Asymmetric Information, Reputation, and Welfare in Online Credit Markets

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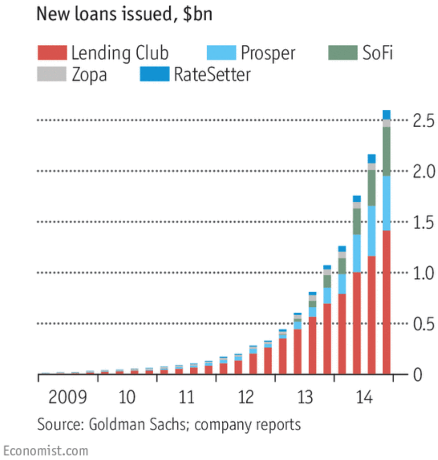
Motivation

- Online credit markets for peer-to-peer lending have developed rapidly over the last several years.



Motivation

- These markets attract dispersed and anonymous borrowers and lenders, and often require no collateral.
- One of the main concerns in this market is the ability of lenders to recover their loans and interests.
- The problems of asymmetric information are two-fold:
  (1) Borrowers differ in their **inherent risk types** $\Longrightarrow$ Adverse Selection;
  (2) **Actions are hidden**; lenders are exposed to default risks $\Longrightarrow$ Moral Hazard.

Motivation

- Most of these online markets rely on a "**reputation/feedback**" system to facilitate transactions. (see Einav, Farronato and Levin, 2015; Tadelis, 2016)

- Reputation mechanism: history-dependent rating/pricing.
  (1) pay off loans on time $\Longrightarrow$ interest rate $\downarrow$, funding prob $\uparrow$.
  (2) once default $\Longrightarrow$ no future credit access.

- E.g., credit rating (FICO, Prosper), online review systems (eBay, Amazon, Uber, etc.)

Research Question

- The qualitative effect of reputation systems is well-known in theory.[1] Little empirical work to quantify the welfare impact.

- **To what extent and through which channels do reputation/feedback systems improve the total welfare of market participants?**

- Answers to these questions shed light on optimal mechanism design and regulations for
  - markets of unsecured loans. more details
  - fast-growing online marketplaces.
  - traditional credit markets.

[1] see Akerlof (1970), Holmstrom (1999), Bar-Isaac and Tadelis (2008), Stiglitz and Weiss (1983), and Diamond (1989).

What This Paper Does

- Develops a dynamic structural model to formalize
  - borrowers' repayment decisions,
  - lenders' investment strategies,
  - websites' pricing schemes,

  when both **hidden information** (adverse selection) and **hidden actions** (moral hazard) are present.

- Identifies the dist. of borrowers' private types and costs of effort, and utility primitives; estimation using data from Prosper.com.

- Counterfactuals: welfare loss from asymmetric information? value of reputation? any improvement?

Preview of Findings

- 22% of welfare loss from asymmetric information is due to adverse selection, and 78% is due to moral hazard.
- The reputation system recovers 95% of welfare loss by:
  (1) screening out "lemons" over time.
  (2) incentivizing borrowers to repay debts.
  (3) alleviating credit rationing. (Stiglitz and Weiss, 1981)
- Adding Payment Protection Insurance to the market with a reputation system recovers 98% of total welfare loss.

Contributions to the Literature

- Quantifies the total welfare effects of reputation when both adverse selection and moral hazard are present.
  - Regression Analysis: Jin and Kato (2006), Cabral and Hortacsu (2010), etc.
  - Structural: Yoganarasimhan (2013), Saeedi (2014).
- Disentangles the effects of adverse selection and moral hazard.
  - Tests: Chiappori and Salanie (2000), Abbring et al. (2003), etc.
  - Credit Markets (Adverse Selection): Einav et al. (2012), Kawai et al. (2018).
- Contributes to the identification of contract models.
  - Perrigne and Vuong (2011), Gayle and Miller (2015).

Outline

Outline

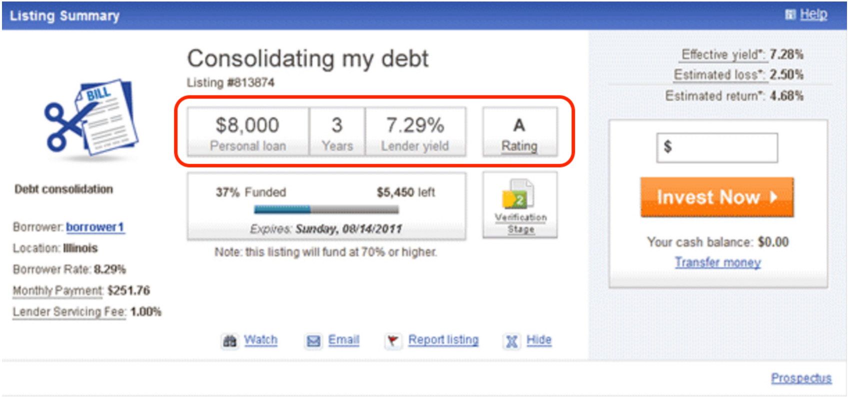
Institutional Background

- Prosper.com is the 2nd largest peer-to-peer lending markets in the US, founded in 2005.
  - Initiated \$9bn in loans, >2m members.
  - Provides services that match lenders with borrowers.
  - Charges commission fees proportional to the amount funded.
  - Small personal loans: amount between \$2k and \$35k.
  - Crowdfunding $\Longrightarrow$ Portfolio diversification.

