Internet Appendix for "The Role of Technology in Mortgage Lending"

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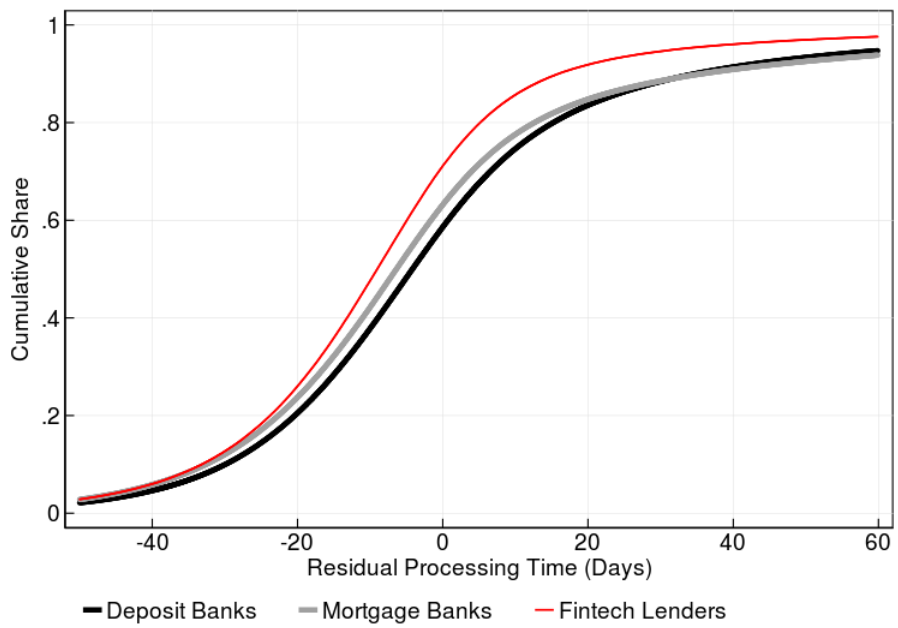
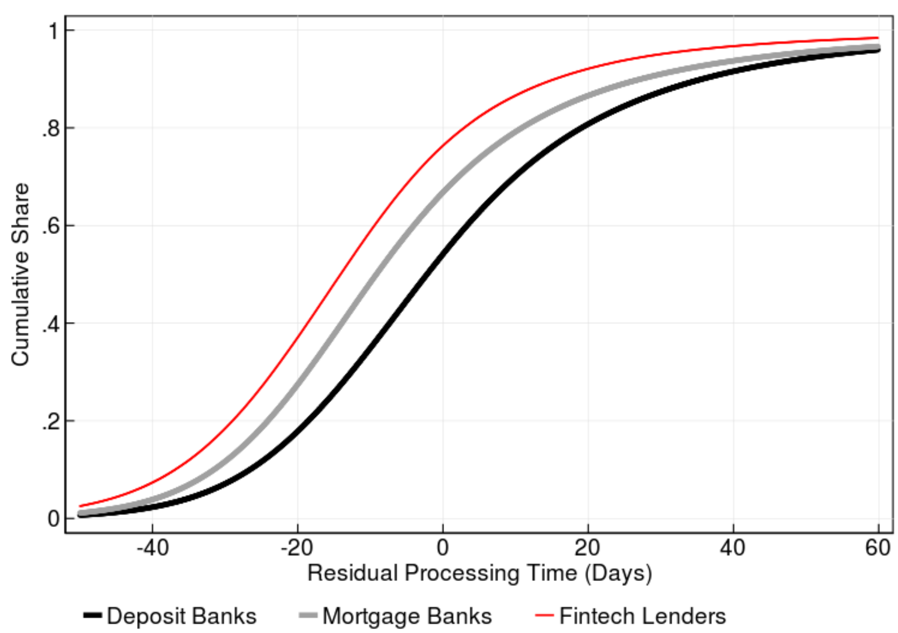
A Processing time: additional analysis

Figure A.1: Distribution of processing times by lender type. (These are residuals after controlling for loan characteristics and census tract $\times$ month fixed effects as in Table 3.)



(a) Purchase mortgages



(b) Refinance mortgages

Table A.1: Testing whether high FinTech probability is associated with slower processing time for non-FinTech lenders.

