Home Is Where Your FinTech Loan Is

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One of the first papers that investigates the impact of FinTech lending on borrower outcomes in other credit markets using a novel instrument

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- **Main Findings:**
  - FinTech lending positively impacts mortgage activity
  - Spillover effect is stronger for
    - New home purchase activity
    - Middle income individuals
  - Decline in interest rates of mortgages
  - No change in mortgage delinquency rates

FinTech Lenders And Information Frictions

In the unsecured loan market ...

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Scenario 1

- Use alternative data
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- Low-cost credit to all borrowers based on traditional metrics
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- Do not expect alleviation of information frictions

Economic Implications

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2. FinTech lending as a market-based mechanism to improve access to a mortgage
3. Fast growing loan market

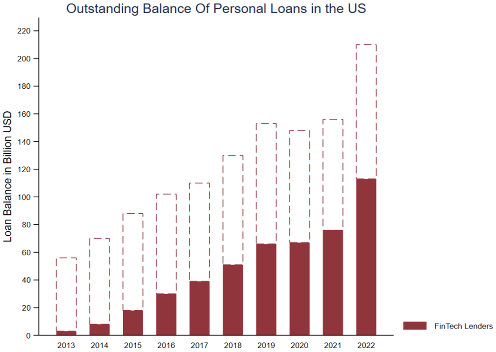
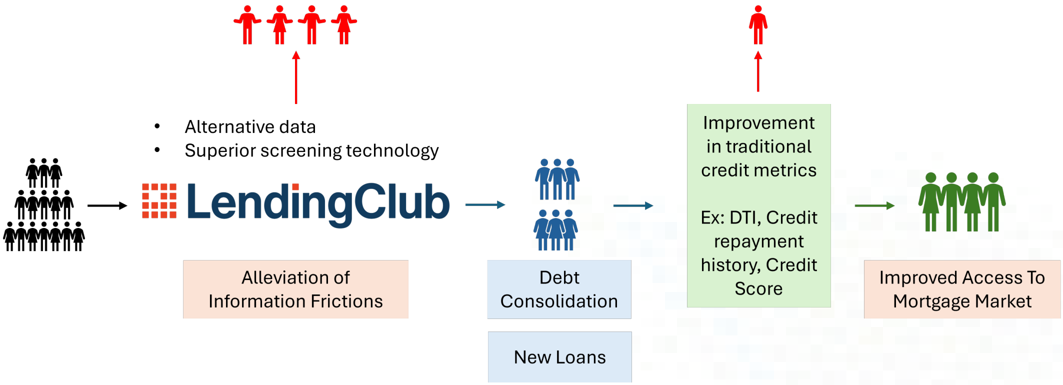


Figure 1: Significant Growth In Unsecured FinTech Lending

Key Mechanism



Contribution

- **Impact of FinTech lending**
  - Unsecured Loans: Balyuk (2023), Chava et al. (2021), Jagtiani and Lemieux (2019) ...
  - Small Business Loans: Gopal and Schnabl (2022), Erel and Liebersohn (2020) ...
  - Mortgage Loans: Buchak et al. (2018), Fuster et al. (2019), Fuster et al. (2022) ...

  This paper shows the impact of unsecured FinTech lending on borrower outcomes in other credit markets

- **Information frictions in credit markets**
  - Cash-flow-based lending: Holmstrom and Tirole (1997), Lian and Ma (2021) ...
  - Collateral-based lending: Kiyotaki and Moore (1997), Benmelech et al. (2020) ...

  This paper shows how cash-flow based lending can help collateral-based lending in consumer credit markets

- **Financial innovation to alleviate credit market frictions**
  - Real Effects: Dubey and Purnanandam (2023), Jack and Suri (2014)
  - Credit Frictions: Parlour et al. (2022), Ghosh et al. (2022), He et al. (2023)

  This paper shows how FinTech lending can alleviate credit market frictions in other large loan markets

Empirical Design

Data

- **FinTech loans:**
  - Loan-level data of about 3 million loans from 2010 to 2019 by LendingClub
  - Includes loan terms, income, debt-to-income, credit score, and employment details

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  - HMDA: Application-level data of the near universe of US mortgages
  - Fannie Mae and Freddie Mac: Loan-level data of conforming loans
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- **Data Construction:** I aggregate loan-level data at 3-digit zip code level

Descriptive Statistics

- **A 3-digit zipcode area**
  - No of Areas: 905
  - LendingClub loans in a year: 335
  - Mortgage Applications: 17,095
  - Mortgage Loans: 10,570

- **An average LendingClub Loan**
  - Amount: $14,045
  - Interest Rate: 12.7%
  - Debt-to-Income: 18.2%
  - FICO: 696

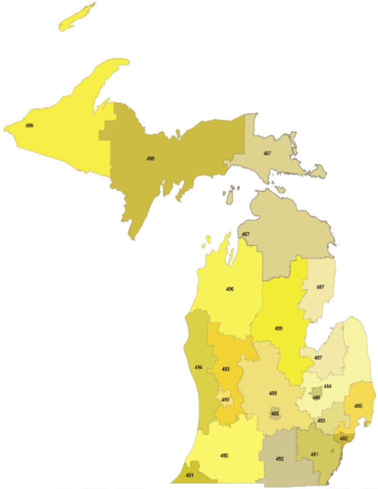

Figure 2: Area Map of Michigan

‣ Stats LendingClub ‣ Stats HMDA ‣ Stats Fannie and Freddie

Large Variation In LendingClub Activity

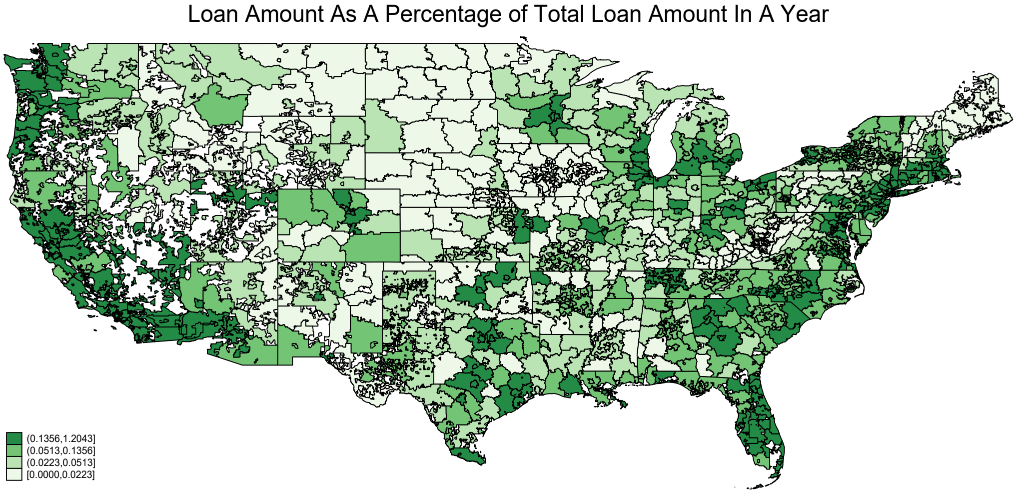

Figure 3: Geographic Distribution Of LendingClub Loan Activity

FinTech Lending Positively Impacts Mortgage Lending

$$Y_{z,s,t} = \alpha + \beta_k \times log(No\_LendingClub\_Loans)_{z,t-k} + \gamma_z + \phi_{s\times t} + \epsilon_{z,s,t};\ k \in \{0,1,2\}$$

