Peer-to-Peer Lenders versus Banks: Substitutes or Complements?

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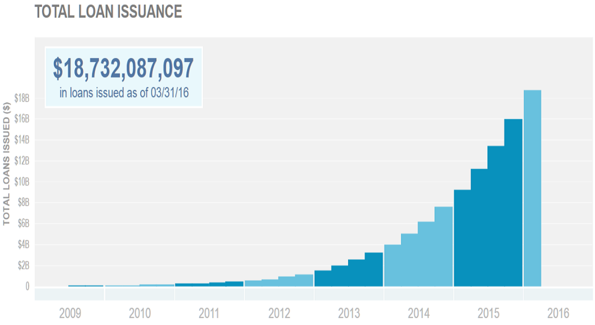
U.S. P2P Market

- FinTech lenders account for 30% of the unsecured installment loan sector in 2016



Research Question

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- **Challenge**: P2P borrower's access to equivalent bank lending is unobservable

- **Solution**: Exogenous (negative) shock to bank credit supply
  $\Rightarrow$ Does the quality of P2P borrower pool improve or decline?

Literature

- **P2P investors**
  - Herding (Duarte, Siegel, and Young 2012; Lin, Prabhala and Viswanathan 2012); Lending in relation to borrower characteristics, e.g. appearance, disclosure, and social networks (Kim and Viswanathan 2016; Zhang and Liu 2012)

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- **Information production and efficiency** (Franks, Serrano-Velarde, and Sussman 2016; Balyuk 2016; Iyer, Khwaja, Luttmer and Shue 2015)

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- **Information production and efficiency** (Franks, Serrano-Velarde, and Sussman 2016; Balyuk 2016; Iyer, Khwaja, Luttmer and Shue 2015)
- **P2P lending in relation to bank lending**
  - FinTech lenders serve risky borrowers in residential lending market (Buchack, Matvos, Piskorski and Seru, 2017WP) and in consumer credit market in Germany and China (De Roure, Pelizzon, and Thakor 2018WP; Liao, Wang, Xiang, and Zhang, 2017WP)
  - U.S. banks lose market share to P2P lenders (Wolfe and Yoo, 2017WP)

Key findings

- P2P platforms <u>substitute</u> banks and do not go beyond the customer base of banks
- P2P platforms <u>complement</u> banks by providing small-size loans

Plan

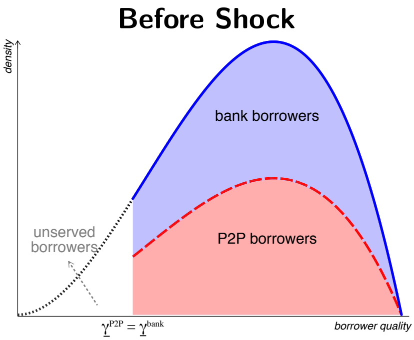
Assumptions

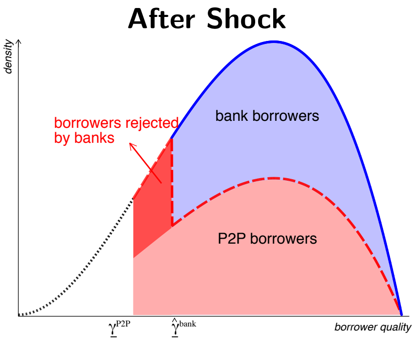
- A pool of borrowers with heterogenous quality γ
- Banks and P2P platforms serve all borrowers with sufficient quality:

$$\gamma \geqslant \underline{\gamma}^{bank} \quad or \quad \gamma \geqslant \underline{\gamma}^{P2P}$$

- Of borrowers with access to bank credit and P2P credit, a fraction α choose P2P