	(1)	(2)	(3)	(4)
$\widehat{\text{FinTech}}$	2.547***	-0.808***	3.109***	-0.559***
	(0.163)	(0.144)	(0.216)	(0.183)
Loan controls	Yes	Yes	Yes	Yes
Lender-Month FE	Yes	Yes	Yes	Yes
Lender-Census Tract FE	No	Yes	No	Yes
R2	0.22	0.27	0.30	0.33
Observations	47180463	44210993	28616765	26127401
Loan type	All	All	Refi	Refi
Sample	Non-Fintech	Non-Fintech	Non-Fintech	Non-Fintech

Table regresses loan processing time (in days) for non-FinTech lenders on the predicted probability that an application would go to a FinTech lender ($\widehat{\text{FinTech}}$), lender-month fixed effects, lender-census tract fixed effects, and loan controls. $\widehat{\text{FinTech}}$ comes from an unreported first-stage OLS regression where, in the full sample including all lender types, an indicator for a loan being originated by a FinTech lender is regressed on census tract-month fixed effects and loan controls. In both stages, loan controls include the log of applicant income, the log of the loan amount, indicators for FHA loans, VA loans and jumbo loans, applicant race, gender, loan purpose (purchase or refinancing), whether the loan has a coapplicant, whether a preapproval was obtained, the occupancy and lien status of the loan, the property type, and a dummy indicating whether income is missing. Both purchase and refinance loans are included in columns (1)-(2), while only refinance loans are included in columns (3)-(4). Standard errors reported in parentheses are clustered by lender-month. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

B Is FinTech lending cheaper?

Table A.2: FHA mortgage interest rate regressions based on Ginnie Mae data. Includes 30-year fixed-rate mortgages originated 2013-2017.

	(1)	(2)	(3)	(4)
FinTech	0.000	-0.023**	-0.075***	0.002
	(0.009)	(0.010)	(0.010)	(0.008)
FICO		-0.002***	-0.002***	-0.001***
		(0.000)	(0.000)	(0.000)
LTV		0.000***	0.003***	-0.001***
		(0.000)	(0.000)	(0.000)
DTI		0.000***	0.001***	-0.001***
		(0.000)	(0.000)	(0.000)
Sample	All	All	Purch.	Refi
Purpose FE?	No	Yes	Yes	Yes
Month FE?	Yes	No	No	No
MonthXState FE?	No	Yes	Yes	Yes
Loan cont.?	No	Yes	Yes	Yes
Mean Y	4.00	4.00	4.01	3.96
R2	0.31	0.41	0.42	0.46
Observations	4097569	4097544	2966644	1130881

Table regresses mortgage interest rate on an indicator variable identifying FinTech issuers, state-by-origination month fixed effects, loan controls and borrower controls. The sample consists of FHA-insured 30-year fixed-rate mortgages originated over June 2013 to June 2017, obtained from Ginnie Mae MBS monthly loan-level disclosures. Displayed loan controls include the borrower FICO score, the loan-to-value ratio (LTV) and the debt-to-income ratio (DTI). Suppressed loans controls include loan purpose type, the log of the loan amount, and indicators for the number of borrowers, the property type, whether the borrower received down payment assistance, and for whether FICO, LTV, or DTI are missing. Standard errors reported in parentheses are clustered by issuer-origination month. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

C Is FinTech lending more elastic? Additional results

Table A.3: Elasticity of processing time with respect to demand proxies: FinTech vs. other lenders

	(1)	(2)	(3)	(4)	(5)	(6)
Refi Incentive	4.79***	6.72***	5.14***			
	(0.20)	(0.28)	(0.19)			
Refi Inc. × FinTech	-3.95***	-5.45***	-4.56***			
	(0.64)	(0.74)	(0.65)			
Bartik App. × FinTech				9.73***	13.78***	8.97***
				(0.34)	(0.50)	(0.35)
Bartik App. × FinTech				0.05	-3.27***	-2.51***
				(0.82)	(0.82)	(0.67)
Observations	49,775,312	30,615,852	80,495,817	49,775,312	30,615,852	80,495,817
R^2	0.20	0.25	0.17	0.19	0.24	0.17
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Application Sample	Originated	Refi	All	Originated	Refi	All
Lender Sample	All	All	All	All	All	All

Table A.3 regresses loan processing time on two proxies for aggregate mortgage demand: the average outstanding coupon less the 10-yr Treasury yield (Refi Incentive) and the log of the weighted sum of county-level applications where weights are the unconditional market share of applications received in the county (Bartik Applications). Regressions include an interaction between the proxy and the FinTech indicator, loan controls, lender fixed effects, census-tract fixed effects and calendar month fixed effects. The sample is restricted to application dates from 2010 to 2016Q2. Columns 1 and 4 include all originated loans; Columns 2 and 5 included originated refinancing loans; and Columns 3 and 6 include all applications (including denied applications). The sample of lenders includes all lender types. Loan controls include the log of applicant income, the log of the loan amount, indicators for FHA loans, VA loans and jumbo loans, applicant race, gender, whether the loan has a coapplicant, whether the application was a preapproval, the occupancy and lien status of the loan, the property type, and a dummy indicating whether income is missing. Columns 3 and 6 also include indicators for whether a loan was denied or withdrawn. Standard errors reported in parentheses are clustered by lender-month. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