- z, s, t: Area, state, and year of mortgage application or loan
- γ_z, $\phi_{s\times t}$: Area and State $\times$ Year fixed effects, respectively

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Table 1: Baseline OLS

	(1) Log Apps	(2) Log Apps	(3) Log Apps	(4) Log Loans	(5) Log Loans	(6) Log Loans
Log LC Loans	0.0759***			0.0768***		
	(0.0098)			(0.0096)		
Log LC Loans.L1		0.0589***			0.0560***	
		(0.0070)			(0.0072)	
Log LC Loans.L2			0.0481***			0.0471***
			(0.0070)			(0.0072)
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	7,223	7,223	7,223	7,223	7,223	7,223
Adj R-squared	0.0355	0.0364	0.0348	0.0316	0.0285	0.0289
Number of Zip3s	904	904	904	904	904	904

Ideal Test | DLM Apps | DLM Loans | OLS w/o FT | OLS FM

Identification Strategy

Instrument: Partnership Of LendingClub With BancAlliance

In Feb 2015, LendingClub partnered with BancAlliance, a nationwide consortium of small banks

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BancAlliance

- Redirected personal loan customers to LendingClub
- Invested in LendingClub loans

LendingClub

- Expanded borrower base

Quotes

Geographic Distribution Of Treated Areas

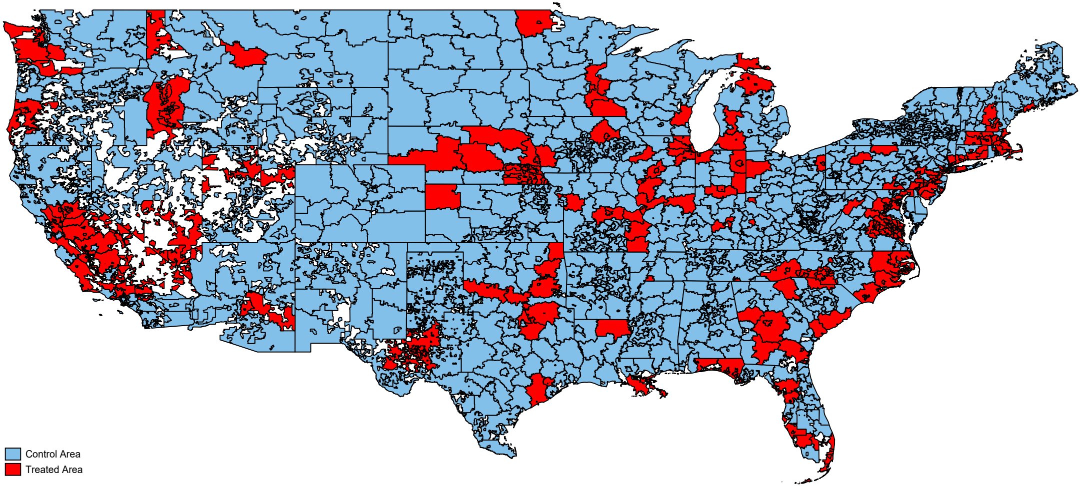

Figure 4: BancAlliance Network In 2015

Impact Of BancAlliance Partnership On LendingClub Loans

$$log(No\_LendingClub\_Loans)_{z,s,t} = \pi_0 + \pi_1 \times Treat_z \times Post_t + \gamma_z + \phi_{s\times t} + \eta_{z,s,t}$$

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Table 2: Impact On LendingClub Loans

	(1) Log No of LC Loans
Treat X Post	0.0925*** (0.0317)
Zip3 FE	Yes
State X Year FE	Yes
Number of Observations	9,034
Number of Zip3s	905

Figure 5: LendingClub Log Loans In Treated Vs Control Areas

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BancAlliance LendingClub

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- Invested in LendingClub loans

- Expanded borrower base

Key Identification Assumptions

- Partnership at the national level, LendingClub could not target specific areas
- BancAlliance member banks sought to diversify into consumer loans

More On BancAlliance

Dynamic Effects Of BancAlliance Partnership In Mortgage Market

$$Y_{z,s,t} = \delta_0 + \delta_1 \times \sum_k Treat_z \times Post_{t-k} + \gamma_z + \phi_{s\times t} + \zeta_{z,s,t}$$

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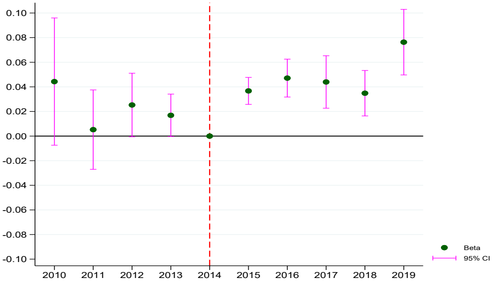
(a) Mortgage Applications



(b) Mortgage Loans

Figure 6: Impact On Mortgage Activity In Treated Vs Control Areas

▸ Dynamic Tract ▸ Dynamic w/o FT ▸ Dynamic FM

ISB

Impact Of BancAlliance Partnership On Mortgage Activity

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Table 3: Differences-In-Differences: Impact on Mortgage Applications and Loans

	(1) Log Mortgage Apps	(2) Log Mortgages
Treat X Post	0.0297**	0.0302**
	(0.0123)	(0.0127)
Zip3 FE	Yes	Yes
State X Year FE	Yes	Yes
Number of Observations	9,033	9,033
Number of Zip3s	905	905

▸ DID w/o FT ▸ DID FM

Impact Of LendingClub Loans On Mortgage Applications

$$1^{st}\ Stage:\ log(No\_LC\_Loans)_{z,s,t} = \pi_0 + \pi_1 \times Treat_z \times Post_{t-k} + \gamma_z + \phi_{s\times t} + \eta_{z,s,t}$$

$$2^{nd}\ Stage:\ log(No\_Mort\_Apps)_{z,s,t+k} = \beta_0 + \beta_1 \times log(No\widehat{\_LC\_}Loans)_{z,t} + \gamma_z + \phi_{s\times t} + \varepsilon_{z,s,t};\quad k \in \{0,1,2\}$$

