

The Role of Technology in Mortgage Lending

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Technology and mortgage lending

- Technology is rapidly reshaping the U.S. residential mortgage industry
 - Traditional model: **branches and brokers** (physical location + personal interaction + labor-intensive underwriting)
 - New business model (“**FinTech**”): (i) fully online application, (ii) centralized and (iii) automated underwriting
 - Market share (based on our classification): 2% in 2010 (\$34bn in originations), 8% in 2016 (\$161bn)

- Example: Rocket Mortgage by Quicken

- Quicken now **largest** U.S. mortgage lender
- No local branches. Centralized operations.
- **Fully online application** via website or app. Approval in as little as 8 minutes.



This paper

Is FinTech lending improving efficiency of U.S. mortgage market?

1. Faster processing?
2. Lower defaults?
3. More elastic?
4. Faster or more optimal refinancing?
5. Who borrows from FinTech lenders?

Alternative hypothesis: FinTech lending growth driven by factors unrelated to technology (e.g., regulation)

Why study FinTech in mortgage markets?

1. Largest component of household debt ($\sim 70\%$ of total)
2. Among main activities of US financial sector; principal driver of growth since 1970s (Greenwood and Scharfstein, 2013)
3. Market (i) in which people make mistakes and (ii) with unequal access to finance
4. Transmission of monetary policy: interest rate pass-through limited by capacity constraints and suboptimal refinancing
5. Measurable: Technology adoption well underway and lots of data!

Related literature

1. **Technology in mortgage lending.** Buchak, Matvos, Piskorski and Seru (2018); Bartlett, Morse, Stanton and Wallace (2018); Fuster, Goldsmith-Pinkham, Ramadorai and Walther (2018); LaCour-Little (2000).
2. **Mortgage lending post crisis.** D'Acunto and Rossi (2017); Gete and Reher (2017); DeFusco, Johnson and Mondragon (2017).
3. **Origination frictions and effects on monetary transmission.** Campbell (2013); Beraja, Fuster, Hurst and Vavra (2017); Di Maggio, Kermani and Palmer (2016); Fuster, Lo and Willen (2017).
4. **Inefficient mortgage refinancing.** Campbell (2006); Agarwal, Driscoll and Laibson (2013); Andersen, Campbell, Nielsen and Ramadorai (2015); Agarwal, Rosen and Yao (2015); Keys, Pope and Pope (2016).

The FinTech business model

FinTech: End-to-end online application platform and centralized underwriting and processing augmented by automation.

Key features:

- Online application and document submission
- Automated systems to process information and underwrite loan
 - Log in to bank account to verify balances & income sources
 - Automated checks against employment databases, divorce records, property deed records etc.
 - Algorithms to identify patterns associated with fraud or misstatement
- Centralized operations rather than individual branches or brokers
 - Standardized, repeatable process: “pin factory” model

How do we classify FinTech lenders?

- Test: Does lender enable fully online application? (e.g., Rocket)
 - Proxy for automation, electronic document capture and processing.
 - Important feature of FinTech model; systematically measurable for large number of lenders.
- To measure, we submit “dummy” mortgage application on website. Evaluate how much can be done online (goal: pre-approval).
 - Classify top 100 purchase + refi mortgage lenders in HMDA.
 - Use Wayback Machine to classify lenders historically.
- Classification mostly agrees with Buchak et al. (2018), as well as anecdotal sources of evidence.
- Online lending diffusing rapidly (next slide). Window of opportunity.
 - Through 2016, six FinTech lenders, all are **non-banks**.

Diffusion of online lending



Name	FinTech Since	2016 Originations (Bn)	Market Share (%)	Rank
Quicken Loans	2010	90.553	4.52	2
LoanDepot.com	2016	35.935	1.80	5
Guaranteed Rate	2010	18.444	0.92	12
Movement Mortgage	2014	11.607	0.58	23
Everett Financial (Supreme)	2016	7.620	0.38	39
Avex (Better.com)	2016	0.490	0.02	531

Data sources

1. Mortgage applications and originations from **Home Mortgage Disclosure Act (HMDA)**, 2010-2016
 - Confidential version includes application date and “action” date
→ processing time
2. Mortgage servicing data linked to credit records from **Equifax/McDash (CRISM)**
3. Segment-level FHA volume and default data from **FHA Neighborhood Watch System**
4. Loan-level information from **Ginnie Mae**
5. Internet Connectivity from **NTIA National Broadband Map and Federal Communications Commission**
6. Age and credit score distributions from **NY Fed/ Equifax Consumer Credit Panel**
7. Demographics from **U.S. Census** and **ACS**
8. Bank branch distance from **FDIC Summary of Deposits**
9. Home prices and macro data from **Zillow** and **FRED**