D FinTech & refinancing: additional analysis

A.1 Sample construction

We pull all active loans in CRISM in December 2013 and select the 500 counties with the highest number of loans. To limit the sample size while still having sufficient data coverage across the counties, we take 12,000 loans from each county (roughly the number of loans in the smallest county in the top 500). We then take the individual CRISM identifiers that were associated with these loans, and pull all records associated with those individuals from 2010 through 2016. By restricting to the largest counties, we are able to get accurate refinance propensities for a cross-section of the country at the county level while limiting our sample size for computational reasons. This sample selection procedure gives us a sample of over 325 million loan-month observations, made up of 7.2 million distinct loans from 5.1 million distinct borrowers.

We identify refinances and calculate refinance propensities and cashouts at the county level following the same procedure in Beraja et al. (2017). Refinance propensities at the county level are defined as the percentage of loans from month $t-1$ that are refinanced in month t. We create panels both at the county and individual level with these identified refinances.

Figure A.2 shows the average refinance propensity over time as well as the number of originated refinance loans in the same counties, as recorded in HMDA (where we sum loans by application month). We track the evolution of originations fairly closely.[1]

A.2 Additional results

In Table A.4 we complement the findings in Section VI by studying the properties of 30-year FRMs that were refinanced into new 30-year FRMs over our sample period. The first two columns of the table study whether a refinance was optimal (i.e. whether the interest rate saving was large enough) according to the ADL rule. In column (1), we do this based on comparing the rate on the old mortgage to the market rate at the time the refinance happened (similar to how we define refinancing incentives in the main text). In column (2), we instead directly use the rate on the new (refinance) mortgage. We see that in both cases, a higher local FinTech market share increases the probability that a refinance is classified as optimal. Interestingly, the association is stronger when we use the actual mortgage rate rather than the market rate, even though based on that metric, actually fewer refinances

[1] Note that our CRISM sample design (explained above) over-samples the relatively smaller counties among the top 500; if we weight counties similarly in HMDA, the two lines become even closer.

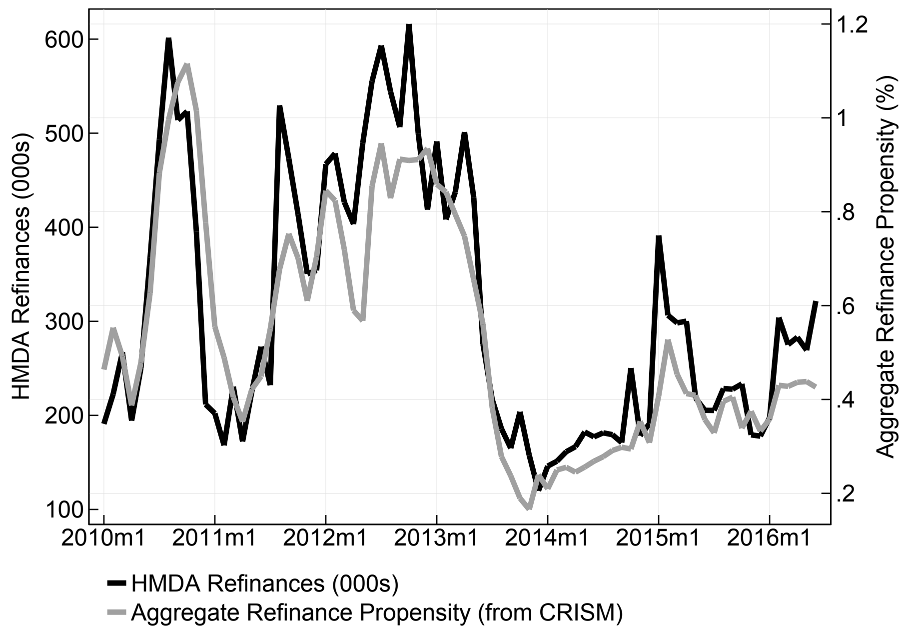


Figure A.2: Refinance propensity over time: comparing CRISM-derived measure to number of refinance mortgages in top 500 counties recorded in HMDA.

(only 41%) are classified as optimal.[2]

In column (3), instead of relying on the ADL calculation, we directly look at the gap between the old mortgage rate and the new mortgage rate, which averages 1.35%. There, again, a higher local FinTech share is associated with a larger gap. Finally, the last columns shows that in places with higher FinTech shares, borrowers were more likely to also withdraw some home equity when refinancing.[3]

[2]This reflects the fact that, on average, rates on actually originated mortgages tend to be somewhat higher than the rate reported in the Freddie Mac Primarly Mortgage Market Survey, which applies to the highest credit quality borrowers.

