P2P Lending: Information Externalities, Social Networks and Loans' Substitution

Ester Faia* & Monica Paiella**

** Goethe University Frankfurt and CEPR. **University of Naples Parthenope*

P2P lending developments

- P2P lending platforms: markets for consumer and business debt where lenders and borrowers match and trade directly, hence in absence of intermediation
- Emerged in 2005 (US Prosper). Highest growth in the aftermath of the crisis, in coincidence with the *fragility* of the banking system as well as the distrust of investors towards it
- Success story: relatively low loan rates and default rates down from 34% in 2009 to very low figures

Main features of P2P markets

- Dis-intermediated, uncollateralized debt markets:
  - Asymmetric information
  - Availability of costless public signals that facilitate screening and mitigate lemon's market adverse selection
    - Hard information (FICO scores and other official credit-worthiness measures);
    - Soft information (e.g. recommendation from other investors);
    - Borrowers' self reports
  - Innovation in screening technology: machine learning collects and makes information public, mitigating adverse selection

P2P lending markets: costs and benefits

- Borrowers:
  - Lower costs, no need of collateral guarantees, no risk of early liquidation due to banks' liquidity shortages
  - Higher interest rates
- Lenders:
  - Attractive returns (compared to standard investment by banks) and no risk of *haircut* due to banks' distress
  - More risk (in the absence of a delegated monitor that screens and monitors projects)

Our analysis

- General equilibrium model (focus on price formation)
  1. Households/investors/lenders solve dynamic portfolio problem
  2. Borrowers seek funds for projects of heterogeneous and unobservable quality

  3.a P2P market (adverse selection):
  - Distribution of loan rates with risk and information premia
  - Public signals reduce adverse selection and information premia

  3.b Traditional banks: competitive; subject to risk of distress

- Empirical analysis: US data from Prosper and Lending Club (merged with measures of bank fragility)

Focus of the paper

- Assessment of the impact of information on P2P loan returns
  - Loan returns capture both default risks of projects and information premia due to asymmetric information

  Main result: signals, of both *hard and soft* type, mitigate information premia

- Assessment of potential substitutability between digital platforms and traditional banking
  - Most of the increase in participation in the platforms seems to be due to erosion of trust in and perception of fragility of traditional banking sector

  Main result: higher banking sector fragility (captured by currency-deposit ratio and bank failures) lowers P2P loan returns

Related literature 1/2

- Focus on the relationship between borrowers' attributes and listing outcomes in P2P markets
  - Pope and Syndor [2011, JHR] and Ravina [2012]: discrimination
  - Duarte, Siegel and Young [2012, RFS]: trust
  - Paravisini, Ravina and Rappoport [2017, MS]: risk aversion
- On asymmetric information and signals in P2P markets:
  - Freedman and Jin [2016]: learning by doing by returning lenders
  - Iyer, Khwaja, Luttmer and Shue [2016, MS] and Kawai, Onishi and Uetake [2016]: interest rates as a signal of creditworthiness

Related literature 2/2

- No studies of the substitution between traditional banking and digital intermediation
- Literature on markets vs. banks (Allen and Gale, 1999 JFI; 2000)
  - In markets the relevant friction is information asymmetry.
    The crucial innovation of the P2P markets is the availability of public signals that lessen the information asymmetry.

Households/Lenders

$$max E_0 \sum_{t=0}^{\infty} \beta^t U(C_t)$$

$$s.t. \quad C_t + r_t X_t + D_t \leq Y_t + X_{t-1} + R_{t-1}^d D_{t-1}$$

$$r_t X_t = \alpha_t W_t; \quad D_t = (1 - \alpha_t)\mathrm{W_t}$$

Households/Lenders

Price of P2P loans

Gross return on deposits

$$max E_0 \sum_{t=0}^{\infty} \beta^t U(C_t)$$

$$s.t. \quad C_t + r_t X_t + D_t \leq Y_t + X_{t-1} + R_{t-1}^d D_{t-1}$$

$$r_t X_t = \alpha_t W_t; \quad D_t = (1 - \alpha_t) \mathrm{W_t}$$

P2P loans

Bank deposits

Borrowers

- Risk neutral
- Projects' quality is heterogeneous:

  succeed and deliver R^I_t, with probability p^i, or fail and return zero:

