	2,425	13,019.7	658,639	19.84%		-
Robot	1,095	13,421,524	1,900	12,257.1	630,937	19.86%		8.01%
Advanced	521	7,618,145	3525	14,622.4	658,639	19.80%		-
Monitor-Only	126	1,699,350	1,925	13,486.9	155,575	16.54%		-

Empirical Analysis

Investor Screening (1/2)

 We first explore whether investors screen differently according to their level of sophistication.

$$Prob(TypeAccount_i = 1) = \beta \times BorrowerCharacteristics + IR_i + m_t + \epsilon_i, (1)$$

Investor Screening (2/2)

	1	Lending Club			Prosper			
Logit on Loan being selected by:	Robot (1)	Advanced (2)	Monitored (3)	Robot (4)	Advanced (5)	Monitored (6)		
Loan amount	0.005***	0.008***	0.015***	0.015***	0.012***	0.018***		
	(18.89)	(27.97)	(36.16)	(25.83)	(19.00)	(21.22)		
FICO Score	0.000	0.001***	-0.001***	-0.000	0.000*	-0.000***		
	(1.44)	(11.62)	(-10.56)	(-0.01)	(1.76)	(-2.95)		
Annual Income	0.001***	0.001***	0.000***	-0.000***	0.001***	-0.000*		
	(7.18)	(13.42)	(9.83)	(-2.90)	(5.67)	(-1.78)		
Employment Length	0.002***	0.007***	0.001***	0.000	0.002***	0.002***		
	(8.96)	(19.42)	(5.47)	(1.43)	(6.27)	(4.01)		
Debt to Income	-0.001***	-0.002***	0.001***	0.041	-0.108*	0.137***		
	(-4.67)	(-10.36)	(8.71)	(1.37)	(-1.74)	(3.95)		
Own Home Ownership	0.033***	0.054***	0.006**	-0.017**	0.024**	0.006		
	(8.96)	(14.33)	(2.53)	(-2.71)	(2.53)	(1.27)		
Open Accounts	0.002***	0.001***	0.000	0.001***	0.002**	0.000		
	(7.04)	(5.73)	(0.89)	(3.30)	(2.50)	(0.03)		
First Credit Line	-0.000	-0.001**	-0.001***	-0.000	-0.001***	-0.001**		
	(-1.56)	(-2.50)	(-9.17)	(-0.62)	(-5.19)	(-2.50)		
Delinquency	-0.005***	-0.019***	-0.006***	-0.000	-0.002***	-0.001***		
	(-6.70)	(-18.68)	(-6.73)	(-0.24)	(-4.34)	(-3.78)		
Term	-0.012	-0.066***	0.045***	-0.000	-0.004***	0.004***		
	(-1.59)	(-7.65)	(6.89)	(-0.42)	(-5.31)	(8.40)		
Inquiries, last 6 months	-0.038***	-0.068***	-0.003**	-0.008***	-0.045***	-0.001		
	(-14.47)	(-28.10)	(-2.00)	(-3.59)	(-11.45)	(-0.45)		

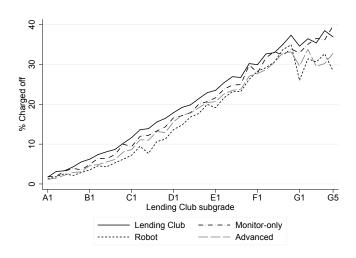


Investor Performance (1/3)

- Different investors indeed screen differently (shown in paper).
- We explore whether screening by sophisticated investors translate into out-performance.
- We plot whether loans in which robot and advanced accounts invest in are less likely to default against different risk buckets.
- We also run a regression analysis, controlling for interest rate level and monthly vintage (details in paper):

$$Prob(ChargedOff = 1)_i = \beta_1 \times \mathbb{1}_{TypeAccount} + IR_i + m_t + \epsilon_i,$$
 (2)

Investor Performance (2/3) 2014-2016 Issuances



Investor Performance (3/3)

	Prob(Charged-Off)								
Account Type	Robot (1)	Advanced (2)	Monitor (3)	Robot (4)	Advanced (5)	Monitor (6)	Robot (7)	Advanced (8)	Monitor (9)
Account Type	-0.031*** (-10.84)	-0.044*** (-18.04)	-0.008*** (-4.68)	-0.084*** (-20.56)	-0.070*** (-19.86)	-0.005 (-1.27)	0.012* (1.66)	-0.015*** (-3.64)	0.007** (2.21)
Account Type x 2015				0.051*** (10.38)	0.029*** (7.11)	-0.006 (-1.27)			
Account Type x 2016				0.075*** (13.66)	0.050*** (12.42)	-0.002 (-0.45)			
Account Type x Grade B							-0.041*** (-3.72)	-0.019*** (-3.36)	-0.009** (-2.11)
Account Type x Grade C							-0.058*** (-6.36)	-0.030*** (-5.28)	-0.015*** (-3.07)
Account Type x Grade D							-0.052*** (-5.97)	-0.037*** (-6.06)	-0.027*** (-4.58)
Account Type x Grade E							-0.049*** (-4.62)	-0.047*** (-4.58)	-0.019** (-2.22)
Account Type x Grade F							-0.026** (-2.43)	-0.039*** (-3.19)	-0.005 (-0.48)
Account Type x Grade G							-0.089*** (-4.31)	-0.081*** (-3.66)	-0.006 (-0.31)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interest Rate FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Int. Rate	Int. Rate	Int. Rate	Int. Rate	Int. Rate	Int. Rate	Int. Rate	Int. Rate	Int. Rate
Observations	365,691	365,691	365,691	365,691	365,691	365,691	365,691	365,691	365,691
Pseudo R ²	0.062	0.064	0.061	0.062	0.065	0.061	0.062	0.064	0.061