[3]The cash out indicator that is used as the left-hand side variable here is equal to 1 if, after subtracting 2 percent from the new loan to cover closing costs, the new mortgage is at least $5,000 above the old mortgage (including junior liens) that is being paid off.

Table A.4: Testing for link between local FinTech share and properties of realized refinances of 30-year fixed-rate mortgages.

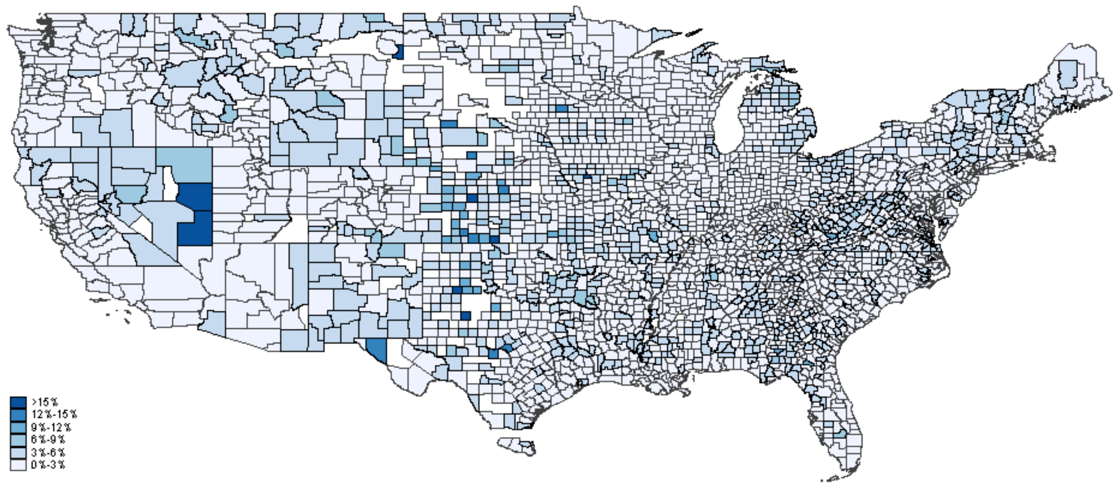
	(1) Opt. refi? (mkt rate)	(2) Opt. refi? (actual rate)	(3) Rate gap (old−new)	(4) Cash out?
FT Share$_{Q-1}$ (MA)	0.266***	0.610***	0.939***	0.175**
	(0.083)	(0.092)	(0.122)	(0.081)
County FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Mean Y	0.55	0.41	1.34	0.17
R2	0.35	0.25	0.42	0.13
Obs.	666,070	666,070	666,070	666,072

Table shows results of four different regressions of characteristics of refinance loans in CRISM where both the old and new mortgage are 30-year FRMs. The left-hand side variables are, by column, 1) an indicator for whether a refinancing occurred at a time where the market interest rate was below the rate at which the Agarwal et al. (2013) (ADL) rule would prescribe that the borrower refinance (so "1" would mean the refinancing was "optimal" in that sense); (2) an indicator of whether the mortgage rate on the new (refinance) loan is below the ADL rate; (3) the difference between the old mortgage rate and the new mortgage rate (winsorized at 1%); (4) an indicator variable for the refinance involving "cashing out" home equity (set equal to 1 if the balance of the new loan exceeds the balance of the old loan by more than $5000 plus closing costs (assumed to correspond to 2 percent of the loan amount). Independent variables in each case include the one-quarter-lagged four-quarter county-level FinTech market share, county fixed effects, month fixed effects, and the following loan controls: 5-point bins of CLTV, 20-point bins of FICO, a cubic function in the age of the refinanced loan, the log of the balance of the refinanced loan, and an indicator for whether the refinanced loan was an FHA/VA loan. Standard errors reported in parentheses are clustered by county. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