Institutional Background

- How the market works?
  - Verification, website decides on interest rates.
  - Borrowers accept/withdraw, listings posted for 14 days.
  - Lenders make investment decisions.
  - Borrowers repay in the following 12-60 months.
  - If defaults occur, *only* lenders bear the loss; borrowers who default are *not* allowed to enter again.

A Listing



Listing Summary
Help
Consolidating my debt
Listing #813874
BILL
$8,000
Personal loan
3
Years
7.29%
Lender yield
A
Rating
Debt consolidation
Borrower: borrower1
Location: Illinois
Borrower Rate: 8.29%
Monthly Payment: $251.76
Lender Servicing Fee: 1.00%
37% Funded
$5,450 left
Expires: Sunday, 08/14/2011
Verification Stage
Note: this listing will fund at 70% or higher.
Effective yield*: 7.28%
Estimated loss*: 2.50%
Estimated return*: 4.68%
$
Invest Now
Your cash balance: $0.00
Transfer money
Watch
Email
Report listing
Hide
Prospectus

A Listing

Borrower's Credit Profile Help

Prosper rating:	A	Inquiries last 6m:	0	Debt/Income ratio:	9%
Prosper Score (1-10):	8	First credit line:	Mar-2000	Employment status:	Employed
Credit score:	700-719 (Jun-2011)	Current / open credit lines:	9 / 7	Length of status:	1y 7m
Now delinquent:	0	Total credit lines:	19	Stated income:	$50,000-$79,999
Amount delinquent:	$0	Revolving credit balance:	$9,948	Occupation:	Professional
Public records last 12m / 10y:	0 / 0	Bankcard utilization:	8%		
Delinquencies in last 7y:	0	Home ownership:	Yes		

Prosper Activity

Loan history		Payment history		Credit score history
Active / total loans	0 / 1	On-time:	35 (100%)	
Principal borrowed:	$3,500.00	<31 days late:	0 (0%)	700-719 (Latest)
Principal balance:	$0.00	31+ days late:	0 (0%)	520-539 (Nov-2006)
		Total payments billed:	35	

Improvement by more than 50 points since last loan

Repeated Borrowing Patterns

- Data ranges from Jan. 2011 to Dec. 2014, containing 114,804 listings and 102,528 unique borrowers.

Data Category	Freq.	Percent
appear once	91,891	89.63
appear twice: first loan paid off	3,247	3.17
appear twice: first loan ongoing	5,163	5.04
appear twice: first listing withdrawn or unfunded	597	0.58
appear three times	1,630	1.59
Total	102,528	100.00

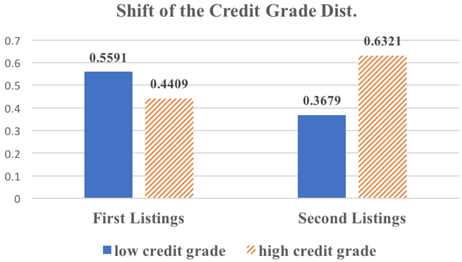
Summary Statistics by Credit Grades

Credit Grade	Avg. Amount Requested	Avg. Interest Rate(%)	Default Rate (%)	# of Obs
AA	13250.31	7.53	6.37	8,231
A	12974.22	10.99	14.15	21,166
B	12982.66	14.72	21.53	22,271
C	11813.24	18.58	28.55	24,964
D	9197.09	23.57	31.56	18,046
E	5106.38	28.20	33.93	12,196
HR	3586.34	31.53	34.19	7,930
Overall	10662.36	18.34	24.23	114,804

Cont'd Other Summary Stats

Composition of Borrowers

- Borrowers in the second listings are more likely to have high credit grades (AA, A, B).
  (1) **Selection**: those who pay off the first loans are better borrowers.
  (2) **Updating**: credit grades get updated after the first loan.



decomposition seven groups

Reputation System Provides Dynamic Incentives?

- Yes, and through two channels:

  (1) once default $\Longrightarrow$ no entry again
  (incentive effects of terminations, Stiglitz and Weiss, 1983)

  (2) interest rates vary with past outcomes: regression results

  - pay off the first loan $\Longrightarrow r \downarrow$
  - previous loan ongoing $\Longrightarrow r \uparrow$
  - late payments $\Longrightarrow r \uparrow$

Borrowers Respond to Reputational Incentives?

- Consider borrowers with two overlapping loans.
- Arrange the two loans based on their closing dates.

Myopic

- Default driven by types
- Same default rates for the first- and second-closed loans

Forward-looking

- Once default, lose incentives to pay
- Default more in the second-closed loans

Data Show

Second-closed loans have a much higher default rate.

regression results

Empirical Evidence

- Takeaways:

    (1) The reputation system imposes dynamic incentives through history-dependent pricing schemes and entry restrictions.