HMDA summary statistics, 2010-2016

	Banks		Non-FT Nonb.		FinTech Nonb.	
	Mean	p50	Mean	p50	Mean	p50
Applicant Income	121	86.00	102	82.00	102	84.00
Loan-to-income (LTI)	1.96	1.80	2.46	2.40	2.34	2.19
Purpose = Refi	0.66	1	0.48	0	0.78	1
Loan Type:						
Conventional	0.86	1	0.61	1	0.70	1
FHA	0.09	0	0.28	0	0.20	0
VA	0.05	0	0.11	0	0.09	0
Jumbo	0.05	0	0.02	0	0.02	0
Owner Occupied	0.88	1	0.92	1	0.92	1
Male	0.67	1	0.69	1	0.59	1
No Coapplicant	0.45	0	0.52	1	0.50	0
Race: White	0.79	1	0.78	1	0.68	1
Race: Black/AA	0.04	0	0.06	0	0.05	0
Race not provided	0.11	0	0.09	0	0.22	0
Nr Loans	32,751,662		14,742,227		2,306,237	

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1) Is FinTech lending faster?

- Loan-level data on originated mortgages in HMDA, 2010-2016
- Processing Time $_{ijct} = \delta_{ct} + \beta \text{FinTech}_j + \gamma \text{Controls}_{it} + \epsilon_{ijct}$
 - *ProcessingTime* $_{ijct}$: Days from mortgage application to closing.
 - *FinTech* $_j$: dummy for FinTech lender. Hypothesis: $\beta < 0$.
 - *Controls* $_{it}$: combinations of (i) loan and borrower characteristics (income, loan amount, gender, race, loan type, coapplicant, etc.) and (ii) census tract x month fixed effects.
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 - Estimated separately for purchase and refinance mortgages.
- Even if FinTech is faster: **technological advantage** or **selection**?
 - Selection story: FinTech lenders cherry-pick 'fast' borrowers?

Processing time: purchase mortgages

- ‘Assembly line around 10 days shorter for FinTech lenders, or $\approx 20\%$.
- Magnitude stable across sets of controls & fixed effects.

	(1)	(2)	(3)	(4)	(5)
FinTech	-7.93*** (0.52)	-9.44*** (0.61)	-8.33*** (0.43)	-9.24*** (0.48)	-7.46*** (0.45)
ln(loan amt)		4.47***		4.90***	6.10***
ln(income)		-0.56***		-1.00***	-0.45***
FHA		0.61***		0.23**	-0.40***
VA		1.67***		1.49***	1.87***
Jumbo		3.14***		5.28***	5.94***
Census tr. \times Month FEs?	No	No	Yes	Yes	Yes
Loan controls?	No	Yes	No	Yes	Yes
R2	0.00	0.02	0.23	0.24	0.34
Observations	19159345	19159345	18551855	18551855	7185042
Sample	All	All	All	All	Nonbanks

The dependent variable is mortgage processing time: the time from loan application to closing. Other controls include indicators for gender and race of the borrower, and dummies for occupancy, presence of co-applicant, and pre-approval. Robust standard errors in parentheses (clustered by lender-month). ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Processing time: refinancings

- Similar finding (relative to mean of 51; median of 45 days); effects larger once loan controls are added.
- Effect one-third smaller when restricting sample to nonbanks.
 - Why? Even non FinTech mortgage banks are quicker in processing refis than banks (more so than for purchase).