$$p^i \in \mathbb{U}\left[\bar{p} - \frac{\varepsilon}{2}; \bar{p} + \frac{\varepsilon}{2}\right]$$

  p^i is know to borrowers, but not to lenders

Banks 1/2

- Costly screening technology: pay μ and learn project's quality (p^i) perfectly
- Fragility risk, from liquidity shortage (e.g. run or liquidity freezes) or failure, with probability ζ_t
- With probability ζ_t, bank liquidate projects early at a discount, θ
- Given the risk of distress, banks' expected return from project i is $\bar{\theta}_t p^i R_t^I$,

where: $\bar{\theta} = \theta\zeta_t + (1 - \zeta_t)$

Banks 2/2

- Banks are fully competitive; they fund loans with deposits; all project returns are rebated to depositors
- Banks realize returns only if projects are successful, but they have to pay depositors and the screening cost in any case
- In case of distress, absent insurance on banks' demand deposits, the loss from project early liquidation is eventually transferred onto depositors
- Depositors' expected return from deposits is $\bar{\theta}_t R_t^d$

Signals and pricing

- Signals (as in Ruckes 2004, Petriconi 2016):

$$\sigma_{i,\lambda} = \begin{cases} s_i = p^i & with\ probability\ \lambda \\ s_i \sim \mathbb{U}\left[\bar{p} - \frac{\varepsilon}{2}; \bar{p} + \frac{\varepsilon}{2}\right] & with\ probability\ 1-\lambda \end{cases}$$

Signals and pricing

- Signals (as in Ruckes 2004, Petriconi 2016):

$$\sigma_{i,\lambda} = \begin{cases} s_i = p^i & with\ probability\ \lambda \\ s_i \sim \mathbb{U}\left[\bar{p} - \frac{\varepsilon}{2}; \bar{p} + \frac{\varepsilon}{2}\right] & with\ probability\ 1-\lambda \end{cases}$$

Fully informative signal

Signals and pricing

- Signals (as in Ruckes 2004, Petriconi 2016):

$$\sigma_{i,\lambda} = \begin{cases} s_i = p^i & with\ probability\ \lambda \\ s_i \sim \mathbb{U}\left[\bar{p} - \frac{\varepsilon}{2}; \bar{p} + \frac{\varepsilon}{2}\right] & with\ probability\ 1-\lambda \end{cases}$$

Un-informative signal

Signals and pricing

- Signals (as in Ruckes 2004, Petriconi 2016):

$$\sigma_{i,\lambda} = \begin{cases} s_i = p^i & with\ probability\ \lambda \\ s_i \sim \mathbb{U}\left[\bar{p} - \frac{\varepsilon}{2}; \bar{p} + \frac{\varepsilon}{2}\right] & with\ probability\ 1-\lambda \end{cases}$$

- Once they receive the signal, lenders update their estimate of project's success probability which, given Bayesian updating of beliefs, results in the following posterior expectation:

$$E_t\left(p^i \middle| \sigma_{i,\lambda} = s_i\right) = \lambda s_i + (1-\lambda)\bar{p}$$

and the expected return from the project is: $E_t\left(p^i \middle| \sigma_{i,\lambda} = s_i\right) R_t^I$

No arbitrage condition 1/2

- From households/lenders FOCs for P2P loans (X_t) and bank deposits (D_t),
- allowing for bank probability of distress (which affects lenders expected return from deposits, $\bar{\theta}_t R_t^d$) …
- allowing for signals (which affect the expected return from P2P loans, $E_t\left(p^i \middle| \sigma_{i,\lambda} = s_i\right) R_t^I$),
- we obtain the following optimality condition (for given signal precision, λ):

$$E_t\left(p^i \middle| \sigma_{i,\lambda} = s_i\right) R_t^I = \frac{1}{\beta} E_t \left\{ \frac{U'(C_t)}{U'(C_{t+1})} \right\} = \bar{\theta}_t R_t^d$$

No arbitrage condition 2/2

- The following optimality condition (for given signal precision, λ):

$$E_t\left(p^i \middle| \sigma_{i,\lambda} = s_i\right) R_t^I = \frac{1}{\beta} E_t \left\{ \frac{U'(C_t)}{U'(C_{t+1})} \right\} = \bar{\theta}_t R_t^d$$