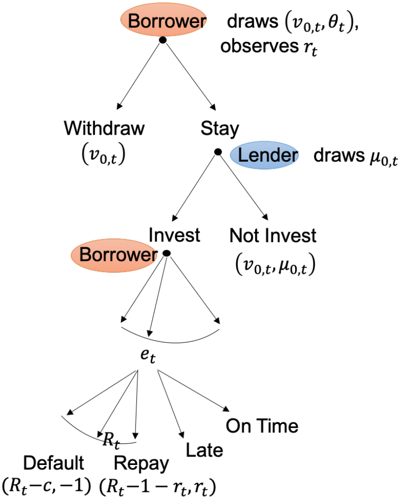
    (2) Borrowers respond to dynamic incentives, default rates increase when incentives are reduced.

Outline

Players

- A borrower:
  - forward-looking, discounts future at the rate of δ;
  - privately observes his default cost $c \in \Theta_c$; $F_c(\cdot) : \Theta_c \to [0, 1]$ is common knowledge;
  - utility associated with a given loan $U(\cdot; \alpha)$, where α is the risk-aversion parameter;
  - assume $U'(\cdot; \alpha) > 0$ and $U''(\cdot; \alpha) < 0$.
- A lender: risk-neutral and live for only one period.

Timing and Payoffs



$v_{0,t} \in \Theta_v$ -- borrower's outside option

$\theta_t \in \Theta_\theta$-- marginal cost of effort

$r_t \in [0, \bar{r}]$-- interest rate, decided by the website

$\mu_{0,t} \in \Theta_\mu$ -- lender's outside option

$e_t \in [0, \infty)$ -- effort level

$\phi(e_t, \theta_t)$ -- cost of exerting effort

$R_t \in [0, \bar{R}]$-- revenue, drawn from $F_{R|e}(\cdot\,|e_t)$

Histories and Strategies

- For $t \geq 2$, public histories

$$H^t = (\underbrace{W_1}_{\text{withdraw}}, \underbrace{I_1}_{\text{invest}}, \underbrace{L_1}_{\text{late}}, \underbrace{D_1}_{\text{default}}, \cdots, W_{t-1}, I_{t-1}, L_{t-1}, D_{t-1}) \in \mathcal{H}^t.$$

- Lender's investment strategy $\sigma : \mathcal{H}^t \times [0, \bar{r}] \times \Theta_\mu \to \{0, 1\}$.

- The borrower with type c
  - withdrawal strategy $w_{c,t} : \mathcal{H}^t \times [0, \bar{r}] \times \Theta_\theta \times \Theta_v \to \{0, 1\}$.
  - effort-exerting strategy $e_{c,t} : \mathcal{H}^t \times [0, \bar{r}] \times \Theta_\theta \to [0, \infty]$.

- A belief for the lender at the beginning of period t with history H^t is a distribution $\xi(H^t) \in \Delta(\Theta_c \times \mathcal{H}^t_B(H^t))$.

$$H^t_B = (H^t, r_1, v_{0,1}, \theta_1, e_1, R_1, \cdots, r_{t-1}, v_{0,t-1}, \theta_{t-1}, e_{t-1}, R_{t-1}) \in \mathcal{H}^t_B(H^t).$$

Equilibrium

- Define $w_c = (w_{c,1}, w_{c,2}, \cdots, w_{c,T})$ and $e_c = (e_{c,1}, e_{c,2}, \cdots, e_{c,T})$.

- A Perfect Bayesian Equilibrium is a tuple $< \sigma^*, (w_c^*, e_c^*)_{c \in \Theta_c}, \xi^* >$ such that for any H^t:

  - $\sigma^*(H^t, r_t, \mu_{0,t})$ is sequentially rational given $\xi^*(H^t)$ and $(w_c^*, e_c^*)_{c \in \Theta_c}$.
  - $w_{c,t}^*(H^t, r_t, \theta_t, v_{0,t})$ and $e_{c,t}^*(H^t, r_t, \theta_t)$ are sequentially rational given σ^*.
  - $\xi^*(H^t)$ is derived from strategies via Bayes's rule whenever possible.

The Borrower's Effort-Exerting Strategy

- Value function

$$
\begin{aligned}
&\tilde{V}_{c,t}(e, H^t, r_t, \theta_t) \\
&= \int_{1+r_t}^{\bar{R}} \left[U(R-1-r_t) + \delta \sum_{l\in\{0,1\}} Pr(L_t = l|e)\,\mathrm{E}[V_{c,t+1}|L_t = l, D_t = 0, H^t] \right] dF_{R|e}(R|e) \\
&+ \int_{0}^{1+r_t} \left[U(R-c) + \sum_{\tau=t+1}^{T} \delta^{\tau-t}\,\mathrm{E}(v_{0,\tau}) \right] dF_{R|e}(R|e) - \phi(e,\theta_t).
\end{aligned}
$$

- Optimal effort-exerting strategy

$$
e^*_{c,t}(H^t, r_t, \theta_t) = \arg\max_{e\in[0,\infty)} \tilde{V}_{c,t}(e, H^t, r_t, \theta_t).
$$

The Borrower's Withdrawal Strategy

- Value associated with "staying in the market"

$$\bar{V}^0_{c,t}(H^t, r_t, \theta_t, v_{0,t}) = P(H^t, r_t) \max_{e \in [0,\infty)} \tilde{V}_{c,t}(e, H^t, r_t, \theta_t) + (1 - P(H^t, r_t)) \left(v_{0,t} + \delta \, \mathrm{E}[V_{c,t+1} | I_t = 0, H^t]\right).$$

