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Working Papers
RESEARCH DEPARTMENT

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WP 23-11

PUBLISHED
June 2023

FRB CFI
PHILADELPHIA

ISSN: 1962-5361

DOI: https://doi.org/10.21799/frbp.wp.2023.11

Market Concentration in Fintech[1]

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March 2023

Abstract

This paper discusses concentration in consumer credit markets with a focus on fintech lenders and residential mortgages. We present evidence that shows that concentration among fintech lenders is significantly higher than that for bank lenders and other nonbank lenders. The data also show that the overall concentration in mortgage lending has declined between 2011 and 2019, driven mostly by a reduction in concentration among bank lenders. We present a simple model to show that changes in lender financial technology (interpreted as improvements in quality of loan services) explain more than 50 percent of the increase in fintech market shares and 43 percent of the increase in fintech concentration. This change in concentration in the fintech industry may have important implications for regulatory policy and financial stability.

Keywords: Fintech, Concentration, Mortgage Lending
JEL Codes: G2, L1, L5

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I. INTRODUCTION

Fintech is affecting many areas of financial services, from traditional credit markets to peer-to-peer lending and payment systems.[5] This paper focuses on the role of fintech lenders in consumer credit markets. We study the evolution of lender concentration in the market for residential mortgages in the USA (the largest consumer loan market) between 2011 and 2019 (ie, after the Great Financial Crisis and before the pandemic).[6] Based on previous research, we classify institutions originating loans on this market into three types: (traditional) banks, non-fintech nonbanks and fintech nonbanks.[7] Banks are subject to tighter regulations (e.g., capital requirements, liquidity requirements), have access to insured deposits and hold a significant fraction of their loan originations on the balance sheet, while nonbanks fund their originations through securitisation financed with short-term securities.[8] As described by others, fintech lenders have a significant presence online and process mortgages faster than non-fintech lenders.[9]

The period analysed is of particular interest as the Dodd-Frank Act of 2010 (henceforth the DFA) introduced significant changes to banking regulation. For example, the DFA authorized the Federal Reserve System to impose more stringent capital requirements on banks. Furthermore, the DFA created the Consumer Finance Protection Bureau (henceforth CFPB) which has the authority to impose additional compliance requirements on mortgage lenders. In line with evidence in past research, we find that the market share of nonbanks has almost doubled in the last ten years.[10] There is a significant decline in the loan origination market share among banks. This suggests that technology and regulation might play a role in explaining aggregate dynamics. We document that overall concentration (i.e., when concentration is computed using all lenders) in the market for mortgage loans is significant, with the top three lenders taking, on average, 25 percent of the market.[11] Concentration within the fintech sector is remarkably high,

[5] Fintech is understood here as technology-enabled innovation in financial services, pursuant to the definition of the Financial Stability Board in 'FinTech and Market Structure in Financial Services: Market Developments and Potential Financial Stability Implications' (Financial Innovation Network, 2019).

[6] We focus on the residential mortgage market because we have access to the universe of originations with information on the lender identity and borrower characteristics.

[7] The classification into fintech or non-fintech relies on G Buchak, G Matvos, T Piskorski, and A Seru, 'Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks' (2018) 130 *Journal of Financial Economics* 453 (http://dx.doi.org/10.1016/j.jfineco.2018.0). Specifically, they classify a lender as a fintech lender if it has a strong online presence and if nearly all of the mortgage application process takes place online with no human involvement from the lender. An institution (or lender) is a bank if it is a depository institution and a nonbank otherwise. While popular literature often calls unregulated, non-depository financial institutions 'shadow banks', we refer to such institutions as 'nonbanks', as classified by the Financial Stability Board (n 2). See section II for further details.

[8] D Corbae and P D'Erasmo, 'Capital Buffers in a Quantitative Model of Banking Industry Dynamics' (2021) *Econometrica* 2975 (http://dx.doi.org/10.3982/ECTA16930) have studied regulatory arbitrage in a model where big banks with market power interact with small, competitive fringe banks as well as nonbank lenders and showed that regulatory policies can have an important impact on banking market structure.

[9] A Fuster, M Plosser, P Schnabl, and J Vickery, 'The Role of Technology in Mortgage Lending' (2019) *Review of Financial Studies* 1854 (http://dx.doi.org/10.1093/rfs/hhz018) showed that fintech lenders process mortgage applications 20 percent faster than other lenders, controlling for observable characteristics. Fintech lenders adjust supply more elastically than other lenders.