Substitutes

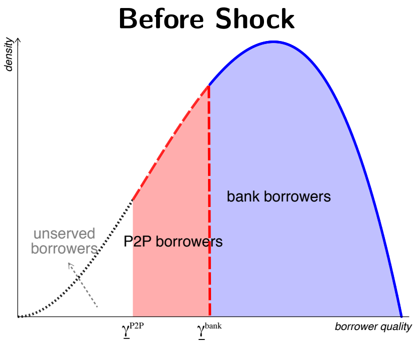


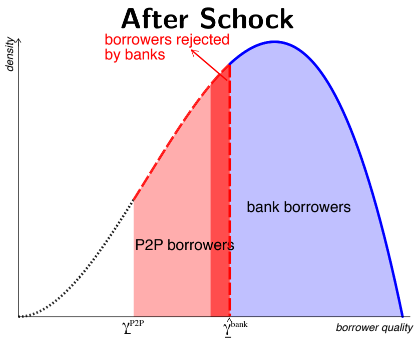


Banks and P2P serve the same borrower segment

Banks cut lending to low-quality borrowers

Complements





P2P serves low-quality borrowers

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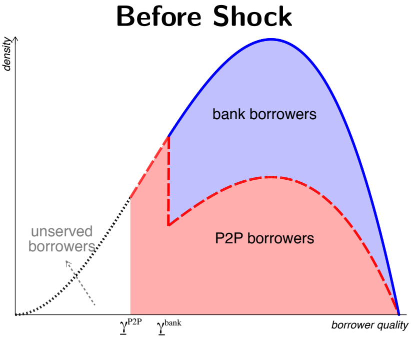
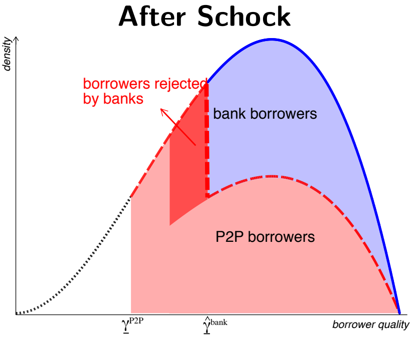
An intermediate case



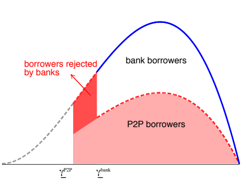


P2P serves the same borrower segment as bank & low quality borrowers

Banks cut lending to low-quality borrowers

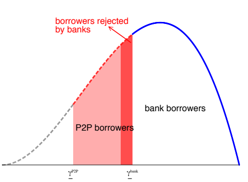
Predictions

Case I. “Substitute”



(1) Volume: P2P loan volume ↑

Case II. “Complement”



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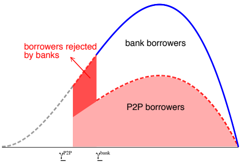

(1) Volume: P2P loan volume ↑

(2) Quantiles: mean and quantiles ↓

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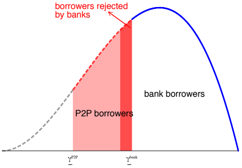

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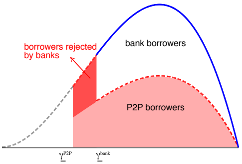

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(3) Frequency: higher frequency at the left tail

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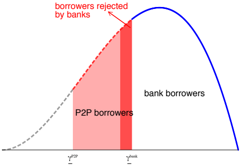

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Identification: Shock to local bank credit supply

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  - FAS 166/167 (2011) ⇒ Banks consolidate $400bn off-B/S assets (of which 80% are revolving loans)
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    - Reduce lending to small businesses by 16% (Dou, 2017)
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- **Stage 2**: Effects on P2P borrower distribution

$$Percentile^{N}_{c,t} = \beta\, Treated_c \times Post_t + Controls_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t}$$

$$N \in \{5, 15, 25, ..., 95\}$$

$$\left.\begin{array}{l} \beta > 0 \Rightarrow \textit{complements} \\ \beta < 0 \Rightarrow \textit{substitutes} \end{array}\right\} \text{opposite}$$

Plan

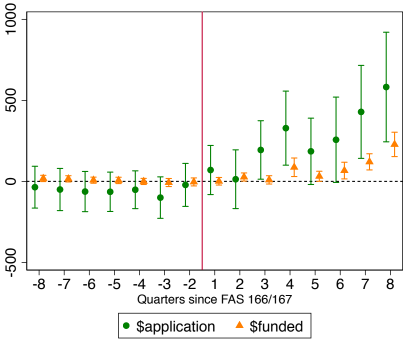
Data

- **LendingClub data (2009-2012)**
  - Loan level: size, borrower location, loan characteristics
  - County level: total volume, distribution of quality and size
  - Borrower quality:
    (1) FICO score
    (2) Alternative measure (using FICO, DTI ratio, and employment history)
- **FAS 166/167**:
  - Call Reports: amount of consolidated assets
  - Summary of Deposits: bank branches

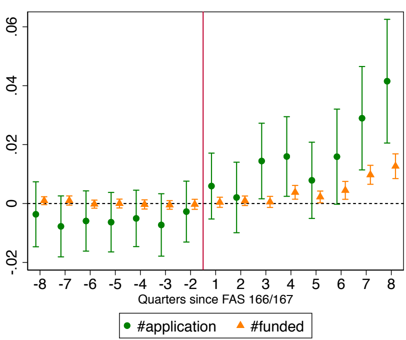
Prediction 1: P2P loan volume

$$y_{c,t} = Treated_c \times \sum_{t=-8}^{t=8} \beta_t D_t + Controls_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t}$$