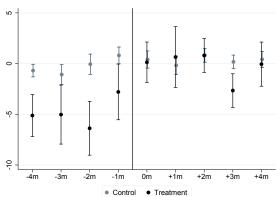
Increases in Investor Screening Cost: Difference-in-Differences Methodology

- Recall the Lending Club shock in November 2014.
- We implement a difference-in-differences analysis on investor performance, comparing robot accounts to the rest of the platform or to monitor-only investors, controlling for loan risks.
- We run the following specification (details in paper):

$$\begin{aligned} \textit{Prob}(\textit{ChargedOff} = 1)_i &= \beta_1 \times \mathbb{1}_{\textit{robot}} + \beta_2 \times \mathbb{1}_{\textit{robot}} \times \textit{Post} \\ &+ \beta_3 \times \mathbb{1}_{\textit{advance}} + \beta_4 \times \mathbb{1}_{\textit{advance}} \times \textit{Post} \\ &+ \beta_5 \times \mathbb{1}_{\textit{monitor}} + \beta_6 \times \mathbb{1}_{\textit{monitor}} \times \textit{Post} + \textit{IR}_i + \textit{m}_t + \epsilon_i \end{aligned} \tag{3}$$

Increases in Investor Screening Cost: Results (1/2)

Full Lending Club fractional loan sample as Control



Increases in Investor Screening Cost: Results (2/2)

	-3/+3 months Window (1)	Grade below C (2)	-2/+2 months Window (3)	Control Group: Monitor (4)
Robot account	-0.072*** (-7.00)	-0.076*** (-5.34)	-0.074*** (-6.98)	-0.098*** (-10.85)
Robot account x Post	0.040*** (3.20)	0.049*** (3.01)	0.037** (2.68)	0.043*** (3.65)
Advanced account	-0.057*** (-8.03)	-0.064*** (-6.20)	-0.053*** (-6.14)	
Advanced account x Post	0.013* (1.73)	0.008 (0.71)	0.015 (1.42)	
Monitor-only account	0.013* (1.88)	0.020** (2.15)	0.001 (0.16)	
Monitor-only account \times Post	-0.001 (-0.09)	-0.002 (-0.19)	0.016 (1.71)	
Month FEs	Yes	Yes	Yes	Yes
Interest rate FEs	Yes	Yes	Yes	Yes
Cluster	Int. rate	Int. rate	Int. rate	Int. rate
Observations	65,859	35,880	37,615	11,283
Pseudo R ²	0.059	0.030	0.060	0.071

Platform Increases Investor Screening Cost

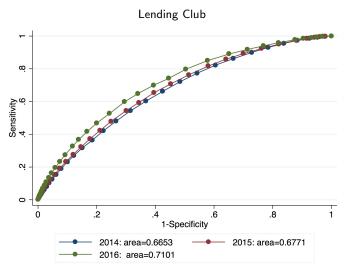


→ Our framework provides a rationale: mitigating adverse selection.

Platform Pre-screening

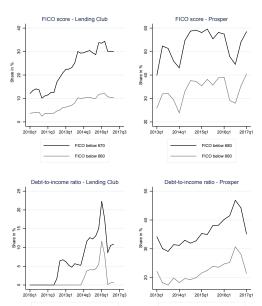
- Our theoretical model predicts that platforms also adjust their pre-screening intensity according to pre-screening cost and economic conditions.
- We therefore explore changes in platform prescreening.
- These changes of policy also affect volumes as well as sophisticated investor out-performance (more results in paper).

Platform Pre-screening: Intensive Margin





Platform Pre-screening: Extensive Margin





Conclusion: A New Banking Paradigm?

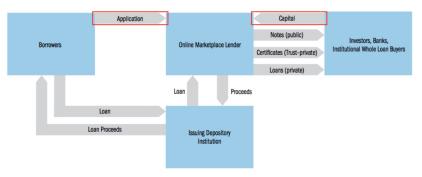


- Marketplace lending: a new banking paradigm?
 - One concrete step forward to tackle this broad question.

Next Steps

- Effects of competition among Fintech lenders?
- Adverse selection on the borrower side?

The Two-Sided Market Structure



Source: Lending Club. Form 10-K, Filed February 27, 2015.