  - It determines the P2P project that will be funded at the margin (threshold)
  - **Three testable predictions** regarding P2P market liquidity and prices

Substitution between banks and platforms

1) An increase in the risk of a shock in the banking sector (ζ) raises platform liquidity and lower P2P loans' returns (because it lowers expected defaults)

   An increase in ζ decreases the threshold of projects funded through P2P $\rightarrow$ more projects go to the platform $\rightarrow$ participation increases

   Intuition: more borrowers with good projects are expected to choose P2P markets and more lenders do too.
   Loan spreads decrease as lenders require lower returns on P2P loans.

$$E_t\left(p^i \middle| \sigma_{i,\lambda} = s_i\right) R_t^I = \frac{1}{\beta} E_t \left\{ \frac{U'(C_t)}{U'(C_{t+1})} \right\} = \overline{\boldsymbol{\theta_t}} R_t^d$$

Information and selection

2) An increase in signal's precision, i.e. in the probability that the signal is informative, λ, increases platform liquidity, and reduces information premia.

   Intuition: if signal precision increases, lenders are better at discerning the quality of projects. This reduces adverse selection and lenders are willing to receive lower returns.

3) An increase in the average quality of projects, $\bar{p}$, increases platform liquidity and lowers loans' returns.

Prosper Data (2006-2014)

- Borrower personal profiles: amount requested, interest rate, term and purpose of loan

  + independently verified information on credit history (FICO score, open credit lines, delinquencies), income and other debts

- Prosper creates social networks:
  - links borrowers in groups (tied by geography, common interests, or common loan purpose)
  - collects endorsements of other Prosper members (friends)

Prosper loans

- Loan size – Min: $1,000; max: $35,000
- Term – 12, 36, 60 months
- Fees of up to 2 percent of loan amount
- FICO>520
- Minimum bid: $50
- *In 2009, Prosper registered with the SEC and changed its business model from eBay-style auctions to rates determined by proprietary algorithm based on credit history, ect.*

Summary statistics

Year of the loan	2006	2007	2008	2009	2010	2011	2012	2013	2014
Borrower lending rate	0.191	0.177	0.186	0.193	0.213	0.230	0.220	0.184	0.153
	(0.069)	*(0.064)*	*(0.085)*	*(0.091)*	*(0.098)*	*(0.079)*	*(0.077)*	*(0.061)*	*(0.054)*
Estimated effective yield				0.103	0.106	0.213	0.201	0.162	0.134
				(0.052)	*(0.055)*	*(0.074)*	*(0.071)*	*(0.054)*	*(0.048)*
Size of loans	4763	7050	6022	4355	4767	6692	7834	10545	11912
	(4404)	*(6126)*	*(5400)*	*(4070)*	*(3714)*	*(4273)*	*(5527)*	*(6575)*	*(6684)*
Term (months)	36	36	36	36	36	37	43	45	44
Time for funding (median)	9	11	10	14	12	10	8	6	5
Median investment	96	58	45	29	35	78	89	3,000	9,000
No. of investors (median)	36	92	95	93	103	55	53	1	1
Loans by 1 investor (%)	2	1	1	1	<1	1	2	51	75
For debt consolidation (%)		42	46	47	48	48	74	79	42
home improvement		5	9	10	11	11	6	4	5
business (%)		16	11	10	11	9	4	3	16
other (%)		37	34	33	30	32	16	14	37
# observations	5,906	11,460	11,552	2,047	5,652	11,228	19,553	33,910	11,734

Loan riskiness

Year of the loan	2006	2007	2008	2009	2010	2011	2012	2013	2014	Total
Completed	61%	61%	67%	85%	83%	49%	28%	7%	1%	34%
Current	-	-	-	-	-	29%	54%	89%	99%	49%
Past Due (1-120 days)	-	-	-	-	-	3%	4%	3%	-	2%
Chargedoff	16%	26%	24%	11%	14%	16%	12%	1%	-	11%
Defaulted	23%	14%	9%	4%	3%	3%	2%	0%	-	4%
	100%	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*

- Decline in loan riskiness: the share of loans classified as 'Charged off' or in 'Default' was relatively high at the onset of the platform, but has fallen significantly after 2009
- In 2014, US banks charged off or reported as delinquent 16.6 percent of all consumer loans (18.5 percent in 2013)