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- z, s, t: Area, state, and year of mortgage application
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Table 4: Instrumented Difference-in-Differences: Impact On Mortgage Applications

	(1) Log Apps.T	(2) Log Apps.T+1	(3) Log Apps.T+2
Log LC Loans	0.3067**	0.4022***	0.3434***
	(0.1462)	(0.1414)	(0.1187)
Zip3 FE	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes
Number of Observations	9,033	8,127	7,223
Number of Zip3	905	904	904

Impact Of LendingClub Loans On Mortgage Loans

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- z, s, t: Area, state, and year of mortgage loan
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Table 5: Instrumented Difference-in-Differences: Impact On Mortgage Loans

	(1) Log Loans.T	(2) Log Loans.T+1	(3) Log Loans.T+2
Log LC Loans	0.3119** (0.1508)	0.3664*** (0.1413)	0.2972** (0.1188)
Zip3 FE	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes
Number of Observations	9,033	8,127	7,223
Number of Zip3	905	904	904

Quick Recap

- FinTech lending positively impacts mortgage lending
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- I use LendingClub's partnership with BancAlliance as an instrument to establish causality
- Significant increase in both LendingClub loan activity and mortgage activity
- Increase in mortgage activity is mediated by increase in LendingClub loan activity

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Economic Mechanism

From FinTech Lending To Mortgage Lending

FinTech Personal Loan Market

Mortgage Market

From FinTech Lending To Mortgage Lending

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Mortgage Market

New Data And Improved Screening

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- New borrowers: increased access to credit

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- Improvement in traditional credit metrics
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- 50% of mortgage applications denied due to poor repayment history and debt-to-income

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    - Low, Middle, High
- Price and delinquency

LendingClub Loans Benefit New Home Purchases

$$Y_{z,s,t,p} = \beta_0 + \beta_1 \times Treat_z \times Post_t \times New_p + \lambda_{z\times p} + \phi_{s\times t} + \varepsilon_{z,s,t,p}; \quad k \in \{0,1,2\}$$

- z, s, t, p: Area, state, and year of taking a mortgage loan, and type of mortgage product
- $\lambda_{z\times p}$, $\phi_{s\times t}$: Area $\times$ Product and State $\times$ Year fixed effects, respectively

ISB

LendingClub Loans Benefit New Home Purchases

$$Y_{z,s,t,p} = \beta_0 + \beta_1 \times Treat_z \times Post_t \times New_p + \lambda_{z\times p} + \phi_{s\times t} + \varepsilon_{z,s,t,p}; \quad k \in \{0,1,2\}$$

- z, s, t, p: Area, state, and year of taking a mortgage loan, and type of mortgage product
- $\lambda_{z\times p}$, $\phi_{s\times t}$: Area $\times$ Product and State $\times$ Year fixed effects, respectively

Table 6: Triple Differences: New Home Purchases Versus Refinancings

	(1) Log Mortgage Apps	(2) Log Mortgage Loans
Treat X Post X New	0.0346*	0.0465**
	(0.0182)	(0.0194)
Zip3 X New FE	Yes	Yes
State X Year FE	Yes	Yes
Number of Observations	18,066	18,066
Adj R-squared	0.3845	0.4319
Number of Zip3s	905	905

Middle Income Borrowers Benefit The Most

$$Y_{z,s,t,b} = \beta_0 + \beta_1 \times Treat_z \times Post_t \times IncBand_b + \lambda_{z\times b} + \phi_{s\times t} + \varepsilon_{z,s,t,b}; \quad k \in \{0,1,2\}$$

- z, s, t, b: Area, state, year of taking a mortgage loan, and income band of borrower
- $\lambda_{z\times b}$, $\phi_{s\times t}$: Area $\times$ Income Band and State $\times$ Year fixed effects, respectively

Table 7: Triple Differences: Borrowers Across Income Bands

	(1) All Apps	(2) All Loans	(3) New Apps	(4) New Loans	(5) Refi Apps	(6) Refi Loans
Treat X Post X IB 40-60K	0.0231**	0.0581***	0.0550***	0.0622***	0.0081	0.0457***
	(0.0102)	(0.0124)	(0.0163)	(0.0184)	(0.0082)	(0.0108)
Treat X Post X IB 60-80K	0.0412***	0.0790***	0.0955***	0.0979***	0.0111	0.0569***
	(0.0126)	(0.0166)	(0.0210)	(0.0240)	(0.0090)	(0.0114)
Treat X Post X IB 80-100K	0.0276**	0.0639***	0.0888***	0.0898***	-0.0032	0.0459***
	(0.0137)	(0.0180)	(0.0230)	(0.0260)	(0.0109)	(0.0136)
Treat X Post X IB 100-120K	0.0116	0.0449**	0.0736***	0.0738***	-0.0171	0.0278**
	(0.0137)	(0.0176)	(0.0235)	(0.0266)	(0.0124)	(0.0137)
Treat X Post X IB >120K	0.0177	0.0496***	0.0824***	0.0857***	-0.0214*	0.0250*
	(0.0126)	(0.0171)	(0.0243)	(0.0277)	(0.0125)	(0.0139)
Zip3 X IncBand FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	54,156	54,156	54,156	54,156	54,156	54,156
Number of Zip3s	905	905	905	905	905	905

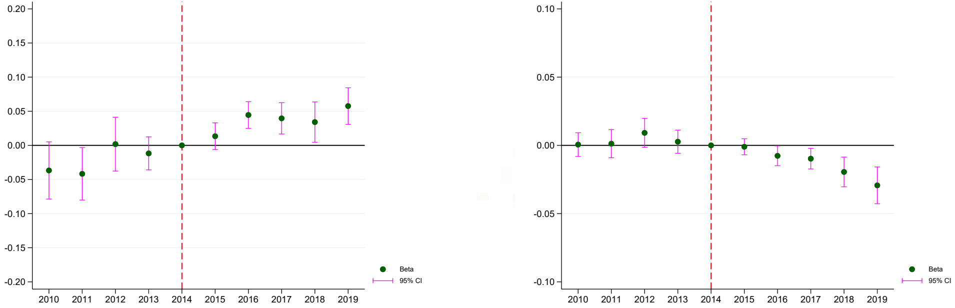
Across All Across New Across Refi

Pricing Effect

FinTech Lending Reduces Mortgage Interest Rates

$$Y_{z,s,t} = \delta_0 + \delta_1 \times \sum Treat_z \times Post_{t-k} + \gamma_z + \phi_{s\times t} + \zeta_{z,s,t}$$