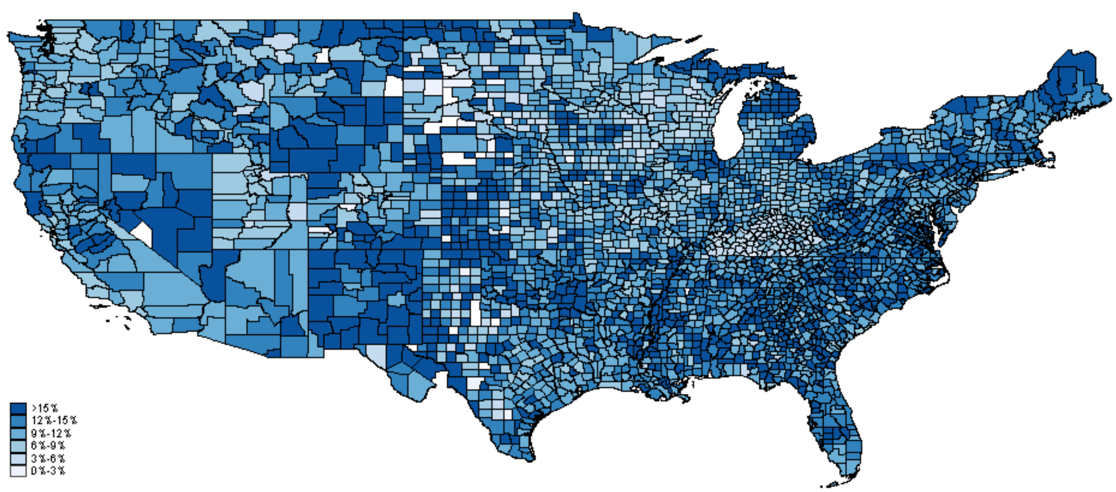
E Spatial Variation in FinTech Mortgage Lending

Figure A.3: Market share of FinTech lenders by county

Calendar year 2010



Calendar year 2016



FinTech market share by county in 2010 and 2016. Figure reflects all lender types and both purchase mortgages and refinancings. FinTech lenders classified using the procedure described in Section II. Data source: HMDA.

F Cross-sectional regressions: Additional results

Dependent variable: = 100 if fintech lender, = 0 otherwise

	Purchases				Refinances			
	All		Nonbanks		All		Nonbanks	
	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate
Borrower income and demography								
Log(income)	-0.0932***	0.104***	0.761***	0.701***	-0.549***	-0.833***	-2.677***	-0.159***
	(0.00777)	(0.00650)	(0.0242)	(0.0173)	(0.00877)	(0.00725)	(0.0321)	(0.0275)
Gender:								
Female	0.00683	0.0592***	-0.502***	0.184***	-0.130***	0.756***	0.199***	3.056***
	(0.00973)	(0.00947)	(0.0218)	(0.0208)	(0.0119)	(0.0126)	(0.0380)	(0.0379)
Unknown	3.027***	2.887***	13.09***	10.13***	8.712***	6.728***	30.88***	24.99***
	(0.0334)	(0.0421)	(0.120)	(0.117)	(0.0384)	(0.0437)	(0.0990)	(0.100)
Race and ethnicity:								
Black	0.0808***	-0.306***	-1.181***	-0.387***	-0.218***	-0.415***	-2.862***	1.166***
	(0.0276)	(0.0254)	(0.0568)	(0.0495)	(0.0298)	(0.0291)	(0.0877)	(0.0814)
Hispanic	-0.729***	-0.880***	-3.314***	-1.577***	-1.542***	-1.432***	-7.162***	-1.982***
	(0.0180)	(0.0200)	(0.0370)	(0.0391)	(0.0253)	(0.0250)	(0.0759)	(0.0629)
Unknown	2.594***	1.551***	8.604***	3.220***	7.206***	3.632***	19.53***	6.540***
	(0.0262)	(0.0294)	(0.0796)	(0.0658)	(0.0303)	(0.0310)	(0.0814)	(0.0710)
% black or hispanic$^{\text{TRACT}}$	0.0449***	-0.228***	-0.816***	-1.064***	0.288***	-0.256***	-1.452***	-2.273***
	(0.0102)	(0.0166)	(0.0224)	(0.0394)	(0.0117)	(0.0165)	(0.0393)	(0.0501)
Access to finance								
Credit score$^{\text{TRACT}}$	-0.0777***	-0.279***	0.408***	-0.731***	-0.532***	-1.068***	-2.523***	-3.002***