- Value associated with "withdrawing the listing"

$$\bar{V}^1_{c,t}(H^t, v_{0,t}) = v_{0,t} + \delta \, \mathrm{E}[V_{c,t+1} | W_t = 1, H^t].$$

- Optimal withdrawal strategy

$$w^*_{c,t}(H_t, r_t, \theta_t, v_{0,t}) = \begin{cases} 0 & \text{if } \bar{V}^0_{c,t}(H^t, r_t, \theta_t, v_{0,t}) \geq \bar{V}^1_{c,t}(H^t, v_{0,t}) \\ 1 & \text{otherwise} \end{cases}.$$

The Lender's Investment Strategy

- The lender's revenue

$$\tilde{\pi}(H^t, r_t, \theta_t, c) = \int_{1+r_t}^{\bar{R}} (1 + r_t) dF_{R|e}(R|e^*_{c,t}(H^t, r_t, \theta_t)) - 1,$$

- Let $\pi(H^t, r_t)$ denote the lender's expected revenue after integrating over (θ_t, c) under the belief $\xi^*(H^t, W_t = 0)$.

- Optimal investment strategy

$$\sigma^*(H^t, r_t, \mu_{0,t}) = \begin{cases} 1 & \text{if } \pi(H^t, r_t) \geq \mu_{0,t} \\ 0 & \text{otherwise} \end{cases}.$$

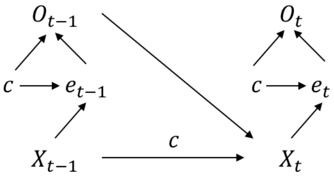
Outline

Dynamic Structure

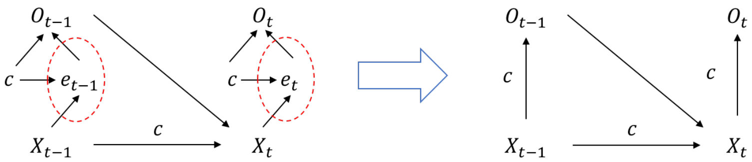
- Let the index for two loans be $t-1$ and t.

- Key elements in the model:
  (1) Outcomes of the loan: O_t, O_{t-1};
  (2) Observed characteristics: X_t, X_{t-1};
  (3) Effort choices: e_t, e_{t-1};
  (4) Borrower's type: c.

- Dynamic structure – how to separate the type and effort?



Step 1: Identify Type Distribution



- Joint distribution of observables across loans

$$f(O_t, X_t, O_{t-1}, X_{t-1}) = \sum_{c} \underbrace{f(c, X_{t-1}, O_{t-1})}_{\text{Init. Char.}} \underbrace{f(X_t|X_{t-1}, O_{t-1}, c)}_{\text{Transition of States}} \underbrace{f(O_t|c, X_t)}_{\text{Outcome Realized}}$$

- Three measurements that are independent conditional on the unobserved type $\Rightarrow$ type distribution. (Hu and Shum, 2012).

Step 2: Identify Unobserved Choice Probabilities

- Loan outcomes include borrowers' default and late payment performances, $O_t = \{D_t, L_t\}$.

$$\underbrace{f(O_t|c, X_t)}_{\text{identified}} = \sum_{e_t} f(D_t|e_t) f(L_t|e_t) f(e_t|c, X_t)$$

  - Conditional on effort, default and late payment are independent.
  - Effort choice is related to borrower's type.

- Following similar strategies, unobserved choice probabilities and the effects of effort on loan outcomes are identified.

Outline

Estimation Setup

- Let $i = 1, 2, \cdots, N$ index individual borrowers; $t-1$ and t represent two loans.
- Observed data: $O_{i\tau} = \{r_{i\tau}, D_{i\tau}, L_{i\tau}, X_{i\tau}, W_{i\tau}, I_{i\tau}\}_{\tau=t-1,t}$.
  - $r_{i\tau}$ interest rate;
  - $D_{i\tau}$, $L_{i\tau}$ default and late payment performances;
  - $W_{i\tau}$, $I_{i\tau}$ withdraw and investment decisions;
  - Borrower's characteristics $X_{i\tau}$: dti ratio, credit grade, amount requested, loan purpose (whether used for debt consolidation).
- Parameters to be estimated:
  (1) nonparametric: $\{F_c(\cdot), F_{e|c}(\cdot|c), F_{X_t|X_{t-1},c}\}$;
  (2) parametric: $\{\alpha, \beta, \gamma, R_h, R_l, v_x, v_d, \mu_0, \sigma_\mu\}$.

Estimation Results

- Utility primitives. results
- Probabilities of small cost of effort. results
- Probabilities of high type. results
- Transition probabilities of states. results

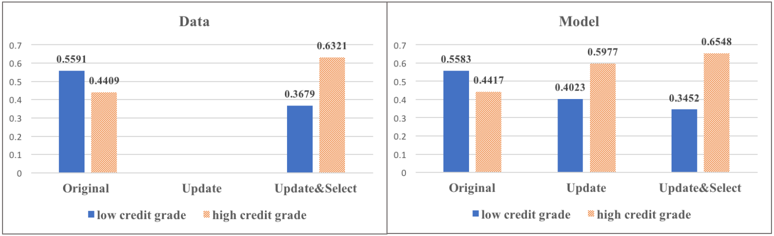
Model Fit

- Weighted average over combinations of observed characteristics.