- z, s, t: Area, state, and year of taking a mortgage loan
- γ_z, $\phi_{s\times t}$: Area and State $\times$ Year fixed effects, respectively



(a) Mortgage Loans

(b) Mortgage Interest Rates

Figure 7: Impact On Mortgage Loans And Rates

DID Pricing

ISB

Mortgage Loan Performance

No Change In Mortgage Delinqencies

$$1^{st}\ Stage: log(No\_Mortgages)_{z,s,t} = \pi_0 + \pi_1 \times Treat_z \times Post_t + \gamma_z + \phi_{s\times t} + \eta_{z,s,t}$$

$$2^{nd}\ Stage: log(No\_Mort\_Delinqs)_{z,s,t+k} = \beta_0 + \beta_1 \times log(No\_\widehat{Mortgages})_{z,s,t} + \gamma_z + \phi_{s\times t} + \varepsilon_{z,s,t};\ k \in \{1,2,3\}$$

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Table 8: Instrumented Difference-in-Differences: Impact On Mortgage Delinquencies

	(1) Log No Mortgages	(2) Delinq 12 mth	(3) Delinq 24 mth	(4) Delinq 36 mth
Treat X Post	0.0555***			
	(0.0182)			
Log No Mortgages		0.7328**	0.9916***	1.0089***
		(0.3478)	(0.3817)	(0.3695)
F-Test ($\boldsymbol{H_0: \beta_1 = 1}$)		0.59	0.00	0.00
(p-value)		(0.4426)	(0.9825)	(0.9808)
Zip3 FE	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes
Number of Observations	9,035	9,035	9,035	9,035
Number of Zip3	905	905	905	905

Robustness

Some Other Questions

1. **Is the spillover driven by mortgage FinTech lenders?**
   - Uses HMDA data after removing mortgage activity processed by mortgage FinTech lenders (Buchak et al., 2018)
   - Results show that spillover cannot be explained by mortgage FinTech lenders alone

▸ Dynamic ▸ DID ▸ DDIV Apps ▸ DDIV Loans

2. **Can I use results from Fannie Mae and Freddit Mac data?**
   - Uses Fannie Mae and Freddie Mac mortgage data
   - Results substantiate using this data to study risk of new mortgages and pricing effect

▸ Dynamic ▸ DID ▸ DDIV

Conclusion

- Unsecured FinTech lending positively impacts mortgage lending via alleviation of information frictions

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Appendix

LendingClub Data

Table 9: Summary Statistics: LendingClub Borrower And Loan Characteristics In An Area

	N	Mean	SD	Min	P25	P50	P75	Max
Loan Amount (USD)	8,278	14,047	2,679	1,250	13,077	14,417	15,541	35,000
Median Int Rate (%)	8,278	12.70	1.46	5.32	11.99	12.62	13.53	23.63
Median DTI (%)	8,278	18.16	3.36	0.00	16.44	18.62	20.26	56.72
Median FICO	8,278	696	14	660	690	695	700	795
Nunber of Loans	8,278	335	564	1	33	131	367	5,364
Borrower Income (USD)	8,278	69,199	13,660	15,000	61,801	68,126	75,488	205,169

Descriptive Stats

HMDA Mortgage Data

Table 10: Summary Statistics: Mortgage Applications And Loans in an Area

	N	Mean	SD	Max	P25	P50	P75
All Mortgage Apps	9,034	17,095	23,170	3,616	8,830	21,082	305,952
All Mortgage Loans	9,034	10,570	14,405	2,192	5,487	12,975	194,259
New Mortgage Apps	9,034	6,735	9,689	1,363	3,339	8,057	119,107
New Mortgage Loans	9,034	4,798	6,922	923	2,358	5,760	84,279
Refi Mortgage Apps	9,034	8,769	12,276	1,694	4,419	10,586	181,780
Refi Mortgage Loans	9,034	4,991	7,341	916	2,401	5,887	115,789
FinTech Mortgage Apps	9,034	1,824	4,604	201	536	1,494	112,644
FinTech Mortgage Loans	9,034	1,077	2,711	110	304	894	70,921
Applicant Income (USD)	9,034	90,480	30,468	72,754	82,035	96,763	435,407
Loan Amount (USD)	9,034	167,569	92,496	110,464	137,776	188,292	884,499
Population	9,034	336,751	368,346	109,860	207,338	428,341	2,975,626

Descriptive Stats

Fannie Mae And Freddie Mac Data

Table 11: Summary Statistics: Fannie Mae And Freddie Mac Mortgages in an Area

	N	Mean	SD	Min	P25	P50	P75	Max
All Mortgage Loans	8,875	4,025	5,649	1	713	1,968	4,903	80,448
New Mortgage Loans	8,875	1,698	2,412	0	285	797	2,042	26,123
Refi Mortgage Loans	8,875	2,326	3,716	0	375	1,018	2,682	67,270
Delinquencies Within 12mths	8,875	53	98	0	8	22	58	1,751
Delinquencies Within 24mths	8,875	94	153	0	15	41	107	2,305
Delinquencies Within 36mths	8,875	125	193	0	21	56	145	2,477
Loan Amount (USD)	8,875	187,214	67,758	50,000	142,200	169,534	209,544	959,000
Loan-To-Value (%)	8,875	73.85	5.83	34.93	70.86	74.92	77.71	121.90
Median Credit Score	8,875	763	12	591	756	763	771	818
Median DTI (%)	8,872	33.35	2.91	14.00	31.00	33.00	35.00	50.00

Descriptive Stats Performance

Test For Hypothesis

Ideal Test: Does taking out a FinTech loan increase a borrower's access to a mortgage loan?

Test For Hypothesis

Ideal Test: Does taking out a FinTech loan increase a borrower's access to a mortgage loan?

$$Y_{i,z,s,t} = \alpha_i + \gamma_z + \phi_{s\times t} + \beta \times X_{i,z,t-k} + \varepsilon_{i,z,s,t}; \quad k \in \{0,1,2\}$$

- i, z, s, t: Borrower, area, state and year of mortgage application or loan
- Y: Binary variable which is 1 if borrower i in area z at year t of mortgage application or loan, and is 0 otherwise
- X: Binary variable which is 1 if borrower i in area z at time $t-k$ of an unsecured FinTech loan, and is 0 otherwise
- α_i, γ_z, $\phi_{s\times t}$: Borrower, Area, and State $\times$ Year fixed effects

Test For Hypothesis

Ideal Test: Does taking out a FinTech loan increase a borrower's access to a mortgage loan?

$$Y_{i,z,s,t} = \alpha_i + \gamma_z + \phi_{s\times t} + \beta \times X_{i,z,t-k} + \varepsilon_{i,z,s,t}; \quad k \in \{0,1,2\}$$