	(0.0123)	(0.0192)	(0.0315)	(0.0468)	(0.0120)	(0.0193)	(0.0423)	(0.0618)
Bank branch density$^{\text{TRACT}}$	0.523***	0.467***	1.040***	0.954***	0.266***	0.275***	-1.382***	0.479***
	(0.0239)	(0.0262)	(0.0604)	(0.0574)	(0.0186)	(0.0201)	(0.0623)	(0.0530)
Technology diffusion and adoption								
Population density$^{\text{TRACT}}$	0.269***	0.141***	0.672***	0.920***	-0.000996	-0.0691***	-1.538***	0.421***
	(0.0237)	(0.0275)	(0.0669)	(0.0697)	(0.0194)	(0.0236)	(0.0714)	(0.0607)
Borrower age$^{\text{TRACT}}$	0.0400***	0.119***	0.673***	0.340***	-0.0186	0.263***	1.680***	0.869***
	(0.0154)	(0.0168)	(0.0390)	(0.0400)	(0.0161)	(0.0169)	(0.0538)	(0.0502)
% bachelor degree$^{\text{TRACT}}$	0.116***	0.307***	0.940***	0.920***	-0.199***	0.262***	-1.388***	0.690***
	(0.0175)	(0.0213)	(0.0476)	(0.0529)	(0.0143)	(0.0180)	(0.0489)	(0.0553)
Internet access								
% high speed	0.192***	0.101***	0.294***	0.255***	0.120***	0.0689***	-0.611***	0.371***
coverage$^{\text{TRACT}}$	(0.0118)	(0.0127)	(0.0316)	(0.0316)	(0.0130)	(0.0127)	(0.0575)	(0.0461)
% with broadband	-0.0924***	-0.132***	-0.466***	-0.487***	-0.279***	-0.0344**	-2.864***	-0.0551
subscription$^{\text{CTY}}$	(0.0131)	(0.0179)	(0.0341)	(0.0460)	(0.0138)	(0.0167)	(0.0462)	(0.0555)
Local housing market conditions								
% home price	-0.0522***	-0.0362***	-0.971***	-0.836***	0.315***	0.277***	-1.999***	-1.258***
appreciation$^{\text{CTY}}$	(0.0112)	(0.0114)	(0.0271)	(0.0258)	(0.0137)	(0.0132)	(0.0443)	(0.0382)
Processing time	0.0961***	0.0182	0.204***	0.205***	0.760***	0.588***	1.561***	1.599***
coefficients$^{\text{TRACT}}$	(0.0108)	(0.0111)	(0.0290)	(0.0269)	(0.0133)	(0.0119)	(0.0502)	(0.0397)
Log(2010 home price)$^{\text{CTY}}$	-0.150***	-0.127***	-0.628***	-0.688***	-0.440***	-0.812***	-4.321***	-2.993***
	(0.0111)	(0.0188)	(0.0284)	(0.0471)	(0.0139)	(0.0213)	(0.0411)	(0.0675)
Observations	20790255	20790255	8901875	8901875	32936746	32936746	9888845	9888845
Mean Dependent Var	2.888	2.888	6.745	6.745	6.129	6.129	20.41	20.41