Hard and soft information about borrowers

Year of the loan	2006	2007	2008	2009	2010	2011	2012	2013	2014
Mean FICO score	609	654	674	715	714	709	711	708	703
Number of open credit lines		8	8	9	8	8	8	10	11
Number of credit inquiries	11	10	8	6	4	4	4	4	4
Borrowers w/ delinquencies (%)	52	39	23	11	14	21	20	15	10
Prosper credit rating				4.286	3.837	3.552	3.688	4.258	4.718
Estimated loss				0.075	0.093	0.097	0.091	0.073	0.062
Estimated return				0.103	0.103	0.115	0.110	0.088	0.073
Debt-income ratio	0.249	0.431	0.254	0.228	0.230	0.251	0.264	0.264	0.259
Monthly income	4,744	4,654	4,619	5,092	5,291	5,660	5,710	6,161	6,336
Borrowers in a group (%)	70	51	14	11	9	5	3	1	1
Borrowers w/ recomm. from Prosper friends %		17	18	8	6	3	2	1	<1
Borrowers w/ invest. from Prosper friends (%)		6	7	5	4	1	1	<1	<1
$ investment from friends (cond. on friends)		939	1017	713	773	572	429	233	298
Borrowers w/ previous Prosper loans %	-	4	15	43	34	34	28	19	10
# observations	5,906	11,460	11,552	2,047	5,652	11,228	19,553	33,910	11,734

OLS regressions of lending rates on loan characteristics

	All	Pre-SEC	Post-SEC
Loan size (thousands)	-0.090	-0.078	-0.102
	(0.001)***	(0.003)***	(0.001)***
Loan size^2 (thousands)	0.019	0.025	0.020
	(0.000)***	(0.001)***	(0.000)***
Term (months)	0.011	-	0.012
	(0.000)***		(0.000)***
Debt consolidation$^{(*)}$	0.004	0.014	0.004
	(0.001)***	(0.002)***	(0.001)***
Home improvement$^{(*)}$	-0.003	-0.006	-0.003
	(0.001)***	(0.003)*	(0.001)***
Business funding$^{(*)}$	0.008	0.002	0.010
	(0.001)***	(0.002)	(0.001)***
Adjusted R^2	**0.23**	0.12	0.28
N	107,549	23,425	84,124

Note: dummies for quarter of listing and state of residency are included

OLS regressions of lending rates on loan characteristics and signals

	All	Pre-SEC	Post-SEC	Pre-SEC	Post-SEC	Post-SEC
Loan size (thousands)	-0.043	0.016	-0.063	0.018	-0.063	-0.061
	(0.001)***	(0.002)***	(0.001)***	(0.002)***	(0.001)***	(0.001)***
Loan size (thousands)^2	0.010	0.003	0.015	0.002	0.015	0.014
	(0.000)***	(0.001)***	(0.000)***	(0.001)***	(0.000)***	(0.000)***
Term	0.009		0.011		0.011	0.012
	(0.000)***		(0.000)***		(0.000)***	(0.000)***
Debt consolidation$^{(*)}$	-0.002	-0.001	-0.001	-0.001	-0.001	-0.003
	(0.001)***	(0.001)	(0.001)**	(0.001)	(0.001)**	(0.001)***
Home improvement$^{(*)}$	0.000	0.001	0.000	0.001	0.000	0.004
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)***
Business funding$^{(*)}$	0.006	0.003	0.005	0.003	0.006	0.006
	(0.001)***	(0.002)*	(0.001)***	(0.002)*	(0.001)***	(0.001)***
FICO score (hundreds)	-0.070	-0.071	-0.073	-0.071	-0.073	-0.079
	(0.000)***	(0.001)***	(0.000)***	(0.001)***	(0.000)***	(0.000)***
Open credit lines (tens)	0.003	0.005	0.001	0.005	0.001	0.003
	(0.000)***	(0.001)***	(0.001)	(0.001)***	(0.001)	(0.001)***
Credit enquiries (tens)	0.017	0.009	0.024	0.009	0.025	0.030
	(0.000)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Current delinquencies$^{(*)}$	0.012	0.027	0.008	0.028	0.009	0.009
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Monthly income	-0.001	0.001	-0.001	-0.000	-0.001	-0.001
(thousands)	(0.000)***	(0.001)	(0.000)***	(0.000)	(0.000)***	(0.000)***
Debt/Income	0.012	0.003	0.027	0.004	0.027	0.029
	(0.001)***	(0.000)***	(0.002)***	(0.000)***	(0.002)***	(0.002)***
Group dummy$^{(*)}$				-0.005	-0.019	0.000
				(0.001)***	(0.001)***	(0.001)
Recommend + no invest$^{(*)}$				0.000	-0.025	-0.004
				(0.001)	(0.002)***	(0.002)*
Recommend + investm.$^{(*)}$				-0.019	-0.015	-0.008
				(0.002)***	(0.004)***	(0.004)**
Investm.+ no recomm$^{(*)}$				-0.045	-0.012	-0.008
				(0.007)***	(0.004)***	(0.004)
Previous Prosper loan$^{(*)}$						-0.042
						(0.000)***
Adjustment R^2	0.49	0.59	0.51	0.59	0.51	0.56
N	95,396	18,497	76,899	18,497	76,899	76,899