- i, z, s, t: Borrower, area, state and year of mortgage application or loan
- Y: Binary variable which is 1 if borrower i in area z at year t of mortgage application or loan, and is 0 otherwise
- X: Binary variable which is 1 if borrower i in area z at time $t-k$ of an unsecured FinTech loan, and is 0 otherwise
- α_i, γ_z, $\phi_{s\times t}$: Borrower, Area, and State $\times$ Year fixed effects

My Test: Does increase in unsecured FinTech lending increase mortgage activity in an area?

$$\overline{Y}_{z,s,t} = \alpha + \gamma_z + \phi_{s\times t} + \beta \times \overline{X}_{z,t-k} + \varepsilon_{z,s,t}; \quad k \in \{0,1,2\}$$

- Unable to exploit individual level heterogenity
- Use difference-in-differences approach to address this

Baseline OLS

Instrument: Partnership Of LendingClub With BancAlliance

In Feb 2015, LendingClub partnered with BancAlliance, a nationwide consortium of small banks

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BancAlliance

- Redirected personal loan customers to LendingClub
- Invested in LendingClub loans

LendingClub

- Expanded borrower base

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"Big banks have eaten the small banks' lunch with regards to these types of credits. We understand consumer lending. We just want more of it."

- Mark Pitkin, CEO, Sugar River Bank

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BancAlliance | LendingClub

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"Big banks have eaten the small banks' lunch with regards to these types of credits. We understand consumer lending. We just want more of it."

\- Mark Pitkin, CEO, Sugar River Bank

- Expanded borrower base

"This deal is really an opportunity to gain access to customers who wouldn't necessarily find us otherwise. The small banks have relationships with prospective borrowers who are walking into bank branches instead of going online"

\- Renaud Laplanche, CEO, LendingClub

Source: "Lending Club, Small U.S. Banks Plan New Consumer-Loan Program", Wall Street Journal, February 2015

National Presence And Scale Of BancAlliance

Managed by Alliance Partners

Provides member banks with

- access to lending resources,
- administrative support for regulatory compliance, and
- manage and diversify loan portfolios via collaboration

In 2015, all members together were 4th by branch count and 17th by assets

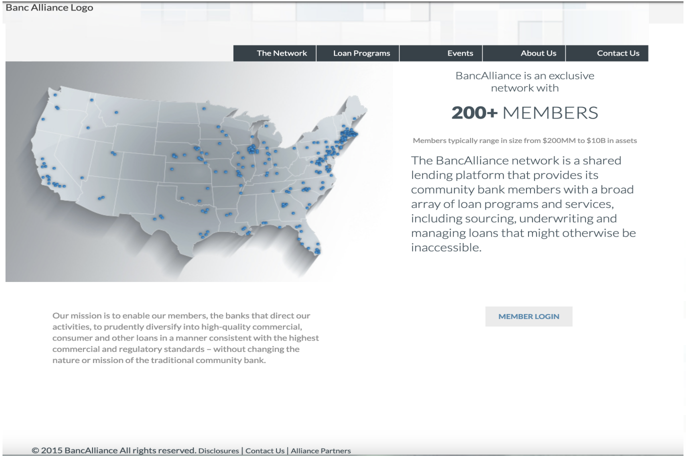


Figure 8: The BancAlliance Network in 2015 in 39 states

Back To Instrument

Impact On Mortgage Applications Over Time

$$log(No\_Mort\_Apps)_{z,s,t} = \alpha + \beta \times log(No\_LendingClub\_Loans)_{z,t-k} + \gamma_z + \phi_{s\times t} + \varepsilon_{z,s,t};\ k \in \{0,1,2\}$$

- z, s, t: Area, state, and year of mortgage application
- γ_z, $\phi_{s\times t}$: Area and *State* $\times$ *Year* fixed effects, respectively

Table 12: Distributed Lag Model With Mortgage Applications

	(1) Log Apps	(2) Log Apps	(3) Log Apps	(4) Log Apps
Log LC Loans	0.0759***			0.0443***
	(0.0098)			(0.0095)
Log LC Loans.L1		0.0589***		0.0292***
		(0.0070)		(0.0052)
Log LC Loans.L2			0.0481***	0.0283***
			(0.0070)	(0.0057)
Zip3 FE	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes
Number of Observations	7,223	7,223	7,223	7,223
Adj R-squared	0.0355	0.0364	0.0348	0.0591
Number of Zip3s	904	904	904	904

Baseline OLS

Impact On Mortgage Loans Over Time

$$log(No\_Mort\_Loans)_{z,s,t} = \alpha + \beta \times log(No\_LendingClub\_Loans)_{z,t-k} + \gamma_z + \phi_{s\times t} + \varepsilon_{z,s,t};\ k \in \{0,1,2\}$$

- z, s t: Area, state, and year of mortgage loan
- γ_z, $\phi_{s\times t}$: Area and *State* $\times$ *Year* fixed effects, respectively

Table 13: Distributed Lag Model With Mortgage Loans

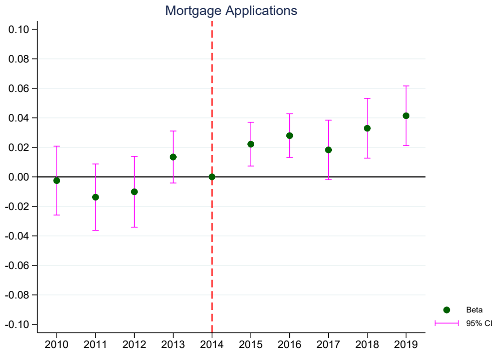
	(1) Log Loans	(2) Log Loans	(3) Log Loans	(4) Log Loans
Log LC Loans	0.0768***			0.0477***
	(0.0096)			(0.0095)
Log LC Loans.L1		0.0560***		0.0254***
		(0.0072)		(0.0056)
Log LC Loans.L2			0.0471***	0.0280***
			(0.0072)	(0.0061)
Zip3 FE	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes
Number of Observations	7,223	7,223	7,223	7,223
Adj R-squared	0.0316	0.0285	0.0289	0.0495
Number of Zip3s	904	904	904	904

Baseline OLS

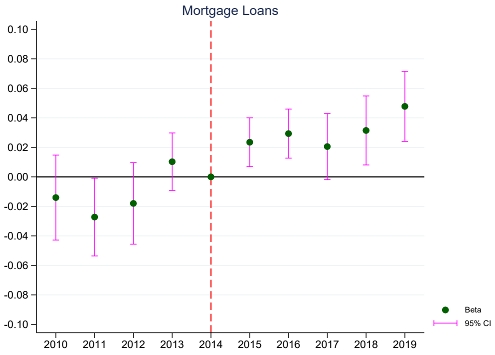
Dynamic Effects On Mortgage Activity In A Tract

$$Y_{ct,z,s,t} = \alpha + \beta \times \sum_k Treat_z \times Post_{t-k} + \rho_{ct} + \phi_{s\times t} + \epsilon_{ct,z,s,t}$$