	(1)	(2)	(3)	(4)	(5)
FinTech	-9.99*** (0.59)	-13.65*** (0.57)	-10.82*** (0.79)	-14.61*** (0.71)	-9.40*** (0.54)
ln(loam amt)		4.75***		4.61***	1.28***
ln(income)		0.03		-0.17***	-0.29**
FHA		5.72***		5.56***	5.42***
VA		1.67***		2.01***	1.37***
Jumbo		6.94***		7.09***	9.21***
Census tr. × Month FEs?	No	No	Yes	Yes	Yes
Loan controls?	No	Yes	No	Yes	Yes
R2	0.01	0.10	0.18	0.24	0.29
Observations	30616247	30616247	30169300	30169300	8041746
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Selection

- Is fast processing due to FinTech lenders being used by borrowers who would have faster processing times anyway?
 - e.g. particularly diligent or in a rush to close
- Several tests suggest no:
 1. Regression coefficients stable to addition of controls (or if anything larger) — no selection on observables
 2. Growth in FinTech strongest in locations that had relatively *long* processing times in 2010 — selection would predict the opposite
 3. Processing times for non-FinTech lenders did not increase disproportionately for borrower/loan types with higher FinTech penetration (as selection would predict)

2) Is FinTech lending riskier?

- Is fast processing simply due to less careful screening?
- Look at outcomes in riskiest market segment – FHA mortgages
 - Buchak et al. study Fannie/Freddie data; find effect of ≈ 0 .
- Two novel data sources:
 1. Ginnie Mae MBS loan-level disclosures (by *issuer*)
 2. FHA Neighborhood Watch Early Warning System
- Finding: In both data sets, FinTech associated with *fewer* ex-post defaults (magnitude: $\approx 25\%$).

Is FinTech riskier? Results

Ginnie Mae: Dependent variable ever 90+ days delinquent

	(1)	(2)	(3)	(4)	(5)
FinTech	-1.29*** (0.33)	-0.97*** (0.30)	-0.93*** (0.27)	-1.51*** (0.46)	-0.79*** (0.16)
Avg. P(default)	3.65	3.65	3.65	4.00	2.73
Loan Sample	All	All	All	Purch.	Refi
Purpose FE	No	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	No	No	No
MonthXState FE	No	No	Yes	Yes	Yes
Loan Controls	No	No	Yes	Yes	Yes
Observations	4097569	4097568	4097544	2966644	1130881

Standard errors clustered by issuer. Sample includes FHA 30-year FRMs originated 2013-2017.

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 - Mixed evidence from additional tests (does default advantage diminish as market share grows? see paper).

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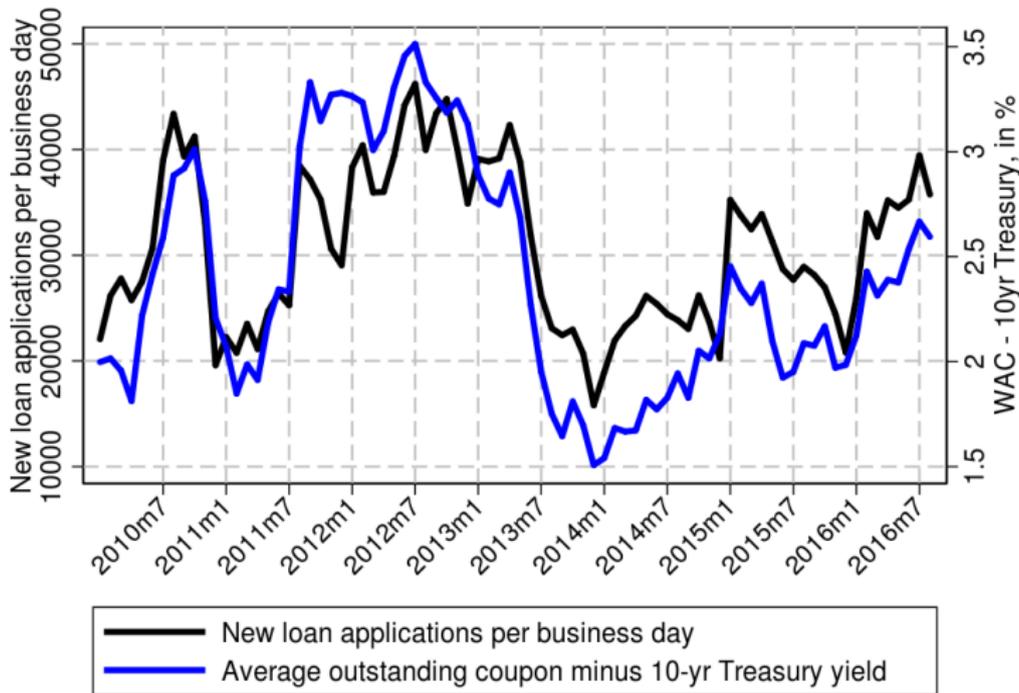
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- “Cream skimming” likely not key issue here (b/c of guarantees).
 - Mixed evidence from additional tests (does default advantage diminish as market share grows? see paper).
- **Summary:** Lower default, consistent with view that automation and electronic record retrieval reduces fraud (e.g. Goodman, 2016).