[10] Buchak et al. (n 4) and Fuster et al. (n 6).

[11] D Corbae and P D'Erasmo, 'Foreign Competition and Banking Industry Dynamics: An Application to Mexico' (2015) *IMF Economic Review* 830 (http://dx.doi.org/10.1057/imfer.2015.40) studied concentration within the bank sector and the role the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 played in the observed increase in concentration between 1984 and 2018. D Corbae and P D'Erasmo, 'Rising Bank Concentration' (2020) *Journal of Economic Dynamics and Control* 103877 (http://dx.doi.org/10.1016/j.jedc.2020.103877), also examined the consequences of government policies that promote foreign competition in a concentrated banking industry.

suggesting relatively large entry thresholds and quality differences. Specifically, the top three fintech nonbanks (in 2019: Quicken Loans, Loan Depot, Guaranteed Rate) account for 70 percent of loan originations within that group. This level of concentration, together with the increase in fintech lending, has led to an increase in overall loan market share among the top three fintech lenders, from 5 to 10 percent. Other nonbanks have also gained in market share and their concentration has increased; the market share of the top three non-fintech nonbanks (in 2019: United Shore Financial Services, Caliber Home Loans, Fairway Independent Mortgage Corporation) has increased from 2 to more than 10 percent in the studied period. The mortgage market share of the top three banks (in 2019: Wells Fargo, JP Morgan Chase, Bank of America) declined from 36 to 16 percent during the same period. This is explained by a consistent reduction in the market share of banks, together with a reduction in the concentration of the bank sector. We show that most of the change in overall concentration is explained by *within-group* changes in concentration (i.e., changes in concentration conditional on lender type), not *between-group* changes (ie, lending shifting from banks to the nonbank sector).

We present a simple model with imperfect competition where three types of lenders compete in the loan market, in line with a previous paper.[12] Unlike in that paper, we introduce heterogeneity within each institution type, allowing us to link the model to data on concentration with a particular focus on fintech. The model captures differences in financing costs, lending quality/technology and regulatory pressure.[13] We calibrate our model to match the market structure and dynamics for the period between 2011 and 2019. We estimate that top lenders (when sorted by origination) offer higher quality services than those at the bottom of the distribution, with top banks having the highest quality, followed by top fintech and non-fintech nonbanks. We also estimate that there is a significant improvement in lender quality for nonbanks (fintech and non-fintech) between 2011 and 2019 and this increase is more significant for the top nonbank lenders (fintech and non-fintech). We also estimate a large decline in bank quality, which we link to the reduction in the fraction of consumers that expresses a preference for the person-to-person and branch-based interaction that is at the core of the (traditional) bank business model. According to previous research, a large portion of branches in the US are old, underoccupied and poorly maintained.[14]

In our main experiment, we show that changes in lender quality, which capture not only consumer preferences regarding the quality of financial services, but also technological advances in the fintech sector, account for more than 50 percent of the increase in the fintech market share and 40 percent of the decline in the bank market share. We estimate that changes in overall and within-type concentration are due almost entirely to changes in quality (technology). More precisely, we find that the decline in concentration in the industry between 2011 and 2019 derives from the decline in concentration within the bank sector that is the result of a decline in the estimated quality of top banks. Our main finding is that changes in quality have led to a substantial rise in fintech concentration. This change in concentration in the fintech industry is potentially important for regulatory policy and financial stability. Given that nonbanks originate-to-distribute loans are implicitly guaranteed by government agencies, there is a potential moral hazard problem along the same lines as for deposit insurance in traditional banks. Thus, growing concentration in fintech nonbanks could lead to a too-big-to-fail problem in that sector of the mortgage market, similar to that for traditional banks.

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[12] Buchak et al. (n 4).

[13] In line with Buchak et al. (n 4) and Fuster et al. (n 6) we understand our estimated differences in quality as capturing relative differences across lenders that derive from technological innovations (for example, impacting processing times), changes in customer accessibility (eg, loan applications that can be completed entirely online and expand access to some borrowers), and the provision of a more comprehensive customer service.

[14] J Frederic et al. 'Reimagining the Bank Branch for the Digital Era' (McKinsey & Company, 6 December 2017) available at https://www.mckinsey.com/industries/financial-services/our-insights/reimagining-the-bank-branch-for-the-digital-era.