OLS regressions of lending rates on loan characteristics and signals

	All	Pre-SEC	Post-SEC	Pre-SEC	Post-SEC	Post-SEC
… …						
FICO score (hundreds)	-0.070	-0.071	-0.073	-0.071	-0.073	-0.079
	(0.000)***	(0.001)***	(0.000)***	(0.001)***	(0.000)***	(0.000)***
Open credit lines (tens)	0.003	0.005	0.001	0.005	0.001	0.003
	(0.000)***	(0.001)***	(0.001)	(0.001)***	(0.001)	(0.001)***
Credit enquiries (tens)	0.017	0.009	0.024	0.009	0.025	0.030
	(0.000)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Current delinquencies(*)	0.012	0.027	0.008	0.028	0.009	0.009
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Monthly income	-0.001	0.001	-0.001	-0.000	-0.001	-0.001
(thousands)	(0.000)***	(0.001)	(0.000)***	(0.000)	(0.000)***	(0.000)***
Debt/Income	0.012	0.003	0.027	0.004	0.027	0.029
	(0.001)***	(0.000)***	(0.002)***	(0.000)***	(0.002)***	(0.002)***
Group dummy(*)				-0.005	-0.019	0.000
				(0.001)***	(0.001)***	(0.001)
Recommend + no invest (*)				0.000	-0.025	-0.004
				(0.001)	(0.002)***	(0.002)*
Recommend + invest (*)				-0.019	-0.015	-0.008
				(0.002)***	(0.004)***	(0.004)**
Invest.+ no recomm (*)				-0.045	-0.012	-0.008
				(0.007)***	(0.004)***	(0.004)
Previous Prosper loan(*)						-0.042
						(0.000)***
Adjustment R^2	0.49	0.59	0.51	0.59	0.51	0.56
N	95,396	18,497	76,899	18,497	76,899	76,899

OLS regressions of lending rates on loan characteristics and signals

- Lending rates are decreasing in the FICO score, increasing in the number of credit lines and credit enquiries and for delinquent borrowers
- Once we control for credit risk, being part of group lowers the lending rate, by 0.5-2 p.p.
- Rates are lower for borrowers with funding from friends, by up to 4.5 p.p. before 2009, up to 1.5 p.p. after 2009
- Borrowers with prior loans pay 4 p.p less; the group dummy becomes insignificant and 'friends' variables coefficients become smaller

Lending rates and signal precision

	Income can be verified All	No open credit lines All	No state of residency Pre-SEC	No reason for borrowing Post-SEC
… …				
Income verifiable(*)	-0.024			
	(0.009)***			
No open credit lines		0.024		
		(0.003)***		
No US State(*)			0.018	
			(0.009)**	
No reason for borrowing(*)				0.006
				(0.001)***
FICO score	-0.070	-0.070	-0.070	-0.073
(hundreds)	(0.000)***	(0.000)***	(0.001)***	(0.000)***
Open credit lines	0.002		0.005	0.001
(tens)	(0.000)***		(0.001)***	(0.001)
Credit enquiries	0.017	0.017	0.008	0.024
(tens)	(0.000)***	(0.000)***	(0.001)***	(0.001)***
Current	0.012	0.011	0.026	0.008
delinquencies(*)	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Monthly income	-0.002	-0.001	-0.001	-0.001
(thousands)	(0.001)***	(0.000)***	(0.000)	(0.000)***
Income • Inc. verif. (*)	0.002			
	(0.001)**			
Debt/Income	-0.000	0.012	0.003	0.027
	(0.001)	(0.001)***	(0.000)***	(0.002)***
Debt/Income •	0.021			
Inc. is verif. (*)	(0.002)***			
Adjustment R^2	0.93	0.49	0.94	0.51
N	95,396	95,396	20,213	76,899