3) Is FinTech lending more elastic?

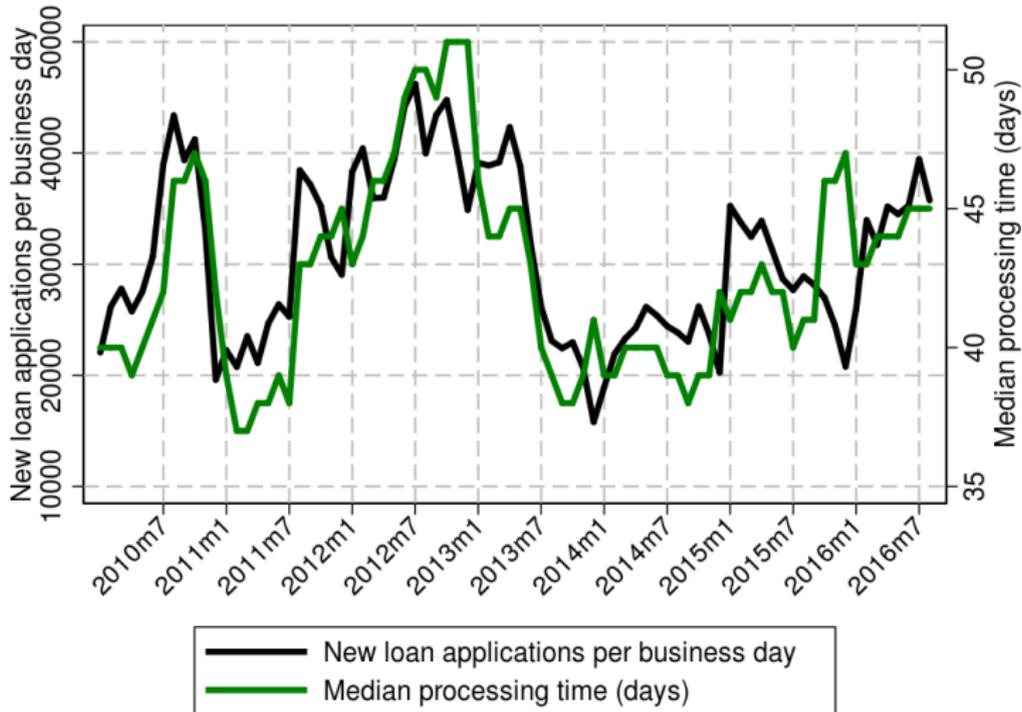
- Evidence of capacity constraints during periods of peak mortgage demand
 - Fuster-Lo-Willen (2017): after increase in demand, lender processing times surge; prices (margins) increase [▶ more](#)
- FinTech lenders may better accommodate shocks because of more automated and less labor intensive process
- Identification challenge: changes in lender-specific application volume represents mix of demand and supply
 - E.g. could solicit more applications when have spare capacity
- Empirical strategy: Use variation in total application volume
 - Not driven by demand for individual lenders
 - Can instrument with long-term interest rates

Mortgage application volume and interest rates



- Significant variation in application volume over 2010 to 2016
- Lower long-term rates \Rightarrow Higher refi incentive \Rightarrow More applications

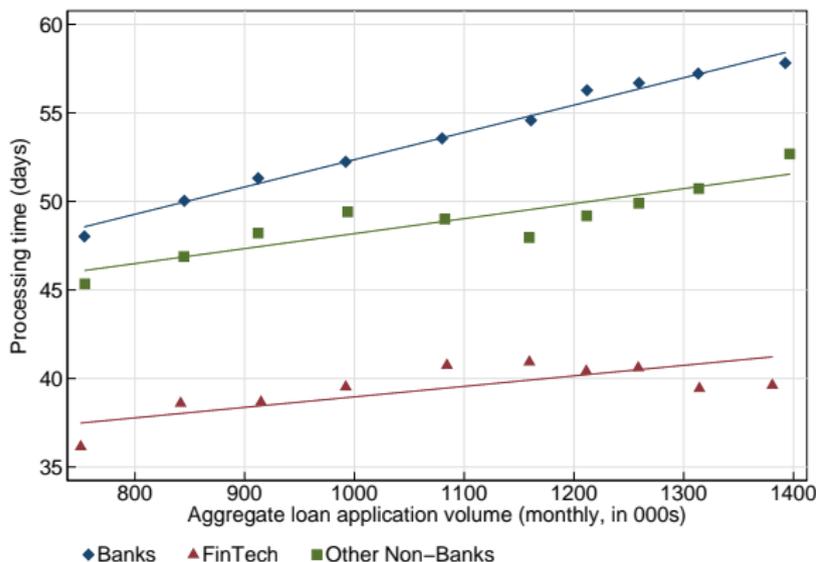
Mortgage application volume and processing time