Our paper is related to previous work on the roles of nonbanks and fintech lenders on credit markets.[15] The most closely related papers study fintech lending and how technology changes shaped the evolution of the industry in the last decade.[16] We use the same definition of fintech lenders as those papers and similar data sources, contributing to the literature by looking at how technology and entry costs affect lending concentration in the overall market for consumer mortgages and, importantly, concentration *within* lender type.[17]

Past research has investigated the connection between bank capital regulation and the prevalence of nonbanks in the US corporate loan market.[18] Others have studied fintech lending to small businesses and found that fintech tends to replace loans from large banks rather than those from small banks.[19] Along the same lines, it has been shown that finance companies and fintech lenders replaced lending from banks to small businesses after the 2008 financial crisis.[20] One paper provides evidence on the terms for direct lending by nonbanks in the market for business credit.[21] Our paper also contributes to this broader literature looking at credit markets and the role of nonbank lending.

II. EVIDENCE ON FINTECH MARKET CONCENTRATION

In this section, we describe the datasets used in this paper and present the main facts.

A. Sample description

We constructed our main sample using the Home Mortgage Disclosure Act (HMDA) loan origination dataset.[22] Our sample period was 2011–2019. We included all loans, ie both purchase and refinance as well as non-conventional loans. Adopting a classification previously used by others, we sorted financial institutions into three types: banks, non-fintech nonbanks and fintech nonbanks.[23] An institution (or lender)

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[15] See T Adrian and AB Ashcraft, 'Shadow Banking: A Review of the Literature' (2016) *Banking Crises* 282 for a review of the literature on credit intermediation outside the bank sector (http://dx.doi.org/10.1057/9781137553799_29).

[16] Buchak et al. (n 4) and Fuster et al. (n 6).

[17] J Jagtiani, L Lambie-Hanson, and T Lambie-Hanson, 'Fintech Lending and Mortgage Credit Access' (2021) 1 *The Journal of FinTech* 2050004 (http://dx.doi.org/10.1142/S2705109920500042), studied whether the growth of fintech lending in mortgage markets results in expanded credit access. G Buchak et al. (2020) 'iBuyers Liquidity in Real Estate Markets', available at https://ssrn.com/abstract=3616555 (http://dx.doi.org/10.2139/ssrn.3616555), studied technological disruptions in the real estate market and the emergence of iBuyers.

[18] RM Irani, R Iyer, RR Meisenzahl, and JL Peydró, 'The Rise of Shadow Banking: Evidence from Capital Regulation' (2020) 35 *Review of Financial Studies* 2181 (http://dx.doi.org/10.1093/rfs/hhaa106).

[19] T Balyuk, AN Berger, and J Hackney, 'What is Fueling FinTech Lending? The Role of Banking Market Structure' (2020) *mimeo*, available at https://ssrn.com/abstract=3633907 (http://dx.doi.org/10.2139/ssrn.3633907).

[20] M Gopal and P Schnabl, 'The Rise of Finance Companies and FinTech Lenders in Small Business Lending' (2022) *The Review of Financial Studies* (forthcoming) (http://dx.doi.org/10.1093/rfs/hhac034).

[21] S Chernenko, I Erel, and R Prilmeier, 'Why Do Firms Borrow Directly from Nonbanks?' (2022) *Review of Financial Studies* (forthcoming) (http://dx.doi.org/10.1093/rfs/hhac016); J Murfin and R Pratt, 'Comparables Pricing' (2019) 32 *Review of Financial Studies* 688 (http://dx.doi.org/10.1093/rfs/hhy047) present evidence on the financing of durable goods through captive finance subsidiaries.

[22] Buchak et al. (n 4). The data are publicly available at https://www.consumerfinance.gov/data-research/hmda/historic-data/ (accessed on 14 June 2022).