	Data Estimates	Model Predictions
Participation Prob.	0.9311	0.9314
Funding Prob.	0.9503	0.9523
Default Prob.	0.2470	0.2226
Late Prob.	0.1079	0.1099

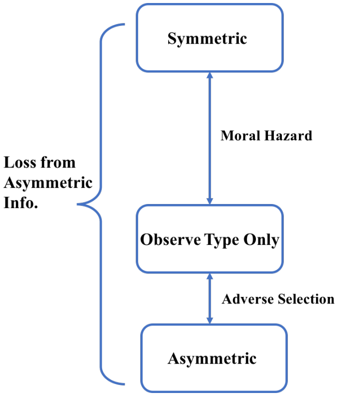
Recap: Shift of Credit Grade Dist Across Two Listings

- The distribution shifts to the right. recap
- Two channels: selection v.s. updating.
- Decompose the two channels using structural estimates.



Outline

Counterfactual Analysis



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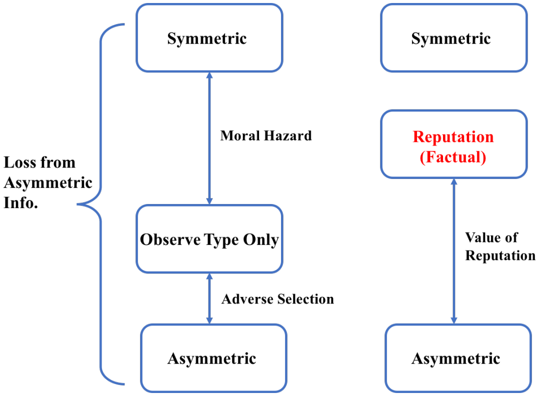

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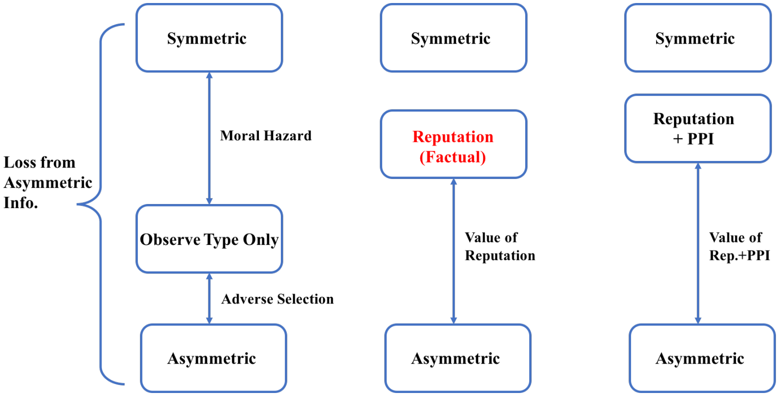


Compare Different Information Structures

Scenarios	Symmetric	Observe type	Asymmetric
Rate of transaction (%)	92.82	55.77	46.57
Participation prob. (%)	92.93	93.59	93.29
Funding prob. (%)	99.88	59.59	49.92
Default prob. (%)	11.65	10.07	20.90
Late prob. (%)	3.02	2.28	11.08
Borrower's avg. util.	0.2487	0.2658	0.2420
Lender's avg. util.	0.0816	0.0628	0.0550

- Asymmetric: high default rate, low transaction rate.
- Observe type only: moral hazard, market collapses for "lemons".
- Symmetric: high transaction rate, high payoff for lenders.
- **22% of welfare loss is due to adverse selection, 78% is due to moral hazard.**

The Value of Reputation

Scenarios	Symmetric	Reputation	Asymmetric
		First Loan	
Rate of transaction (%)	92.82	92.55	46.57
Participation prob. (%)	92.93	92.67	93.29
Funding prob. (%)	99.88	99.88	49.92
Default prob. (%)	11.65	15.63	20.90
Late prob. (%)	3.02	5.96	11.08
Borrower's avg. util.	0.2487	0.2497	0.2420
Lender's avg. util.	0.0816	0.0801	0.0550
		Second Loan	
Rate of transaction (%)	91.86	74.13	44.51
Participation prob. (%)	91.98	74.93	92.39
Funding prob. (%)	99.87	98.93	48.17
Default prob. (%)	11.00	14.81	20.99
Late prob. (%)	3.05	5.95	11.78
Borrower's avg. util.	0.2586	0.2642	0.2392
Lender's avg. util.	0.0836	0.0665	0.0577

The Value of Reputation

- **95% of welfare loss from asymmetric information is recovered by the reputation system.**

- **Confirm three channels:**
  (1) refining the beliefs, “lemons” are excluded gradually. updated beliefs
  (2) inducing higher effort: default rate $\downarrow$, utility for lenders $\uparrow$.
  (3) providing credit access to low type borrowers: reduce inefficiencies from credit rationing (extensive margin).