- Higher application volume \Rightarrow longer processing time
- Bump in October 2015: implementation of “TRID” disclosure rules

Is FinTech lending more elastic?

$$\text{Processing Time}_{ijct} = \delta_j + \alpha \text{AppVolume}_t + \beta \text{FinTech}_j \times \text{AppVolume}_t + \gamma \text{Controls}_{ict} + \epsilon_{ijct}$$



- FinTech **processing time less sensitive** to demand increase

Processing time sensitivity: Regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(\text{App Vol})$	11.76*** (0.52)	13.48*** (0.47)	18.88*** (0.67)	13.43*** (0.47)	8.85*** (0.45)	13.60*** (0.81)	10.55*** (0.79)
$\ln(\text{App Vol}) \times \text{FinTech}$	-7.55*** (1.46)	-6.15*** (1.51)	-9.57*** (1.80)	-7.46*** (1.50)	-2.06 (1.40)	-4.45*** (1.67)	-4.47*** (1.56)
Observations	49,775,550	49,775,312	30,615,852	80,495,817	17,024,138	8,927,175	29,048,184
R^2	0.14	0.20	0.25	0.17	0.20	0.16	0.16
Loan Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Tract FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Application Sample	Originated	Originated	Refi	All	Originated	Refi	All
Lender Sample	All	All	All	All	Nonbanks	Nonbanks	Nonbanks

$\ln(\text{App. Vol.})$ is log of aggregate mortgage applications. Loan controls include borrower income, loan size, loan purpose, loan type, borrower demographic characteristics.

Elasticity: additional evidence

- Finding: FinTech **processing time less sensitive** to demand
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- Not due to “rationing” by FinTech lenders when demand rises:
 - Estimate model for HMDA application denials. Finding: FinTech denial rates *fall* compared to other lenders when mtg demand rises.
 - No difference in origination volume (caveat: trend in FinTech market share makes measurement difficult here).

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 - No difference in origination volume (caveat: trend in FinTech market share makes measurement difficult here).
- Mostly similar message from alternative demand shock measures:
 - Similar findings if use average refinance incentive as proxy (or instrument) for aggregate applications.
 - Directionally consistent results from “Bartik” index based on county-level lender shares (although smaller magnitude)

4) Does FinTech lending affect refinancing behavior?

- Many borrowers seem to refinance suboptimally (Keys et al., 2016).
 - Errors of omission: don't refinance when they should
 - Errors of commission: refinance when savings not worthwhile
- Does FinTech lending increase refi speed or efficiency?
 - Important issue e.g., for monetary policy transmission.
 - Industry evidence (and Buchak et al., 2018): FinTech loans prepay faster. But just a selection effect?
- Relate *aggregate* local refinancing propensities to variation in FinTech presence. Location and time fixed effects.
 - If an effect: errors of omission ↓ or errors of commission ↑ ?
- Data: Equifax CRISM, which allows tracking borrowers in McDash mortgage servicing data across loans (as in Beraja et al. 2017). Focus on top 500 counties (about 80% of loan originations).

Refi propensity: County-level regressions

$$\text{Refi Propensity}_{c,t} = \alpha_c + \alpha_t + \beta \cdot \text{FinTechShare}_{c,t-s} + \Gamma \cdot \mathbf{X}_{c,t} + \epsilon_{c,t}$$