[23] We manually matched lenders in HMDA in year 2019 using lender names to the updated list that Buchak et al. (n 4) have provided (published in 2019). We were able to match 391 of the 566 unique lenders on the list. Complete matching was not possible, as some of the institutions in their list had changed names, merged with other lenders, or were no longer active in 2019 (i.e., they might have existed in previous years, but not in 2019). Once lenders were

was characterised as a bank if it was a depository institution, otherwise it was a nonbank. A lender was considered a fintech if it had a strong online presence and if nearly all of the mortgage application process took place online with no human involvement.[24] An updated classification included some fintech banks (ie, banks that switched from a more traditional application procedure with significant person-to-person interaction to one similar to that of nonbank fintech lenders).[25] No bank fit the fintech definition prior to 2017. Since the adoption of a fintech application procedure is relatively recent, we decided to continue with the original three-type classification for the analysis in this paper.[26]

We focused on the top 200 lenders in each year's HDMA data throughout our sample period since this facilitated a connection between the simple model (see section III) and the data and reduced the measurement error derived from unclassified institutions (i.e., institutions not included in the original sample).[27] On average, the top 200 lenders accounted for 70 percent of total originations by volume. Among them, we called the ones we identified from the previous classification as 'matched' institutions, while those that were not identified were called 'unmatched' institutions. 'Matched' institutions accounted for, on average, 80 percent of the total lending in this group. They corresponded to 110–132 institutions out of 200 in any given year. HMDA provides information on the regulatory status of each institution, so we could classify 'unmatched' institutions by their bank/nonbank status based on their regulatory agency code. To complete the classification of all institutions in the top 200, we placed 'unmatched' nonbank institutions in the non-fintech bin. Since most of the 'unmatched' institutions were relatively small, this assumption provides a conservative (lower bound) estimate for fintech market shares and concentration. Our sample included 29 unique fintech lenders.[28] Table 1 presents the list of fintech lenders active in 2019, their origination volume, market share within Top 200 lenders, and entry date (or when first observed in our sample of top 200 lenders).

matched, we kept the type of the given lender constant for the length of our sample. Additionally, we classified Better Mortgage Corporation as a fintech lender, following the discussion in Jagtiani et al. (n 14). See the updated list from Buchak et al. (n 4) here: https://sites.google.com/view/fintech-and-shadow-banks (accessed 14 June 2022).
[24] Buchak et al. (n 4).
[25] ibid.
[26] See also Fuster et al. (n 6) and Jagtiani et al. (n 14) for a similar three-type classification.
[27] Buchak et al. (n 4).
[28] The updated list contains 51 fintech nonbanks, while the original list contained 12 fintechs in HMDA (all nonbanks).

Table 1: Fintech lenders in 2019 (top 200 lenders HMDA).

Fintech Lender Name	Fintech Start	Volume (MM)	Market Share
Quicken Loans	2011	141,639	7.61%
loanDepot LLC	2011	44,870	2.41%
Guaranteed Rate Inc.	2011	27,556	1.48%
Guild Mortgage Company	2011	21,269	1.14%
MOVEMENT MORTGAGE, LLC	2011	16,695	0.90%
PENNYMAC LOAN SERVICES LLC	2014	13,796	0.74%
Provident Funding Associates	2011	11,361	0.61%
Eagle Home Mortgage, LLC	2011	9,993	0.54%
Cardinal Financial Company LP	2011	9,702	0.52%
Amerisave Mortgage Corporation	2011	4,919	0.26%
Impac Mortgage Corp. dba CashCall Mortgage	2012	4,474	0.24%
SWBC Mortgage Corporation	2011	3,704	0.20%
Better Mortgage Corporation	2019	3,568	0.19%
LendUS LLC dba RPM Mortgage	2017	3,519	0.19%
NFM, Inc.	2017	3,271	0.18%
PARAMOUNT EQUITY MORTGAGE, LLC	2011	2,451	0.13%
MORTGAGE INVESTORS GROUP	2011	2,008	0.11%
First Savings Mortgage Corporation	2011	1,999	0.11%

Note: Loan level data from HMDA. Classification based on latest version of lender classification data.[29] Fintech start corresponds to the year the lender first was classified as fintech or the initial year in our HMDA sample. MM stands for millions.

In addition to the HMDA sample, we used data from Fannie Mae and Freddie Mac. These datasets provided information on interest rates and performance on a subset of 15- and 30-year, fully amortising, full documentation, single-family, conforming fixed-rate mortgages. This loan-level data contained geographical information and some important borrower characteristics, such as borrower credit scores. We linked this dataset to the classification described above to analyse differences in loan interest rates across institution types. The combination of Fannie Mae and Freddie Mac data covers the majority of conforming loans issued in the USA.