Lending rates and signal precision

- No official documentation for income: 8% of sample
  - Borrowers whose income is verifiable pay 1 p.p. less
- No open credit lines → cannot tell whether more or less risky: 1% of sample
  - Borrowers with no credit lines pay 2.4 p.p. more
- No state of residency: 30% of sample (pre-2009)
  - Borrowing rates 2 p.p. higher
- No reason for borrowing: 10% of sample (post 2009)
  - Borrowing rates 0.5 p.p. higher

Lending rates, **banking panics** and signals

	All	Pre-SEC	Pre-SEC	Post-SEC
… …				
Currency to deposits	-0.058	-0.115		-0.044
(previous yr average)	(0.010)***	(0.042)***		(0.010)**
Currency to deposits (% change)	-0.041	-0.012		-0.093
	(0.014)***	(0.022)		(0.012)***
Bank run(*)			-0.002	
			(0.001)**	
FICO score (hundreds)		-0.071	-0.071	-0.079
		(0.001)***	(0.001)***	(0.000)***
Open credit lines (tens)		0.005	0.005	0.003
		(0.001)***	(0.001)***	(0.001)***
Credit enquiries (tens)		0.009	0.009	0.030
		(0.001)***	(0.001)***	(0.001)***
Current delinquencies(*)		0.028	0.028	0.009
		(0.001)***	(0.001)***	(0.001)***
Group dummy(*)		-0.005	-0.005	0.000
		(0.001)***	(0.001)***	(0.001)
Recommend + no investm. (*)		0.000	0.000	-0.004
		(0.001)	(0.001)	(0.002)*
Recommend + investm. (*)		-0.019	-0.019	-0.008
		(0.002)***	(0.002)***	(0.004)**
Investm.+ no recommend. (*)		-0.045	-0.045	-0.007
		(0.007)***	(0.007)***	(0.004)
Previous Prosper loan(*)		-0.002	-0.002	-0.041
		(0.001)	(0.001)	(0.000)***
Adjustment R^2	0.23	0.59	0.59	0.56
N	107,549	18,497	18,497	76,899

Lending rates and banking panics

- Consistent with the predictions of our model, fragility of the banking sector increases investors participation in the platform; increased liquidity induces a decline in the rates
- The currency-deposit ratio varies over time. We include state and quarter dummies to control for aggregate shocks
- If the currency deposit ratio raises by 20%, rates drops by 1 p.p.
- Dummy for bank runs: small, but significant coefficient
- Small effect due to substitution through other instruments (besides P2P platform)

Bank runs

1. August 2007, Countrywide Financial suffered a bank run as a consequence of the subprime mortgage crisis;
2. March 2008, Bear Stearns suffered a run. Although it was not an ordinary deposit-taking bank, it had financed huge long-term investments by selling short-maturity bonds, making it vulnerable to panic on the part of its bondholders;
3. June 2008, mortgage lender IndyMac Bank suffered a run when a warning was issued that it might not be viable;
4. September 2008, Washington Mutual, the largest US savings and loan and the sixth-largest financial institution, was shut down due to a massive run.