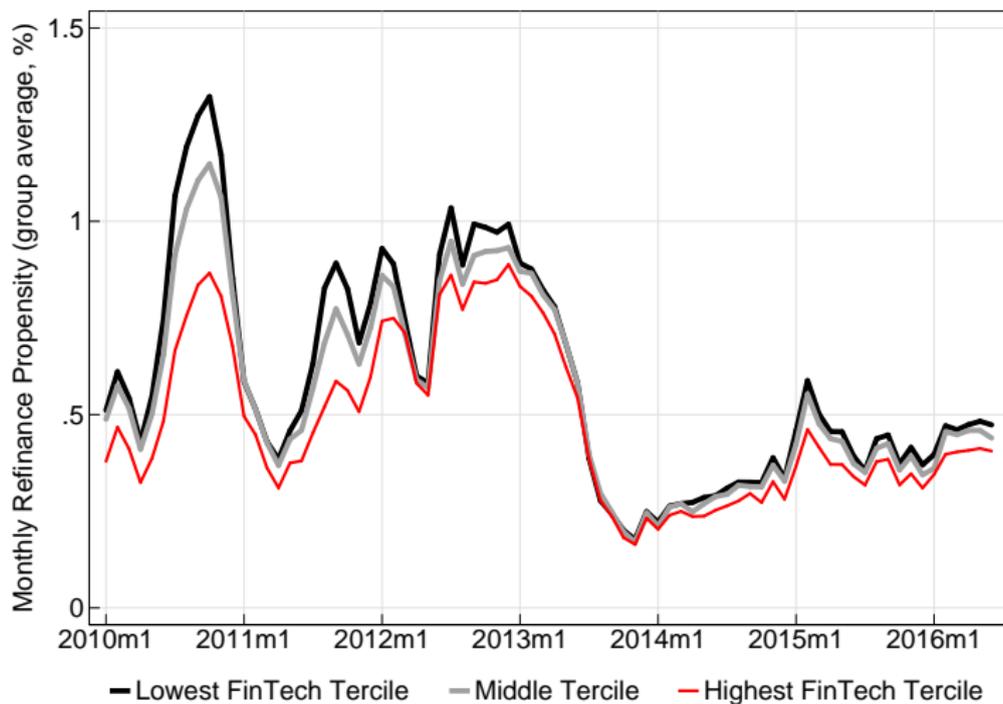
Dependent variable: monthly refinance propensity, in %

	(1) All	(2) All	(3) 30yr FRM	(4) 30yr FRM
FT share _{Q-1} (MA)	1.121*** (0.204)	0.689*** (0.142)	1.195*** (0.223)	0.706*** (0.157)
Average FICO/10		0.067*** (0.012)		0.071*** (0.013)
Average CLTV/10		-0.094*** (0.007)		-0.104*** (0.008)
Average current rate		1.135*** (0.059)		1.202*** (0.062)
FHA/VA share		0.190 (0.315)		0.185 (0.332)
County FEs?	Yes	Yes	Yes	Yes
Date FEs?	Yes	Yes	Yes	Yes
Average Y	0.56	0.56	0.61	0.61
Adj. R2	0.78	0.81	0.77	0.79
Adj. R2 (within)	0.01	0.12	0.01	0.11
Obs.	36000	36000	36000	36000

Note: standard errors clustered at county level.

Evolution of refi propensities

Counties with higher FinTech shares started out with lower refi propensities; have caught up.



More refinances = better refinances?

- Is higher local FinTech presence associated with **fewer errors of omission?** (i.e. more borrowers refinancing when they should) or **more errors of commission?** (...when they should not)?

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- Evaluate based on “square root” rule and baseline calibration from Agarwal-Driscoll-Laibson (2013). 30-year FRMs only.
 - Optimal “trigger rate” depends on current coupon, outstanding principal, transaction cost, discount rate, tax rate etc.

▶ more

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 - Optimal “trigger rate” depends on current coupon, outstanding principal, transaction cost, discount rate, tax rate etc.
- Sort borrowers into groups depending on difference between current rate and trigger rate
 - **Question:** Which borrowers are more likely to refinance?

▶ more

More refinances = better refinances?

Negative values mean borrower should not refinance, by ADL rule. Positive values mean they should. Column (7) pools all bins.