B. Main findings and fintech concentration

In this section, we describe the evolution of the mortgage market since 2011. Subsection II.B.1 presents aggregate dynamics and the evolution of market shares by lender type. Subsection II.B.2 describes the evolution of lender concentration with a focus on fintech lending. Subsection II.B.3 provides a decomposition of lender concentration to help understand the dynamics.

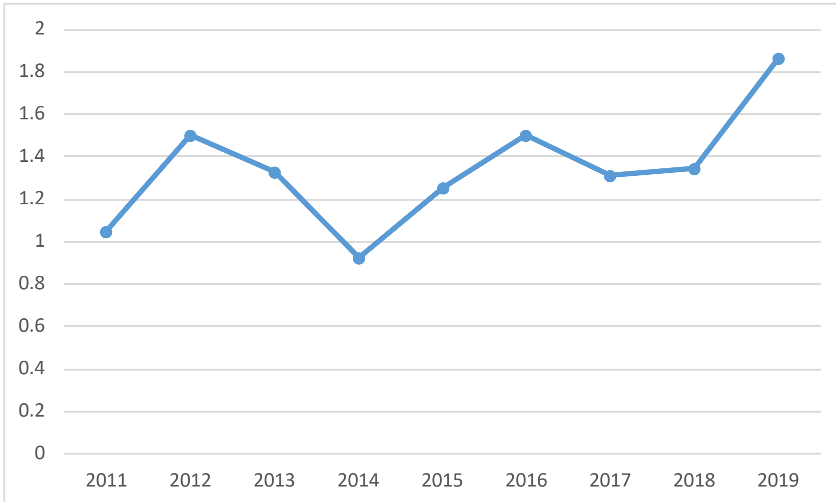
1. Mortgage Market Size and Aggregate Level Concentration

We start by documenting aggregate dynamics in our sample. Our findings are in line with those in previous research.[30] Figure 1 presents the volume of loan originations (in $ trillion) among the top 200 lenders (by value of loan originations). Loan originations increased by more than 80 percent between 2011 and 2019.

[29] Buchak et al. (n 4).

[30] Buchak et al. (n 4), Fuster et al. (n 6) and Jagtiani et al. (n 14).

Figure 1: Total loan originations (volume, $ trillion, top 200 lenders).