- **Potential long-run inefficiencies:**
  (1) Under the reputation system, borrowers’ participation rate in the second loans is lower.
  (2) Good borrowers may receive bad shocks, no entry again.

Payment Protection Insurance

- PPI covers the loan repayments for a set period of time if borrowers are unable to make them in certain situations:
  (1) being made redundant at one's job;
  (2) not being able to work because of an accident or illness.

- Intuition: if a borrower wants to maintain a good reputation (and hence credit access in the future), but also worries about future negative shocks, he/she can purchase this insurance ex-ante to hedge against the risk.

- Empirical relevance for small businesses (Segal, 2015).

Add PPI

Scenarios	Reputation	Reputation+PPI
	First Loan	
Rate of transaction (%)	92.55	92.52
Participation prob. (%)	92.67	92.66
Funding prob. (%)	99.88	99.85
Default prob. (%)	15.63	12.56
Late prob. (%)	5.96	5.05
Borrower's avg. util.	0.2497	0.2578
Lender's avg. util.	0.0801	0.0895
	Second Loan	
Rate of transaction (%)	74.13	76.76
Participation prob. (%)	74.93	92.49
Funding prob. (%)	98.93	82.99
Default prob. (%)	14.81	15.53
Late prob. (%)	5.95	6.36
Borrower's avg. util.	0.2642	0.2752
Lender's avg. util.	0.0665	0.0573

Add PPI

- **98% of welfare loss from asymmetric information is restored when PPI is added.**

- The risk faced by lenders $\downarrow$.
- Borrowers have higher chance to participate in the second loans, transaction rate $\uparrow$.

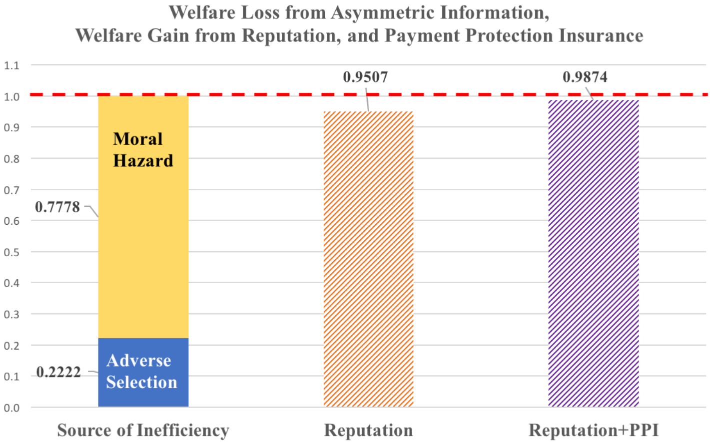
- Only borrowers with high probabilities of being good type are offered with insurance. The insurer takes adverse selection into account when choosing premiums.

A Simple Calculation for Prosper.com

Scenarios	Market Size ($bn)
Symmetric Information	9.18
Reputation+PPI	9.02
Reputation (Factual)	9.00
Under Moral Hazard	5.51
Under Moral Hazard and Adverse Selection	4.59

Outline

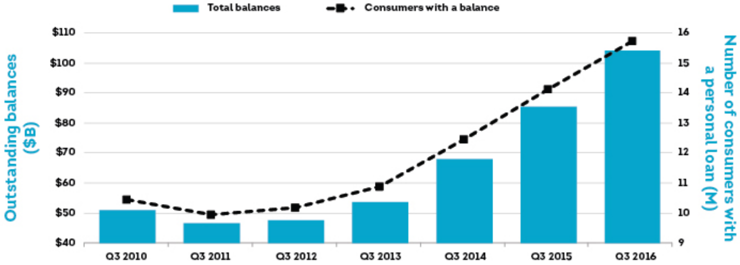
Conclusions



Conclusions

- Policy implications on credit rating system: ex-post monitoring, strengthen debt collection, optimal "forgiveness", etc.
- Provide new identification strategies for contract models.
- In a separate paper, develop general results for dynamic models with unobserved choices. details

Markets for Unsecured Loans - Trend



Source: TransUnion consumer credit database

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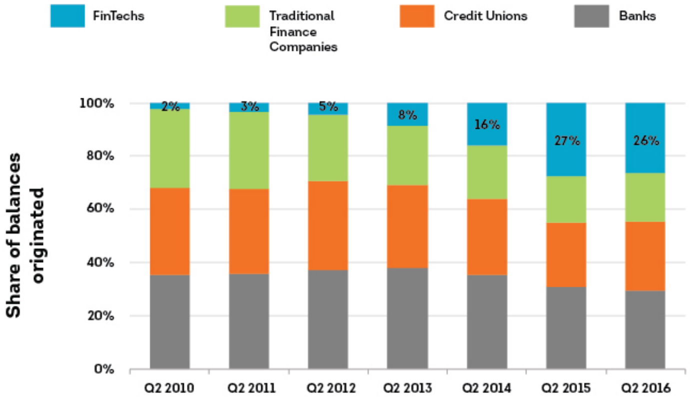
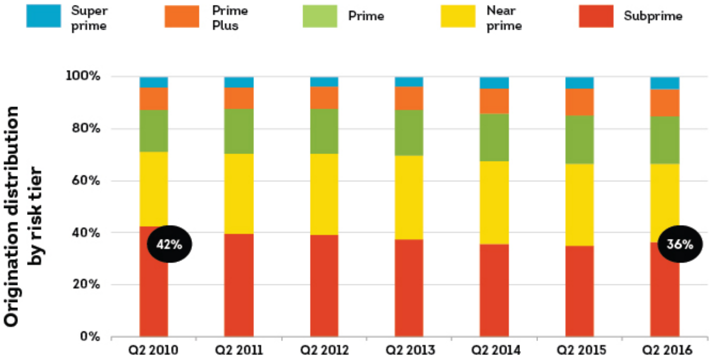
Markets for Unsecured Loans - By Lender Type