Dependent variable: = 100 if fintech lender, = 0 otherwise

	Purchases				Refinances			
	All		Nonbanks		All		Nonbanks	
	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate
Additional race variables								
American Indian/Alaska Native	-0.605***	-0.351***	-1.837***	-1.165***	0.185***	0.873***	0.431**	1.100***
	(0.0471)	(0.0469)	(0.100)	(0.103)	(0.0697)	(0.0681)	(0.200)	(0.199)
Asian	-0.401***	-0.223***	-0.820***	-0.573***	-1.673***	-0.582***	-8.575***	-2.263***
	(0.0289)	(0.0309)	(0.0679)	(0.0698)	(0.0403)	(0.0445)	(0.105)	(0.123)
Hawaiian/Pacific Islander	-0.198***	-0.0433	-1.731***	-0.307***	-0.815***	-0.316***	-5.427***	0.309
	(0.0611)	(0.0614)	(0.114)	(0.113)	(0.0809)	(0.0916)	(0.212)	(0.220)
Missing variable indicators								
Missing Log(income)	-3.037***	-5.187***	-7.263***	-11.55***	-2.545***	-9.490***	-14.23***	-18.42***
	(0.0144)	(0.0297)	(0.0526)	(0.151)	(0.0207)	(0.0290)	(0.0609)	(0.0693)
Missing % black or hispanic$^{\text{TRACT}}$	4.111***	5.285***	2.929***	7.582***	-0.0931	3.341	-5.258	4.777
	(1.214)	(1.383)	(0.556)	(1.971)	(2.551)	(2.698)	(6.680)	(5.378)
Missing Credit score$^{\text{TRACT}}$	-0.916***	-0.589***	-2.476***	-0.948	-1.354***	-0.312	-4.354***	-1.116
	(0.191)	(0.198)	(0.462)	(0.636)	(0.401)	(0.397)	(1.191)	(1.318)
Missing Bank branch density$^{\text{TRACT}}$	0.156***	0.129***	-0.213***	0.0722	0.615***	0.234***	0.468***	0.469***
	(0.0272)	(0.0318)	(0.0670)	(0.0771)	(0.0294)	(0.0305)	(0.108)	(0.101)
Missing Population density$^{\text{TRACT}}$	1.412	-1.939***	1.100	-3.873***	-1.702	-2.794	-6.470*	-1.920
	(1.632)	(0.432)	(1.476)	(0.996)	(1.100)	(1.920)	(3.674)	(5.038)
Missing Borrower age$^{\text{TRACT}}$	-0.724**	0.176	-2.392***	-0.343	-1.070	-0.336	-4.657**	-1.447
	(0.363)	(0.429)	(0.706)	(0.998)	(0.767)	(0.707)	(2.145)	(2.225)
Missing % bachelor degree$^{\text{TRACT}}$	2.803*	0.992	1.941*	0.544	-1.160	-0.289	-6.413	-3.266
	(1.535)	(0.726)	(1.098)	(1.945)	(1.560)	(1.629)	(4.561)	(5.304)
Missing % high speed	-0.947***	-0.886***	-1.532***	-1.917***	-0.718***	-0.652***	-0.575***	-2.222***
coverage$^{\text{TRACT}}$	(0.0251)	(0.0250)	(0.0628)	(0.0604)	(0.0268)	(0.0243)	(0.0979)	(0.0766)
Missing % with broadband	-0.222***	0.613***	2.194***	3.157***	-0.482***	0.0861**	6.369***	2.676***
subscription$^{\text{CTY}}$	(0.0280)	(0.0362)	(0.0968)	(0.116)	(0.0326)	(0.0355)	(0.142)	(0.134)
Missing % home price	-0.675***	0.109**	-0.190**	0.150	-0.395***	0.0437	6.062***	0.391
appreciation$^{\text{CTY}}$	(0.0241)	(0.0518)	(0.0835)	(0.172)	(0.0315)	(0.0747)	(0.123)	(0.270)
Missing Processing time	0.179***	0.0334	-0.594***	-0.314***	0.733***	0.135***	-0.398***	-0.387***
coefficients$^{\text{TRACT}}$	(0.0426)	(0.0475)	(0.0962)	(0.106)	(0.0455)	(0.0475)	(0.140)	(0.136)
Missing Log(2010 home price)$^{\text{CTY}}$	-0.704***	-0.728***	0.0130	-0.906***	-0.415***	0.384***	5.403***	2.375***
	(0.0237)	(0.0536)	(0.0790)	(0.171)	(0.0306)	(0.0762)	(0.118)	(0.273)
Other loan controls								
Log(loan size)	0.0252***	0.0909***	-0.138***	-0.494***	1.295***	2.435***	-5.397***	-1.665***
	(0.00930)	(0.00931)	(0.0264)	(0.0240)	(0.0108)	(0.00762)	(0.0487)	(0.0626)
Jumbo Loans	-1.951***	-2.599***	0.605***	-0.524***	-4.578***	-6.870***	-6.122***	-0.401***
	(0.0226)	(0.0314)	(0.116)	(0.100)	(0.0272)	(0.0358)	(0.132)	(0.129)
Loan Type: FHA	1.078***	1.223***	-1.124***	-0.379***	5.864***	9.225***	-2.041***	2.884***
	(0.0165)	(0.0149)	(0.0358)	(0.0286)	(0.0341)	(0.0362)	(0.0585)	(0.0593)
Loan Type: VA	0.0610***	0.497***	-1.282***	-0.889***	2.990***	7.633***	-3.873***	3.893***
	(0.0229)	(0.0222)	(0.0458)	(0.0444)	(0.0494)	(0.0486)	(0.0846)	(0.0806)
No Coapplicant	0.533***	0.469***	0.498***	0.860***	0.451***	0.138***	-0.755***	-1.694***
	(0.00977)	(0.00945)	(0.0230)	(0.0215)	(0.0121)	(0.0121)	(0.0368)	(0.0343)
Owner Occupied	0.543***	0.0652***	-1.652***	-0.589***	1.881***	0.908***	3.194***	3.855***
	(0.0176)	(0.0193)	(0.0619)	(0.0593)	(0.0203)	(0.0189)	(0.0694)	(0.0658)
Observations	20790255	20790255	8901875	8901875	32936746	32936746	9888845	9888845
Mean Dependent Var	2.888	2.888	6.745	6.745	6.129	6.129	20.41	20.41

Linear probability model based on HMDA data from 2010-16. All continuous right-hand size variables normalized to have mean of zero and standard deviation of one. $^{\text{TRACT}}$ and $^{\text{CTY}}$ indicate variable is measured at the census tract or county level of aggregation, respectively, rather than at the loan level. Robust standard errors in parentheses, clustered by census tract. Regressions include controls for loan size, loan type, dummies for jumbo loan, coapplicant, owner occupied, other race categories, and missing values for any variable with positive incidence of missing values. See Internet Appendix for full results including coefficients on these variables as well as univariate regressions. See Data Appendix for variable definitions and sources.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