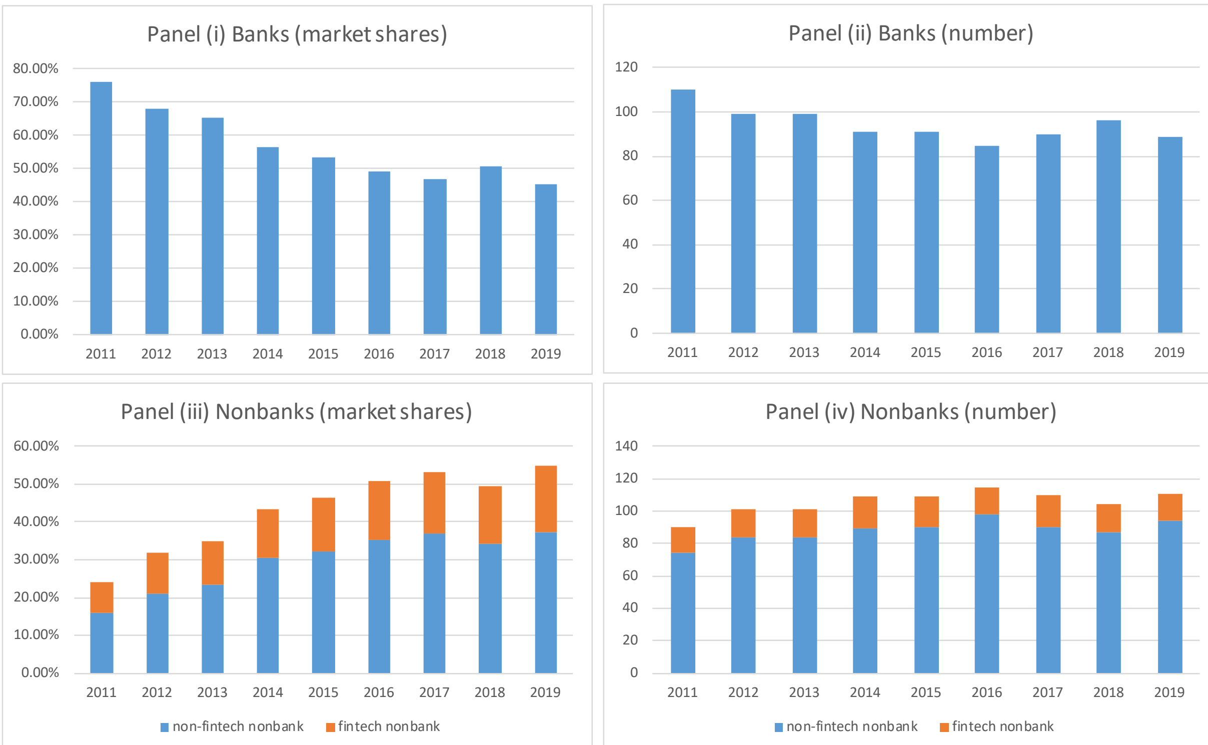


Note: Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans).

Figure 2 shows the evolution of market shares by lender type between 2011 and 2019. The market share of nonbanks more than doubled during this period, from 24 to 55 percent (Figure 2 panel (iii)). There was also an increase in the number of nonbank lenders (from 90 to 111), but the growth in the number of institutions was not as strong (a 23 percent increase). This suggests that a large portion of the increase in the nonbank market share derived from the growth of incumbent nonbank lenders. Within the nonbank sector, both non-fintech and fintech firms showed considerable growth. The non-fintech nonbank lenders' market share increased from 16 to 37 percent, while fintech nonbanks' market share increased from 8 to over 17 percent. The counterpart of the increase in nonbank lending market share was the decline in the presence of traditional banks. The market share for the bank sector fell from 76 to just above 45 percent. The growth of the nonbank sector was not confined to a specific segment of the residential market. Previous research shows that while the growth of nonbanks was more significant in the conforming loan segment, there was also considerable growth in the segment of Federal Housing Administration mortgages.[31]

[31] Buchak et al. (n 4).

Figure 2: Market shares and number of lenders (by bank type).



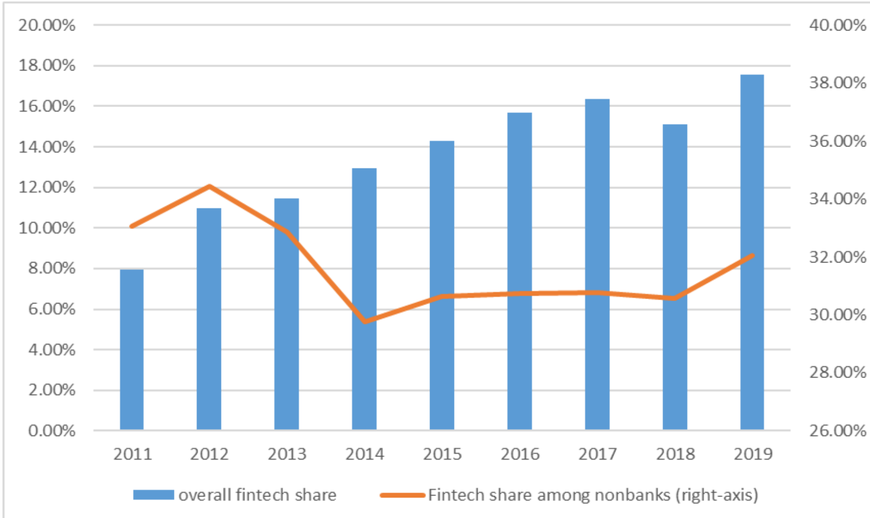
Note: Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans). Classification was based on the latest version of lender classification data.[32] Market shares corresponded to shares of originations among the top 200 lenders.

The financing structure of loan originations differs significantly between banks and nonbanks. The share of bank loans held on balance sheet is 31 percent on average (see Table 1, panel B).[33] In the case of nonbanks, the average is 7.5 percent, with non-fintech lenders at 6.8 percent and fintech lenders at 10.5 percent. A large portion of the loans originated by nonbanks are sold to banks, government-sponsored enterprises, or insurance companies. Previous research has shown a dramatic increase in the role that government-sponsored enterprises play for fintech lenders; in 2015, nearly 80 percent of loans originated in this sector were financed by some underlying government guarantee.[34]

Figure 3 focuses on fintech lending during the period. The market share of fintech lenders increased from close to 8 to more than 17 percent. Fintech lenders grew more slowly than the non-fintech nonbanks during the early years, translating to a decline in their share of nonbank originations between 2012 and 2014. This trend changed and they had recovered some of the lost share of nonbank lending by 2019. The number of nonbank fintech lenders (among the top 200 lenders) fluctuated between 16 and 20.