Dollar amount ($)



Number of loans (#)



Prediction 1: P2P loan volume - cont'd

	Applications		Originations	
	Amount($)	Number(#)	Amount($)	Number(#)
	(1)	(2)	(3)	(4)
Treated × Post	1107.69***	0.07***	300.54***	0.02***
	(2.89)	(2.92)	(6.31)	(4.74)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
N	11,726	11,726	11,726	11,726
R^2	0.710	0.756	0.532	0.557

- Per thousand inhabitants in the county:
  - Application volume: +\$1,100 (+42%)
  - Origination volume: +\$300 (+150%)

Prediction 2: Quantiles of P2P borrower quality

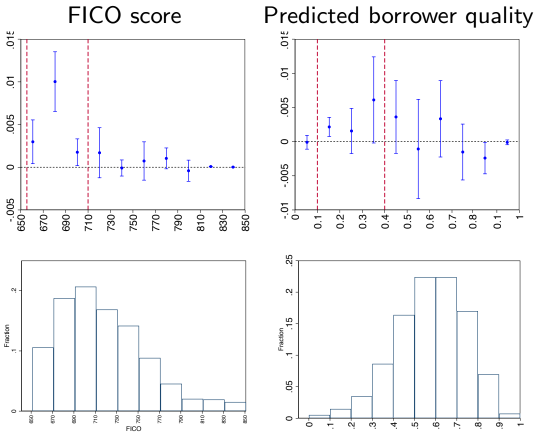
$$Quantile^{N}_{c,t} = \beta \, Treated_c \times Post_t + Controls_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t}$$

	Percentile										Mean
	5th	15th	25th	35th	45th	55th	65th	75th	85th	95th	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A. FICO score											
Treated × Post	-2.36	-0.32	-0.05	-2.40	-2.15	-8.68***	-7.00**	-8.79**	-6.72*	-1.18	-3.71
	(-0.74)	(-0.10)	(-0.02)	(-0.75)	(-0.68)	(-2.61)	(-2.31)	(-2.38)	(-1.71)	(-0.29)	(-1.56)
Panel B. Predicted borrower quality											
Treated × Post	-0.05***	-0.02	-0.01	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.01	-0.02
	(-3.06)	(-1.22)	(-0.40)	(-0.84)	(-0.53)	(-1.54)	(-1.12)	(-1.59)	(-1.35)	(-0.46)	(-1.40)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059

- Negative coefficients: distribution shifts to the left ("substitute")

Prediction 3: Frequency distribution of borrower quality

$$Frequency^{N}_{c,t} = \beta\, Treated_c \times Post_t + Controls_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t}$$



- New borrowers fall in the left tail of the distribution (“substitute”)

Prediction 2: Quantiles of loan size

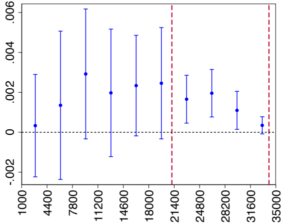
$$Quantile^{N}_{c,t} = \beta Treated_c \times Post_t + Controls_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t}$$

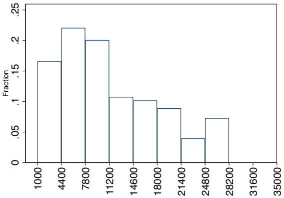
	Percentile										Mean
	5th (1)	15th (2)	25th (3)	35th (4)	45th (5)	55th (6)	65th (7)	75th (8)	85th (9)	95th (10)	(11)
Treated × Post	-431.2	133.1	539.8	315.9	782.4	122.9	860.9	955.8	1562.9**	3869.7***	1066.0**
	(-0.77)	(0.24)	(1.00)	(0.56)	(1.36)	(0.21)	(1.46)	(1.43)	(2.05)	(4.82)	(2.04)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059

- Positive coefficients: distribution shifts to the right ("complement")

Prediction 3: Frequency distribution of loan size

$$Frequency^{N}_{c,t} = \beta Treated_c \times Post_t + Controls_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t},$$





- New borrowers fall in the right tail of the distribution
- Consistent with the "complement" case

Excluded Alternative Explanations

- The deterioration in P2P borrower quality post shock is not driven by:
  - time/location-specific LendingClub pricing policy
  - time/location-specific investor's funding behavior
  - change in demographics or local economic conditions

Conclusion

- P2P platforms substitute banks by serving infra-marginal bank borrowers
- They also complements banks by providing small loans
- The credit expansion occurs among borrowers <u>with</u> access to bank credit