Lending rates, **banking failures** and signals

	All	Pre-SEC	Post-SEC
… …			
Bank failures$_{mo-1}$ (*)	-0.001	-0.007	0.000
	(0.002)	(0.005)	(0.001)
Bank failures$_{mo-2}$ (*)	-0.006	-0.003	-0.003
	(0.002)***	(0.005)	(0.001)**
Bank failures$_{mo-3}$ (*)	-0.003	0.000	-0.002
	(0.002)*	(0.008)	(0.001)*
FICO score (hundreds)		-0.071	-0.079
		(0.001)***	(0.000)***
Open credit lines (tens)		0.005	0.003
		(0.001)***	(0.001)***
Credit enquiries (tens)		0.009	0.030
		(0.001)***	(0.001)***
Current delinquencies (*)		0.028	0.009
		(0.001)***	(0.001)***
Group dummy (*)		-0.005	-0.000
		(0.001)***	(0.001)
Recommend + no investm. (*)		0.000	-0.004
		(0.001)	(0.002)*
Recommend + investm. (*)		-0.019	-0.008
		(0.002)***	(0.004)**
Investm.+ no recommend. (*)		-0.045	-0.008
		(0.007)***	(0.004)*
Previous Prosper loan (*)		-0.002	-0.042
		(0.001)	(0.000)***
Adjustment R^2	0.23	0.59	0.56
N	107,549	18,497	76,899

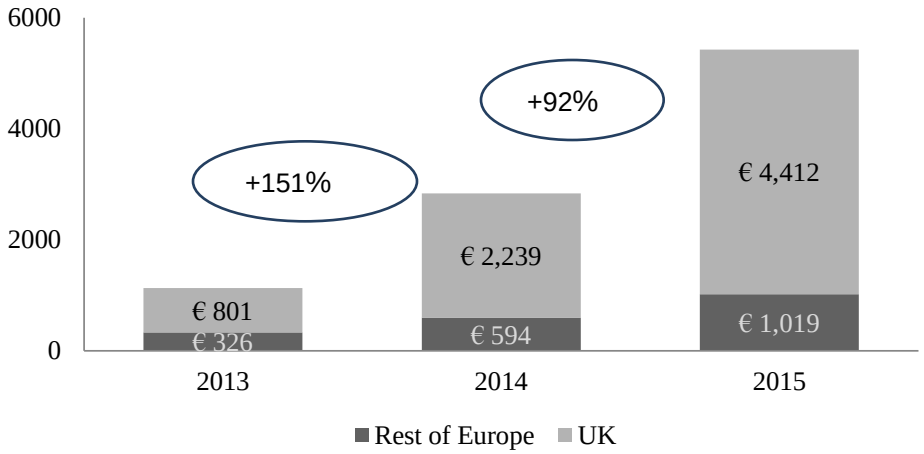
Concluding remarks

- P2P lending has experienced an impressive growth and has penetrated most markets including high growth ones like China
- Despite the lack of delegated monitor and the potential costs of asymmetric information, data suggest that it is performing well relatively to traditional banking, thanks to…

1. The digital technology allows *costless* access to information which increases market transparency and mitigates information asymmetry
2. In times of bank distress the platforms provide a valuable form of borrowing and investment substitution that improves risk-sharing

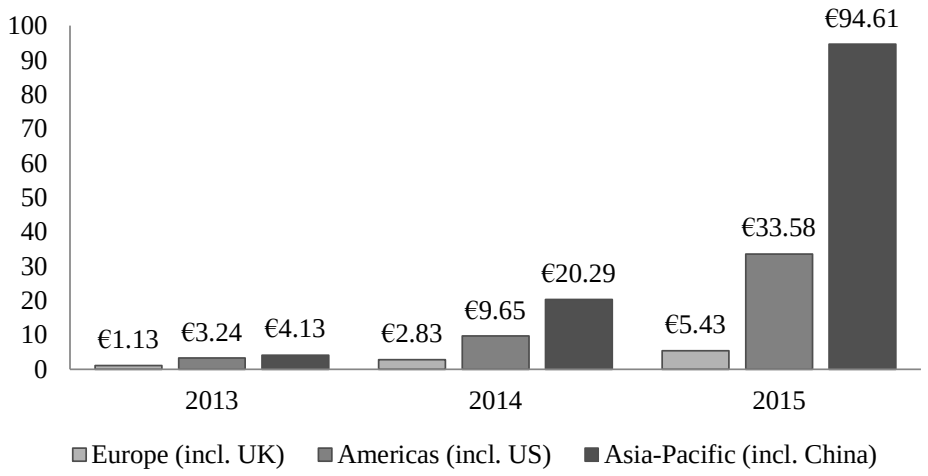
THANK YOU!