Source: TransUnion consumer credit database

Markets for Unsecured Loans - By Risk Tier



VantageScore ® 3.0 Risk Ranges
Subprime = 300-600; Near prime = 601-660; Prime = 661-720; Prime plus = 721-780; Super prime = 781-850

Source: TransUnion consumer credit database

Data Patterns: By Credit Grades (Cont'd)

Credit Grade	Withdraw Prob. (%)	Funding Prob. (%)	Default Prob. (%)	Late Prob. (%)	# of Obs
AA	6.39	89.42	6.37	2.64	8,231
A	5.56	91.11	14.15	5.61	21,166
B	5.66	91.37	21.53	8.58	22,271
C	5.52	92.09	28.55	11.02	24,964
D	7.77	87.70	31.56	15.47	18,046
E	6.13	92.29	33.93	16.50	12,196
HR	11.26	71.82	34.19	20.86	7,930
Overall	6.43	89.51	24.23	10.75	114,804

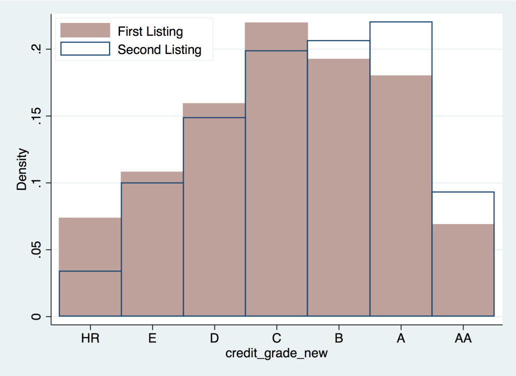
main

Data Patterns: Other Variables

Variable	Mean	Std. Dev.	Min	Max	# of Obs
# of listings	1.1197	0.3706	1	3	102,528
# of loans originated	1.0023	0.4959	0	3	102,528
term (# of months)	42.3681	11.2994	12	60	114,804
borrow for debt consolidation	0.6716	0.4696	0	1	114,804
borrow for home improvement	0.0731	0.2602	0	1	114,804
borrow for business	0.0504	0.2187	0	1	114,804
FICO score below 600	0.3058	0.4607	0	1	114,804
home owner	0.5124	0.4998	0	1	114,804
employed	0.9424	0.2329	0	1	114,804
is the borrower a group member	0.0124	0.1105	0	1	114,804
# of current credit lines	10.7388	5.2876	0	64	114,804
# of delinquencies over 30 days	3.6347	6.8248	0	99	114,804

main

Data Patterns: Histograms of Credit Grades



main

Regression Results of Interest Rate on Past Outcomes

VARIABLES	(1) borrower_rate	(2) borrower_rate	(3) borrower_rate
second_loan	-0.00902***		
	(0.000336)		
overlap		0.00208***	0.00157***
		(0.000409)	(0.000415)
late_ever			0.00452***
			(0.000663)
amount_request	7.37e-08***	-5.57e-08	-5.74e-08*
	(2.84e-08)	(3.43e-08)	(3.42e-08)
debt_to_income_high	0.00200***	0.00188***	0.00184***
	(0.000342)	(0.000428)	(0.000426)
Constant	0.317***	0.303***	0.303***
	(0.000986)	(0.00156)	(0.00156)
Control for Borrowers' Char.	Y	Y	Y
Control for Year Dummies	Y	Y	Y
Control for Loan Char.	Y	Y	Y
Observations	16,820	8,410	8,410
R-squared	0.932	0.937	0.937

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

main

Regression Results of Amount Requested on Past Outcomes

VARIABLES	(1) amount_request
second_loan	127.2
	(91.44)
debt_to_income_high	987.7***
	(92.55)
Constant	-1,372***
	(268.0)
Control for Borrowers' Char.	Y
Control for Year Dummies	Y
Control for Loan Char.	Y
Observations	16,820
R-squared	0.250

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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Positive Correlation of Defaults in Two Loans

VARIABLES	(1) default
first_closed_loan_default	5.008***
	(0.139)
borrower_rate	9.418***
	(3.126)
amount_request	3.97e-05***
	(1.02e-05)
debt_to_income_high	0.313***
	(0.118)
Constant	-5.475***
	(0.987)
Control for Borrowers' Char.	Y
Control for Year Dummies	Y
Control for Loan Char.	Y
Observations	4,822