- ct, z, s, t: census tract, area, state, and year of a mortgage application and loan
- ρ_{ct}, $\phi_{s\times t}$: Tract and State $\times$ Year fixed effects, respectively



(a) Mortgage Applications In Treated vs Control Tracts



(b) Mortgage Loans In Treated vs Control Tracts

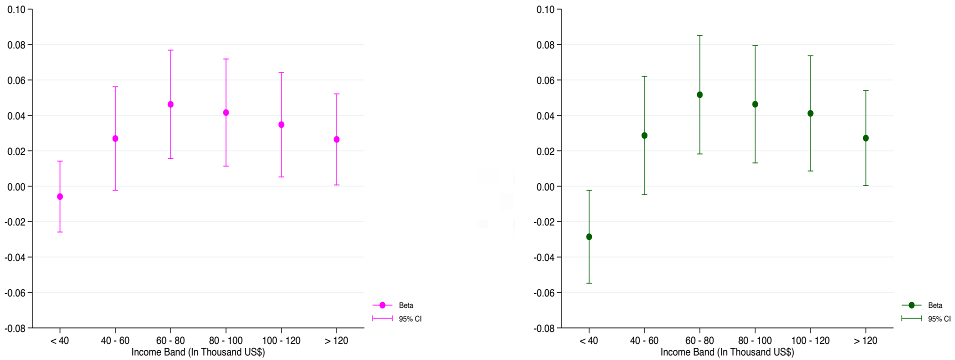
Dynamic Main

ISB

All Borrowers Across Income Bands

$$Y_{z,s,t,b} = \beta_0 + \beta_{1,b} \times Treat_z \times Post_t + \gamma_z + \phi_{s\times t} + \varepsilon_{z,s,t,b}$$

- z, s, t: Area, state, and year of taking a mortgage loan; ib: Income band of the subset
- γ_z, $\phi_{s\times t}$: Area and State $\times$ Year fixed effects, respectively



(a) Mortgage Applications (b) Mortgage Loans

Figure 10: Coefficients Across Income Bands for All Mortgages

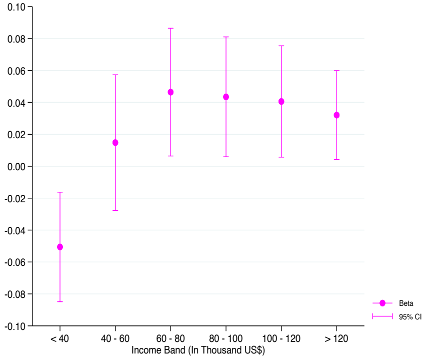
Income Triple All DID Tables

ISB

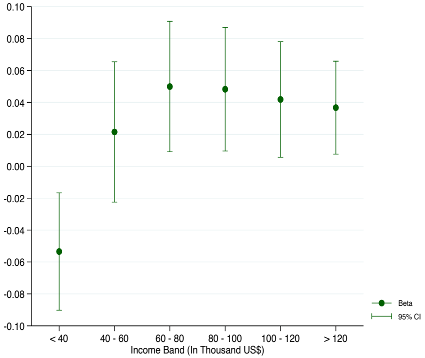
New Home Purchases Across Income Bands

$$Y_{z,s,t,b} = \beta_0 + \beta_{1,b} \times Treat_z \times Post_t + \gamma_z + \phi_{s\times t} + \varepsilon_{z,s,t,b}$$

- z, s, t: Area, state, and year of taking a mortgage loan; ib: Income band of the subset
- γ_z, $\phi_{s\times t}$: Area and State $\times$ Year fixed effects, respectively



(a) New Home Purchase Applications



(b) New Home Purchase Mortgages

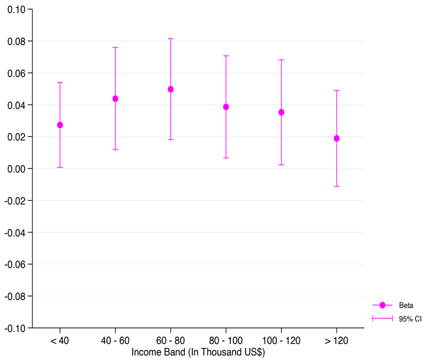
Figure 11: Coefficients Across Income Bands for New Mortgages

Income Triple   New DID Tables

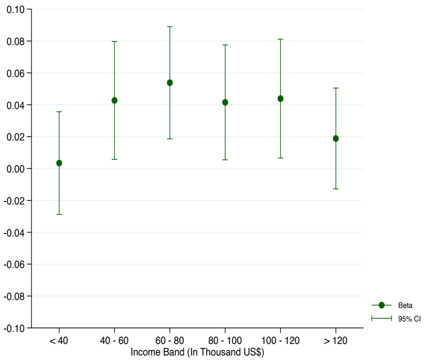
Refinancing Mortgages Across Income Bands

$$Y_{z,s,t,b} = \beta_0 + \beta_{1,b} \times Treat_z \times Post_t + \gamma_z + \phi_{s\times t} + \varepsilon_{z,s,t,b}$$

- z, s, t: Area, state, and year of taking a mortgage loan; ib: Income band of the subset
- γ_z, $\phi_{s\times t}$: Area and State $\times$ Year fixed effects, respectively



(a) Refinancing Applications



(b) Refinancing Loans

Figure 12: Coefficients Across Income Bands for Refi Mortgages

Income Triple Refi DID Tables

All Mortgage Applications And Loans

$$Y_{z,s,t,b} = \beta_0 + \beta_{1,b} \times Treat_z \times Post_t + \gamma_z + \phi_{s\times t} + \varepsilon_{z,s,t,b}$$

Table 14: Difference-in-Differences: All Mortgage Applications

	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	-0.0058	0.0269*	0.0462***	0.0416***	0.0348**	0.0264**
	(0.0102)	(0.0149)	(0.0156)	(0.0154)	(0.0150)	(0.0131)
Income Band (USD)	$<$ 40K	40-60K	60-80K	80-100K	100-120K	$>$ 120K
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,028	9,029	9,026	9,023	9,017	9,033
Number of Zip3s	905	905	905	905	904	905

Table 15: Difference-in-Differences: All Mortgage Loans

	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	-0.0285**	0.0286*	0.0517***	0.0463***	0.0411**	0.0272**
	(0.0134)	(0.0170)	(0.0170)	(0.0169)	(0.0166)	(0.0137)
Income Band (USD)	$<$ 40K	40-60K	60-80K	80-100K	100-120K	$>$ 120K
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,028	9,029	9,026	9,023	9,017	9,033
Number of Zip3s	905	905	905	905	904	905