G Diffusion of Google Fiber in Kansas City

Table A.5: Summary Statistics for Kansas City Regression Variables

	mean	sd	min	p50	max
% with Google Fiber^{CTY}	0.07	0.24	0.00	0.00	1.00
Log(income)	4.41	0.61	0.00	4.41	9.21
Log(loan size)	4.96	0.72	0.00	5.02	10.77
Female	0.26	0.44	0.00	0.00	1.00
Unknown	0.07	0.26	0.00	0.00	1.00
Black	0.04	0.19	0.00	0.00	1.00
Hispanic	0.03	0.17	0.00	0.00	1.00
Unknown	0.10	0.30	0.00	0.00	1.00
American Indian/Alaska Native	0.01	0.07	0.00	0.00	1.00
Asian	0.02	0.15	0.00	0.00	1.00
Hawaiian/Pacific Islander	0.00	0.04	0.00	0.00	1.00
Jumbo Loans	0.02	0.15	0.00	0.00	1.00
Loan Type: FHA	0.19	0.39	0.00	0.00	1.00
Loan Type: VA	0.07	0.26	0.00	0.00	1.00
No Coapplicant	0.47	0.50	0.00	0.00	1.00
Owner Occupied	0.92	0.28	0.00	1.00	1.00

Table A.6: Fintech Mortgage Share & Google Fiber Access

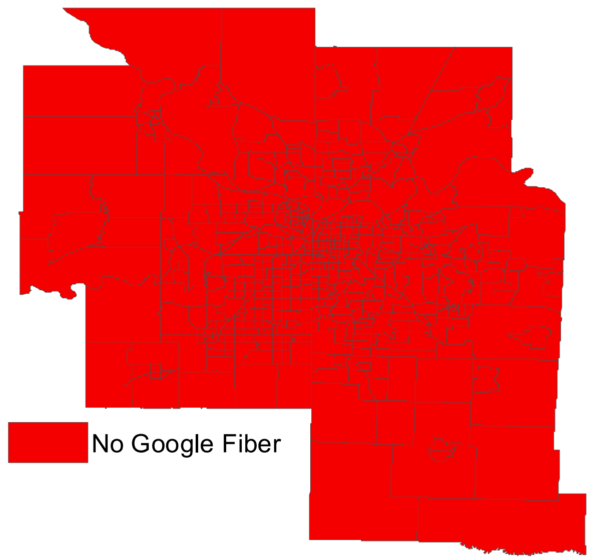
Dependent variable: = 100 if fintech lender, = 0 otherwise

	Purchases				Refinances			
	All		Nonbank		All		Nonbank	
% with Google Fiber$^{\text{TRACT}}$	-0.800***	-0.738***	-1.260	-0.903	-0.487	-0.417	0.0186	0.595
	(0.244)	(0.243)	(0.935)	(0.926)	(0.357)	(0.341)	(1.023)	(0.996)
Year-Month FEs	Y	Y	Y	Y	Y	Y	Y	Y
Census Tract FEs	Y	Y	Y	Y	Y	Y	Y	Y
Borrower & Loan Controls	N	Y	N	Y	N	Y	N	Y
Observations	138306	138306	34796	34796	180777	180777	51890	51890
Mean Dependent Var	2.147	2.147	8.535	8.535	5.189	5.189	18.08	18.08

Linear probability model of borrowing from a FinTech lender on Google Fiber access, based on HMDA data from 2011-16. Robust standard errors in parentheses, clustered by census tract. Borrower and loan characteristics include applicant income, indicator for missing applicant income, loan size, borrower gender, race, & ethnicity indicators, loan type, coapplicant indicator, and owner occupied indicator. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.6: Staggered Entry of Google Fiber

Google Fiber Availability in December 2011



Google Fiber Availability in December 2015

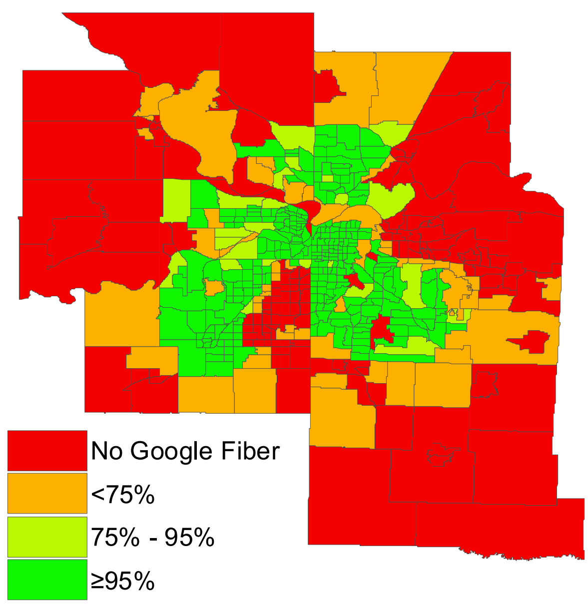


Figure shows the share of the population for each census tract that lives in a census block with Google Fiber in Kansas City. Source: NTIA and FCC data on Internet coverage by census block, provider, and technology in December 2011 and 2015.