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

main

Compare Default Probabilities for Two Closed Loans

VARIABLES	(1) default	(2) default	(3) default	(4) default
second_closed_loan	0.390***	0.359***	0.481***	0.456***
	(0.0480)	(0.0731)	(0.0863)	(0.149)
borrower_rate	13.10***	12.66***	16.09***	17.68***
	(1.347)	(1.979)	(2.238)	(3.678)
amount_request	3.70e-05***	5.92e-05***	6.47e-05***	8.06e-05***
	(4.73e-06)	(7.17e-06)	(9.04e-06)	(1.33e-05)
debt_to_income_high	0.221***	0.211***	0.195**	0.198
	(0.0508)	(0.0751)	(0.0873)	(0.137)
Constant	-4.572***	-4.659***	-5.960***	-6.472***
	(0.414)	(0.608)	(0.706)	(1.136)
Control for Borrowers' Char.	Y	Y	Y	Y
Control for Year Dummies	Y	Y	Y	Y
Control for Loan Char.	Y	Y	Y	Y
Observations	10,166	4,630	3,550	1,696

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Column 1: full sample
Column 2: borrowers whose second loans are not for debt consolidation
Column 3: borrowers whose initial FICO scores are below 600
Column 4: borrowers with long gaps between the starting dates of their two loans

Identification of Effort Choice Probabilities

- The requirement of two discrete state variables can be relaxed.
- I develop new identification strategies that are generally applicable to **dynamic structural models with unobserved choices** when only one state variable (continuous or discrete) is available. For details, see Xin (2017). main

- Suppose O_t is one continuous state variable.

$$\underbrace{f(O_t|c, X_t)}_{\text{identified}} = \sum_{e_t} f(O_t|e_t) f(e_t|c, X_t)$$

- Specify the outcome realization via a nonparametric function:

$$O_t = m(e_t) + \eta_t, \text{ where } \eta_t \perp e_t$$

- Using variations in moments of $O_t|c, X_t$, identify the unobserved choice probabilities and the unknown function $m(\cdot)$.

Estimation Results

Utility Primitives

Parameters	Notations	Estimates	Std. Err.
Risk aversion parameter	α	1.4981	0.0717
Effectiveness of effort parameter	β	2.3738	0.0189
Cost of effort (low)	θ_l	0.0657	0.0038
Cost of effort (high)	θ_h	0.8090	0.0322
Default cost (high)	$R_l - c_h$	-0.5321	0.0190
Default cost (low)	$R_l - c_l$	0.2370	0.0460
High revenue	R_h	1.4949	0.0059
Coef. of dti ratio in b's outside option dist.	v_x	0.0027	0.0125
Coef. of loan purpose in b's outside option dist.	v_d	-0.4797	0.0127
Mean of lender's outside option	μ_0	0.0005	0.0010
Std. Err. of lender's outside option	σ_μ	0.0261	0.0005

main

Estimation Results

Prob. of Small Cost of Effort

Parameters	Estimates	Std. Err.
$Pr(\theta_l \mid c_h, A_h)$	0.8913	0.0126
$Pr(\theta_l \mid c_h, A_l)$	0.9960	0.0006
$Pr(\theta_l \mid c_l, A_h)$	0.6663	0.0123
$Pr(\theta_l \mid c_l, A_l)$	0.6734	0.0118

- Borrowers who have higher default costs and request loans of a lower amount are more likely to draw smaller cost of effort.

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Estimation Results

Prob. of High Type

$Pr(c_h \vert$ Observables)		Estimates	Std. Err.
other purpose	low dti, low credit grade	0.2335	0.0092
	high dti, low credit grade	0.2461	0.0092
	low dti, high credit grade	0.5326	0.0099
	high dti, high credit grade	0.5870	0.0122
debt consolidation	low dti, low credit grade	0.3219	0.0095
	high dti, low credit grade	0.3311	0.0094
	low dti, high credit grade	0.7320	0.0099
	high dti, high credit grade	0.7323	0.0110

- Borrowers with high credit grades and use the loans for debt consolidation are more likely to be "good borrowers".
- Conditional on different debt-to-income ratios, the proportions of high type do not seem to vary much.

main

Estimation Results

State Transition Prob.

Parameters	Estimates	Std. Err.
$Pr(\text{low dti } \vert c_h, \text{ low dti})$	0.6430	0.0099
$Pr(\text{high dti } \vert c_h, \text{ high dti})$	0.8973	0.0089
$Pr(\text{low dti } \vert c_l, \text{ low dti})$	0.4979	0.0102
$Pr(\text{high dti } \vert c_l, \text{ high dti})$	0.9170	0.0079

- High debt-to-income ratios are persistent.
- Type-specific effects: Borrowers with high default costs are more likely to stay with low debt-to-income ratios.

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Belief of High Type Proportion

Observables		Original	After 1st Loan	After 2nd Loan
other purpose	low dti, low credit grade	0.2335	0.4754	0.6396
	high dti, low credit grade	0.2461	0.3841	0.5086
	low dti, high credit grade	0.5326	0.6072	0.6811
	high dti, high credit grade	0.5870	0.5202	0.5554
debt cons.	low dti, low credit grade	0.3219	0.5436	0.7016
	high dti, low credit grade	0.3311	0.4517	0.5774
	low dti, high credit grade	0.7320	0.6759	0.7404
	high dti, high credit grade	0.7323	0.5813	0.6201

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