European Online Alternative Finance Market Volumes 2013-2015 (€ millions)



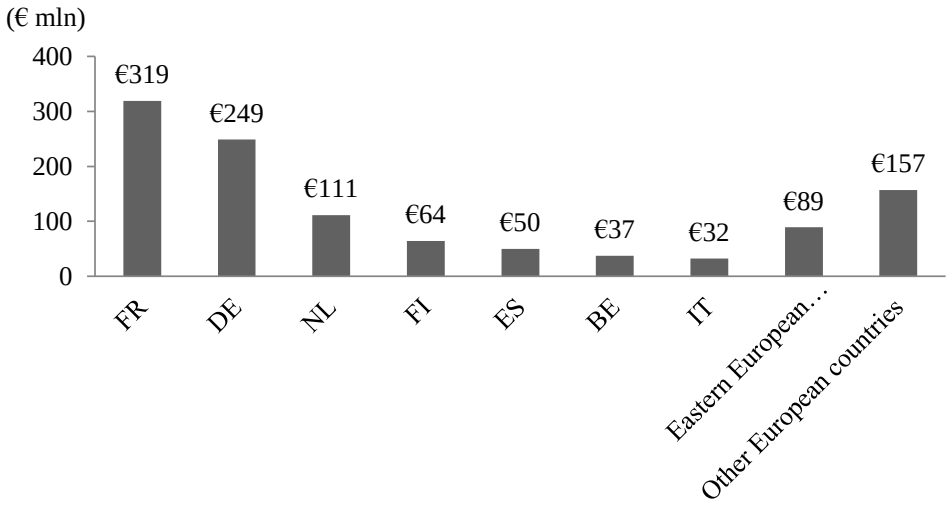
Source: KPMG, Sustaining Momentum. The 2nd Alternative Finance Industry Report (Sept. 2016)

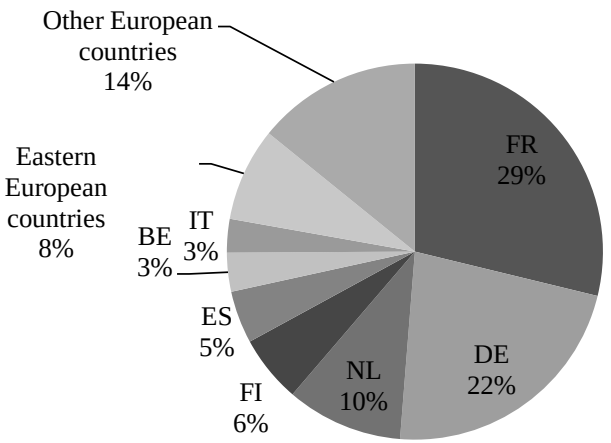
Online Alternative Finance Market Volumes 2013-2015, by region (in € billions)



Source: KPMG, Sustaining Momentum. The 2nd Alternative Finance Industry Report (Sept. 2016)

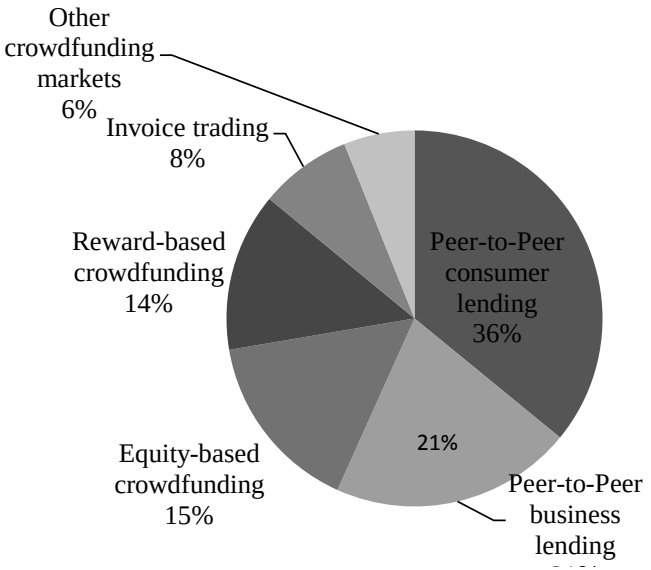
Online Alternative Finance Market in Europe by Country (2015, excl. UK)





Source: KPMG, Sustaining Momentum. The 2nd Alternative Finance Industry Report (Sept. 2016)

Market Shares by Alternative Finance Models in Europe (2015, excl. UK)



Source: KPMG, Sustaining Momentum. The 2nd Alternative Finance Industry Report (Sept. 2016)