Across All

New Home Purchase Applications And Loans

$$Y_{z,s,t,b} = \beta_0 + \beta_{1,b} \times Treat_z \times Post_t + \gamma_z + \phi_{s\times t} + \varepsilon_{z,s,t,b}$$

Table 16: Difference-in-Differences: New Mortgage Applications

	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	-0.0506***	0.0148	0.0464**	0.0435**	0.0406**	0.0320**
	(0.0175)	(0.0217)	(0.0204)	(0.0191)	(0.0178)	(0.0142)
Income Band (USD)	$<$ 40K	40-60K	60-80K	80-100K	100-120K	$>$ 120K
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,028	9,029	9,026	9,023	9,017	9,033
Number of Zip3s	905	905	905	905	904	905

Table 17: Difference-in-Differences: New Mortgage Loans

	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	-0.0535***	0.0215	0.0499**	0.0483**	0.0419**	0.0367**
	(0.0187)	(0.0224)	(0.0208)	(0.0197)	(0.0184)	(0.0148)
Income Band (USD)	$<$ 40K	40-60K	60-80K	80-100K	100-120K	$>$ 120K
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,028	9,029	9,026	9,023	9,017	9,033
Number of Zip3s	905	905	905	905	904	905

Across New

Refinancing Mortgage Applications And Loans

$$Y_{z,s,t,b} = \beta_0 + \beta_{1,b} \times Treat_z \times Post_t + \gamma_z + \phi_{s\times t} + \varepsilon_{z,s,t,b}$$

Table 18: Difference-in-Differences: Refi Mortgage Applications

	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	0.0273**	0.0438***	0.0498***	0.0386**	0.0353**	0.0189
	(0.0135)	(0.0163)	(0.0161)	(0.0163)	(0.0168)	(0.0153)
Income Band (USD)	$<$ 40K	40-60K	60-80K	80-100K	100-120K	$>$ 120K
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,028	9,029	9,026	9,023	9,017	9,033
Number of Zip3s	905	905	905	905	904	905

Table 19: Difference-in-Differences: Refi Mortgage Loans

	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	0.0034	0.0427**	0.0538***	0.0415**	0.0439**	0.0188
	(0.0164)	(0.0189)	(0.0179)	(0.0184)	(0.0190)	(0.0161)
Income Band (USD)	$<$ 40K	40-60K	60-80K	80-100K	100-120K	$>$ 120K
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,028	9,029	9,026	9,023	9,017	9,033
Number of Zip3s	905	905	905	905	904	905

Across Refi

FinTech Lending Expands Mortgage Credit Supply

$$Y_{z,s,t} = \delta_0 + \delta_1 \times Treat_z \times Post_t + \gamma_z + \phi_{s\times t} + \zeta_{z,s,t}$$

- z, s, t: Area, state, and year of mortgage loan
- γ_z, $\phi_{s\times t}$: Area and State $\times$ Year fixed effects, respectively

Table 20: Differences-In-Differences: Impact On Mortgage Loans And Interest Rates

	(1) Log Mortgages	(2) Mortgage Rate
Treat X Post	0.0579***	-0.0162***
	(0.0183)	(0.0037)
Zip3 FE	Yes	Yes
State X Year FE	Yes	Yes
Number of Observations	8,862	8,862
Number of Zip3s	892	892

Dynamic Pricing

Robustness Test 1: OLS Without FinTech Mortgage Lenders

$$Y_{z,s,t} = \alpha + \beta \times log(No\_Of\_LendingClub\_Loans)_{z,t-k} + \gamma_z + \phi_{s \times t} + \epsilon_{z,s,t}; \;\; k \in \{0,1,2\}$$

- z, s, t: Area, state, and year of mortgage application or loan
- γ_z, $\phi_{s \times t}$: Area and State $\times$ Year fixed effects, respectively

Table 21: OLS: Impact On Mortgage Activity Without Mortgage FinTech Lenders

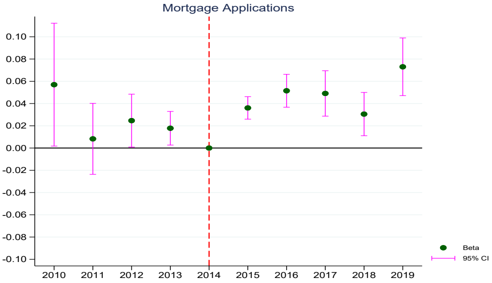
	(1) Log Apps	(2) Log Apps	(3) Log Apps	(4) Log Loans	(5) Log Loans	(6) Log Loans
Log LC Loans	0.0720***			0.0725***		
	(0.0100)			(0.0101)		
Log LC Loans.L1		0.0523***			0.0492***	
		(0.0065)			(0.0068)	
Log LC Loans.L2			0.0417***			0.0411***
			(0.0055)			(0.0060)
Zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	7,223	7,223	7,223	7,223	7,223	7,223
Adj R-squared	0.0295	0.0265	0.0242	0.0251	0.0196	0.0197
Number of Zip3s	904	904	904	904	904	904

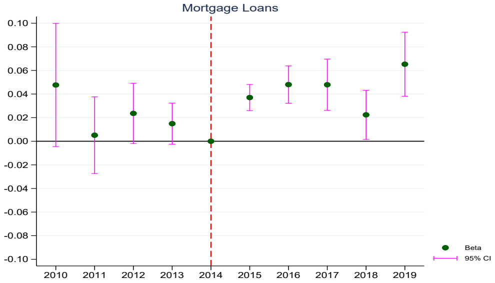
Baseline OLS

Robustness Test 1: Dynamic Effects

$$Y_{z,s,t} = \delta_0 + \delta_1 \times \sum_k Treat_z \times Post_{t-k} + \gamma_z + \phi_{s\times t} + \zeta_{z,s,t}$$

- z, s, t: Area, state, and year of mortgage application or loan
- γ_z, $\phi_{s\times t}$: Area and State $\times$ Year fixed effects, respectively





▸ Dynamic Main ▸ Robustness

Robustness Test 1: Impact On Mortgage Activity

$$Y_{z,s,t} = \delta_0 + \delta_1 \times \mathit{Treat}_z \times \mathit{Post}_t + \gamma_z + \phi_{s\times t} + \zeta_{z,s,t}$$

- z, s, t: Area, state, and year of mortgage application or loan
- γ_z, $\phi_{s\times t}$: Area and State $\times$ Year fixed effects, respectively

Table 22: Differences-In-Differences: Mortgage Applications and Loans

	(1) Log Mortgage Apps	(2) Log Mortgages
Treat X Post	0.0265**	0.0259**
	(0.0124)	(0.0128)
Zip3 FE	Yes	Yes
State X Year FE	Yes	Yes
Number of Observations	9,033	9,033
Number of Zip3s	905	905