<i>Refi incentive (ADL)</i>	(1) < -1	(2) [-1, -0.5)	(3) [-0.5, 0)	(4) [0, 0.5)	(5) [0.5, 1)	(6) ≥ 1	(7) All
FT Share _{Q-1} (MA)	-0.140* (0.073)	1.028*** (0.200)	2.008*** (0.304)	1.985*** (0.353)	1.444*** (0.347)	0.507* (0.267)	1.436*** (0.229)
County and month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Y	0.12	0.46	0.85	1.04	1.05	0.78	0.59
R2	0.00	0.00	0.01	0.01	0.01	0.01	0.00
Obs.	64,866,392	42,085,823	38,988,748	29,249,088	19,039,098	20,745,039	214,996,787

- **Finding:** refi propensity increases with FinTech share for most groups; stronger for those that should refinance (or close).
 - Notably, effect negative for deeply suboptimal refis
- Can also evaluate “optimality” based on realized rate changes. Find higher prob(refi=optimal) when FinTech share is higher
 - Also larger average interest rate saving upon refinancing

5) Who borrows from FinTech lenders?

We analyze variation in FinTech lending growth, based on individual + local geographic characteristics.

Hypotheses:

1. **Access to finance.** High demand if limited access to traditional financial system (few bank branches, women / minority, low income, low credit scores)?
2. **Technology adoption.** Technology adoption often fastest in dense urban areas. True here? Higher adoption for financially literate borrowers? (e.g., educated?) Young vs old?
3. **Internet access.** Is it a constraint? (“digital divide”).
4. **Demand for fast processing.** High FinTech share in ‘hot’ real estate markets where quick closing is important?

Determinants of FinTech mortgage adoption

Dep. var.: FinTech (0/100)	Purchases		Refinances	
	All	Nonbanks	All	Nonbanks
Borrower income and demography				
Log(income)	0.104***	0.701***	-0.833***	-0.159***
Gender:				
Female	0.0592***	0.184***	0.756***	3.056***
Unknown	2.887***	10.13***	6.728***	24.99***
Race and ethnicity:				
Black	-0.306***	-0.387***	-0.415***	1.166***
Hispanic	-0.880***	-1.577***	-1.432***	-1.982***
Unknown	1.551***	3.220***	3.632***	6.540***
% black or hispanic ^{TRACT}	-0.228***	-1.064***	-0.256***	-2.273***
Access to finance				
Credit score ^{TRACT}	-0.279***	-0.731***	-1.068***	-3.002***
Bank branch density ^{TRACT}	0.467***	0.954***	0.275***	0.479***
Technology diffusion and adoption				
Population density ^{TRACT}	0.141***	0.920***	-0.0691***	0.421***
Borrower age ^{TRACT}	0.119***	0.340***	0.263***	0.869***
% bachelor degree ^{TRACT}	0.307***	0.920***	0.262***	0.690***
Internet access				
% high speed coverage ^{TRACT}	0.101***	0.255***	0.0689***	0.371***
% with broadband subscription ^{CTY}	-0.132***	-0.487***	-0.0344**	-0.0551
Local housing market conditions				
% home price appreciation ^{CTY}	-0.0362***	-0.836***	0.277***	-1.258***
Processing time coefficients ^{TRACT}	0.0182	0.205***	0.588***	1.599***
Log(2010 home price) ^{CTY}	-0.127***	-0.688***	-0.812***	-2.993***
Mean of Dependent Variable	2.888	6.745	6.129	20.41

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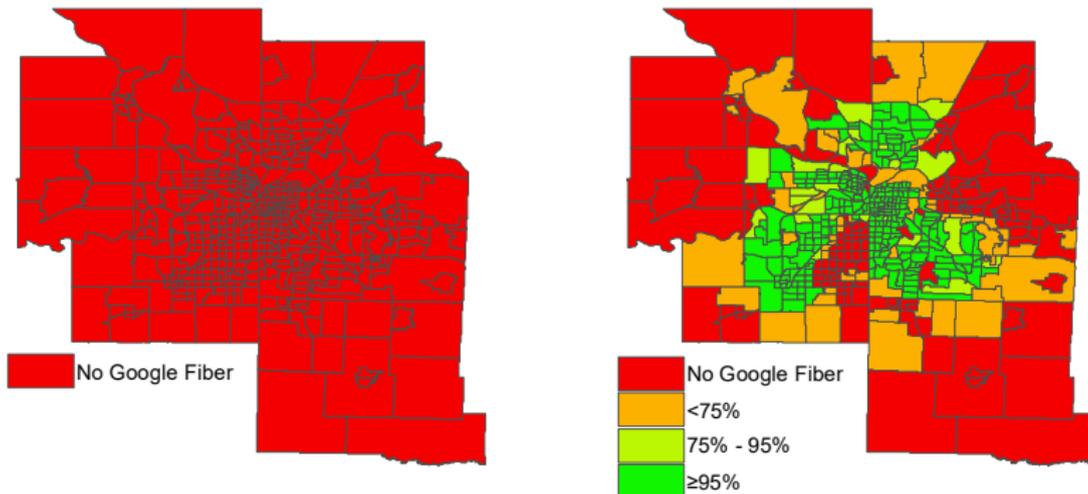
Takeaways

