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

- Does P2P lending mainly serve borrowers under-served by banks or those who could have obtained credit from banks?
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- **Challenge**: P2P borrower’s access to equivalent bank lending is unobservable
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- **Challenge**: P2P borrower’s access to equivalent bank lending is unobservable

- **Solution**: Exogenous (negative) shock to bank credit supply ⇒ 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)
Literature

- **P2P investors**
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- **Information production and efficiency** ([Franks, Serrano-Velarde, and Sussman 2016; Balyuk 2016; Iyer, Khwaja, Luttmer and Shue 2015](#))


Literature

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

Introduction

Research Question

Research Design

Assumptions

Conceptual Framework

Identification

Data and Results

Data

Results
Assumptions

- A pool of borrowers with heterogenous quality $\gamma$

- Banks and P2P platforms serve all borrowers with sufficient quality:

  $\gamma \geq \gamma^{bank}$ or $\gamma \geq \gamma^{P2P}$

- Of borrowers with access to bank credit and P2P credit, a fraction $\alpha$ choose P2P
Substitutes

Before Shock

Banks and P2P serve the same borrower segment

After Shock

Banks cut lending to low-quality borrowers
Complements

Before Shock

P2P serves low-quality borrowers

After Shock

Banks cut lending to low-quality borrowers
An intermediate case

**Before Shock**

- P2P borrowers
- Bank borrowers
- Unserved borrowers

**After Shock**

- P2P borrowers
- Bank borrowers
- Borrowers rejected by banks

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”
(1) Volume: P2P loan volume ↑
Predictions

Case I. “Substitute”

(1) Volume: P2P loan volume ↑
(2) Quantiles: mean and quantiles ↓

Case II. “Complement”

(1) Volume: P2P loan volume ↑
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Predictions

Case I. “Substitute”

(1) Volume: P2P loan volume ↑
(2) Quantiles: mean and quantiles ↓
(3) Frequency: higher frequency at the left tail

Case II. “Complement”

(1) Volume: P2P loan volume ↑
(2) Quantiles: mean and quantiles ↑
(3) Frequency: higher frequency at the right tail
Identification: Shock to local bank credit supply

- **Stage 1**: Regulatory shock to bank credit supply

  - Banks consolidate $400bn off-B/S assets (of which 80% are revolving loans)
  - Treated banks:
    - Reduce lending to small businesses by 16% (Dou, 2017)
    - Improve quality of credit card loans (Tian and Zhang, 2016)
  - Exposure to FAS 166/167 varies across counties
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- **Stage 2**: Effects on P2P borrower distribution

\[
Percentile_{c,t}^{N} = \beta Treated_{c} \times Post_{t} + Controls_{c,t} + \gamma_{c} + \sigma_{t} + \epsilon_{c,t}
\]

\[N \in \{5, 15, 25, ..., 95\}\]

\[
\beta > 0 \Rightarrow \text{complements} \notag \text{ opposite} \notag \\
\beta < 0 \Rightarrow \text{substitutes}
\]
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- **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

\[ y_{c,t} = Treated_c \times \sum_{t=-8}^{t=8} \beta_t D_t + Controls_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t} \]
Prediction 1: P2P loan volume - cont’d

<table>
<thead>
<tr>
<th>Applications</th>
<th>Originations</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Amount($)</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Treated × Post</td>
<td>1107.69***</td>
</tr>
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<td></td>
<td>(2.89)</td>
</tr>
</tbody>
</table>

- 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
- $^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

\[ \text{Quantile}_{c,t}^N = \beta \text{Treated}_c \times \text{Post}_t + \text{Controls}_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t} \]

### Panel A. FICO score

<table>
<thead>
<tr>
<th>Percentile</th>
<th>5th (1)</th>
<th>15th (2)</th>
<th>25th (3)</th>
<th>35th (4)</th>
<th>45th (5)</th>
<th>55th (6)</th>
<th>65th (7)</th>
<th>75th (8)</th>
<th>85th (9)</th>
<th>95th (10)</th>
<th>Mean (11)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treated × Post</td>
<td>-2.36 (-0.74)</td>
<td>-0.32 (-0.10)</td>
<td>-0.05 (-0.02)</td>
<td>-2.40 (-0.75)</td>
<td>-2.15 (-0.68)</td>
<td>-8.68*** (-2.61)</td>
<td>-7.00** (-2.31)</td>
<td>-8.79** (-2.38)</td>
<td>-6.72* (-1.71)</td>
<td>-1.18 (-0.29)</td>
<td>-3.71 (-1.56)</td>
</tr>
</tbody>
</table>

### Panel B. Predicted borrower quality

<table>
<thead>
<tr>
<th>Controls</th>
<th>Y</th>
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<th>Y</th>
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<td>Year FE</td>
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<td>County FE</td>
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- Negative coefficients: distribution shifts to the left (“substitute”)
Prediction 3: Frequency distribution of borrower quality

\[ \text{Frequency}_{c,t}^N = \beta \text{Treated}_c \times \text{Post}_t + \text{Controls}_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t} \]

- New borrowers fall in the left tail of the distribution ("substitute")
Prediction 2: Quantiles of loan size

\[ \text{Quantile}^{N}_{c,t} = \beta \text{Treated}^{c} \times \text{Post}^{t} + \text{Controls}^{c,t} + \gamma^{c} + \sigma^{t} + \varepsilon^{c,t} \]

<table>
<thead>
<tr>
<th>Percentile</th>
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<tr>
<td>Treated × Post</td>
<td>-431.2</td>
<td>133.1</td>
<td>539.8</td>
<td>315.9</td>
<td>782.4</td>
<td>122.9</td>
<td>860.9</td>
<td>955.8</td>
<td>1562.9**</td>
<td>3869.7***</td>
<td>1066.0**</td>
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<td></td>
<td>(-0.77)</td>
<td>(0.24)</td>
<td>(1.00)</td>
<td>(0.56)</td>
<td>(1.36)</td>
<td>(0.21)</td>
<td>(1.46)</td>
<td>(1.43)</td>
<td>(2.05)</td>
<td>(4.82)</td>
<td>(2.04)</td>
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<tr>
<td>Controls</td>
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- Positive coefficients: distribution shifts to the right ("complement")
Prediction 3: Frequency distribution of loan size

\[ Fraction_{c,t}^N = \beta Treated_c \times Post_t + Controls_{c,t} + \gamma_c + \sigma_t + \epsilon_{c,t}, \]

- 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
P2P platforms substitute banks by serving infra-marginal bank borrowers

They also complements banks by providing small loans

The credit expansion occurs among borrowers with access to bank credit