DID Main Robustness

Robustness Test 1: Impact Of LendingClub On Mortgage Applications

$$1^{st}\ Stage:\ log(No\_LC\_Loans)_{z,s,t} = \pi_0 + \pi_1 \times Treat_z \times Post_{t-k} + \gamma_z + \phi_{s\times t} + \eta_{z,s,t}$$

$$2^{nd}\ Stage:\ log(No\_Mort\_Apps)_{z,s,t+k} = \beta_0 + \beta_1 \times log(\widehat{No\_LC\_Loans})_{z,t} + \gamma_z + \phi_{s\times t} + \varepsilon_{z,s,t};\quad k \in \{0,1,2\}$$

- z, s, t: Area, state, and year of mortgage application
- γ_z, $\phi_{s\times t}$: Area and State $\times$ Year fixed effects, respectively

Table 23: Instrumented Difference-in-Differences: Impact On Mortgage Applications

	(1) Log Apps.T	(2) Log Apps.T+1	(3) Log Apps.T+2
Log LC Loans	0.2685* (0.1398)	0.3456*** (0.1321)	0.2628** (0.1075)
Zip3 FE	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes
Number of Observations	9,033	8,127	7,223
Number of Zip3	905	904	904

Robustness

Robustness Test 1: Impact Of LendingClub On Mortgage Loans

$$1^{st}\ Stage:\ log(No\_LC\_Loans)_{z,s,t} = \pi_0 + \pi_1 \times Treat_z \times Post_t + \gamma_z + \phi_{s\times t} + \eta_{z,s,t}$$

$$2^{nd}\ Stage:\ log(No\_Mort\_Loans)_{z,s,t+k} = \beta_0 + \beta_1 \times log(\widehat{No\_LC\_Loans})_{z,t} + \gamma_z + \phi_{s\times t} + \varepsilon_{z,s,t};\quad k \in \{0,1,2\}$$

- z, s, t: Area, state, and year of mortgage loan
- γ_z, $\phi_{s\times t}$: Area and State $\times$ Year fixed effects, respectively

Table 24: Instrumented Difference-in-Differences: Impact On Mortgage Loans

	(1) Log Loans.T	(2) Log Loans.T+1	(3) Log Loans.T+2
Log LC Loans	0.2621*	0.3019**	0.2119*
	(0.1426)	(0.1326)	(0.1124)
Zip3 FE	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes
Number of Observations	9,033	8,127	7,223
Number of Zip3	905	904	904

Robustness

Robustness Test 2: OLS With Fannie Mae And Freddie Mac Data

$$log(No\_Mort\_Loans)_{z,s,t} = \alpha + \beta \times log(No\_Of\_LendingClub\_Loans)_{z,t-k} + \gamma_z + \phi_{s \times t} + \epsilon_{z,s,t};\ k \in \{0,1,2\}$$

- z, s, t: Area, state, and year of mortgage loan
- γ_z, $\phi_{s \times t}$: Area and State $\times$ Year fixed effects, respectively

Table 25: Baseline OLS: Fannie Mae And Freddie Mac Data

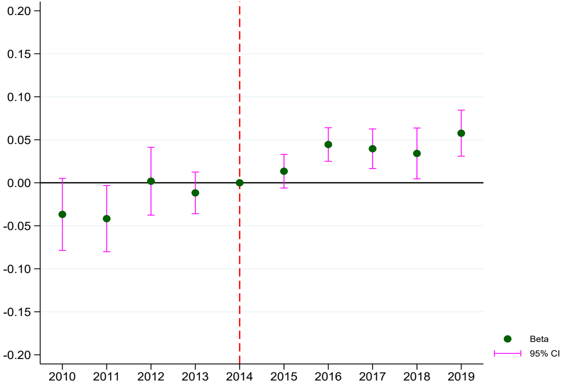
	(1)	(2)	(3)
Log LC Loans	0.0727***		
	(0.0235)		
Log LC Loans.L1		0.0253*	
		(0.0146)	
Log LC Loans.L2			0.0154
			(0.0100)
Zip3 FE	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes
Number of Observations	7,225	7,225	7,225
Adj R-squared	0.0127	0.0025	0.0012
Number of Zip3s	904	904	904

Baseline OLS

Robustness Test 2: Dynamic Effects

$$log(No\_Mort\_Loans)_{z,s,t} = \delta_0 + \delta_1 \times \sum_k Treat_z \times Post_{t-k} + \gamma_z + \phi_{s\times t} + \zeta_{z,s,t}$$

- z, s, t: Area, state, and year of mortgage loan
- γ_z, $\phi_{s\times t}$: Area and State $\times$ Year fixed effects, respectively



Dynamic Main Performance Robustness

Robustness Test 2: Impact On Mortgages

$$log(No\_Mort\_Loans)_{z,s,t} = \delta_0 + \delta_1 \times Treat_z \times Post_t + \gamma_z + \phi_{s\times t} + \zeta_{z,s,t}$$

- z, s, t: Area, state, and year of mortgage loan
- γ_z, $\phi_{s\times t}$: Area and State $\times$ Year fixed effects, respectively

Table 26: Differences-In-Differences: Impact on Mortgage Loans

	(1) Log Mortgages
Treat X Post	0.0555*** (0.0182)
Zip3 FE	Yes
State X Year FE	Yes
Number of Observations	9,035
Number of Zip3s	905

DID Main Robustness

Robustness Test 2: Impact Of LendingClub On Mortgages

$$1^{st}\ Stage:\ log(No\_LC\_Loans)_{z,s,t} = \pi_0 + \pi_1 \times Treat_z \times Post_{t-k} + \gamma_z + \phi_{s\times t} + \eta_{z,s,t}$$

$$2^{nd}\ Stage:\ log(No\_Mort\_Loans)_{z,s,t+k} = \beta_0 + \beta_1 \times log(\widehat{No\_LC\_Loans})_{z,t} + \gamma_z + \phi_{s\times t} + \varepsilon_{z,s,t};\quad k \in \{0,1,2\}$$

- z, s, t: Area, state, and year of taking a mortgage loan
- γ_z, $\phi_{s\times t}$: Area and State $\times$ Year fixed effects, respectively

Table 27: Instrumented Difference-in-Differences: Impact on Mortgage Loans

	(1) Log Mortgages.T	(2) Log Mortgages.T+1	(3) Log Mortgages.T+2
Log LC Loans	0.5489** (0.2343)	0.5619** (0.2393)	0.3724* (0.2062)
Zip3 FE	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes
Number of Observations	9,035	8,129	7,225
Number of Zip3	905	904	904

Robustness