- FinTech market share tends to be higher in neighborhoods where borrowers are older and more educated
 - Matches feedback from practitioners that online lending is more attractive to experienced/financially literate borrowers
- Mixed evidence on FinTech lenders expanding access to finance
 - e.g. lower share of minorities, high local bank branch density
 - but: lower local credit scores, more female borrowers
- Little evidence of “digital divide” playing a big role here
 - Case study: roll-out of Google Fiber in Kansas City (previously had limited high-speed internet) — does not increase FT share

Possible interpretation: FinTech mortgage lending more about improving efficiency of the process for “bread and butter” borrowers rather than expanding access to marginal households.

Google Fiber staggered rollout

Figure: Google Fiber availability in Kansas City: 2011 and 2015



No significant effect of rollout on market share of FinTech mortgage lenders (point estimate if anything negative)

Summing up

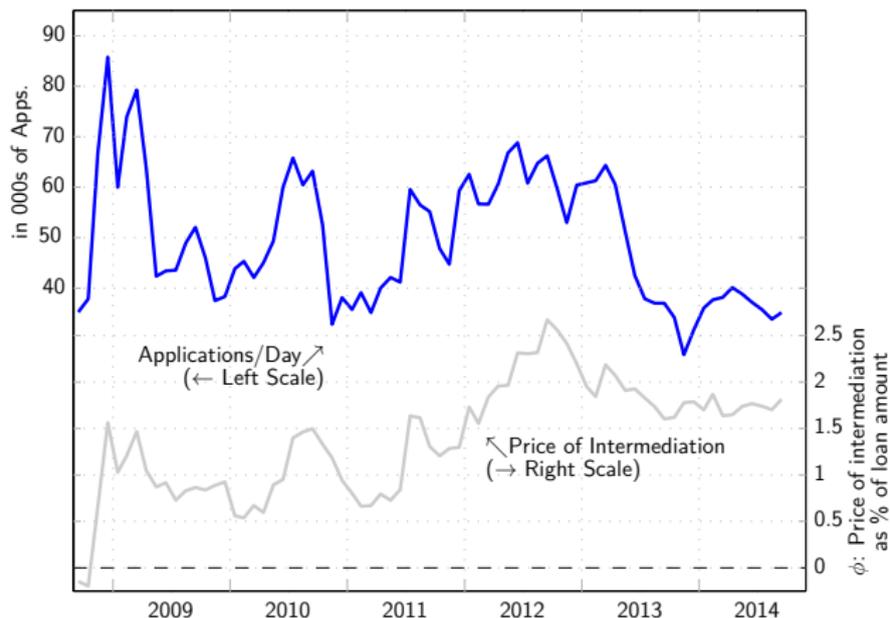
Punchline: Evidence supports view that technological change is reducing intermediation frictions and improving efficiency of the mortgage market.

1. Faster mortgage processing ($\approx 20\%$)
2. Lower defaults ($\approx 25\%$)
3. More elastic processing speeds (reduce bottlenecks)
4. Faster refinancing and fewer refi errors
5. Mixed evidence of expanding access to underserved borrowers.

Broader question: Is FinTech reducing frictions and raising productivity in lending markets? Or mainly about skimming, price discrimination etc.

- Our evidence mainly consistent with “bright side” of FinTech
- May shed light on future evolution of mortgage mkt, other loan mkts

Application volume and lender margins



Price of intermediation = \$ value of a mortgage in the MBS market — what lender pays to borrower

▶ back

Agarwal-Driscoll-Laibson (2013)

(Approximately) optimal to refinance when available mortgage rate is at least x below the current coupon rate.

x depends on the outstanding principal amount, and a number of parameters. Baseline calibration (also used in Keys-Pope-Pope, 2016):

- Transaction cost $\kappa = 2000 + 0.01M$
- Real discount rate $\rho = 0.05$
- Marginal tax rate $\tau = 0.28$
- Annual probability of moving $\mu = 0.1$
- Standard deviation of mortgage rate $\sigma = 0.0109$

▶ back