[32] ibid.
[33] ibid.
[34] ibid, fig 4.

Figure 3: Fintech lending (market shares).



Note: Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans). Classification was based on the latest version of lender classification data.[35] 'Overall fintech share' refers to the share of fintech lending in total lending by top 200 lenders. 'Fintech share among nonbanks' refers to the share of fintech lending in total nonbank lending (also restricted to top 200 lenders).

Figure 4 shows the evolution of three measures of market concentration at the national level: the Herfindahl-Hirschman Index (HHI) (defined as $HHI_t = \sum_{i=1}^{N} s_{i,t}^2$, where $s_{i,t}$ corresponds to the market share of lender i (in percent) in period t), the market share of the top three lenders (C3), and the market share of the top 10 percent lenders (when sorted by originations).[36] The figure shows that there was a decline over time in the degree of market concentration (consistent across the three measures).[37] The HHI dropped from 570 in 2011 to 236 in 2019 (an almost 60 percent decline). The market share of the top three lenders (C3) declined from 36 to 20 percent. There was also a (less pronounced) decline in the market share of the top 10 percent lenders (when sorted by originations), from 61 to 52 percent. Together with the decline in concentration, this created a shift in composition. As we showed in Figure 2, there was a shift towards nonbank lending (fintech and non-fintech). This compositional change was also reflected at the top of the distribution. For example, all the top three lenders in 2013 were banks (Wells Fargo, JP Morgan Chase Bank, Bank of America). During the period 2014–2018, only two of the top three are banks (Wells Fargo, JP Morgan Chase) with the third being a fintech lender (Quicken Loans). In 2019, JP Morgan Chase dropped from the top three lender list to be replaced by a nonbank lender (United Shore Financial Services) and Quicken Loans replaced Wells Fargo at the very top. We have explored these compositional effects and changes in concentration by type below.

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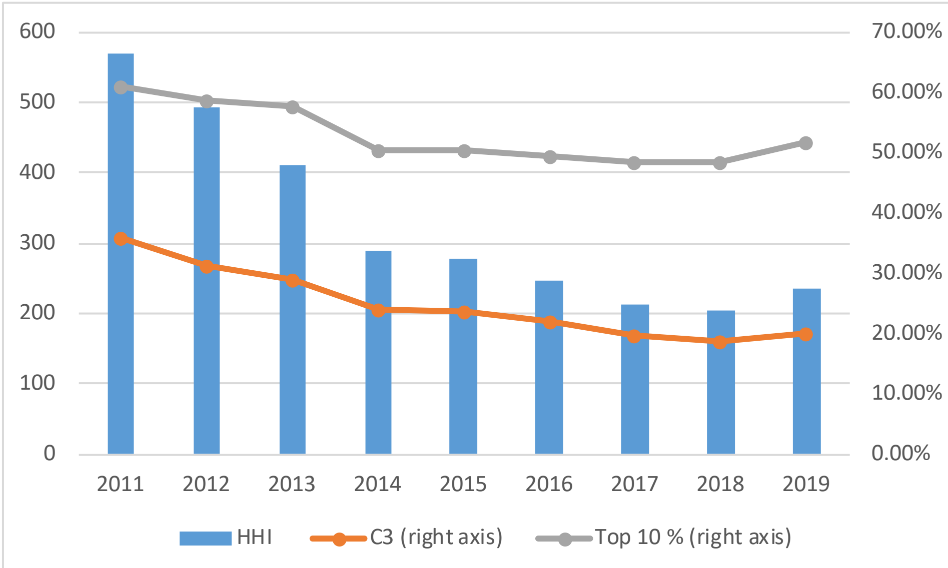
[35] ibid.

[36] The HHI is a widely used measure of market concentration and can assume values between $[\frac{1}{N}, 10{,}000]$, where N is the number of lenders in the industry. See, eg, E Rossi-Hansberg, PD Sarte, and N Trachter, 'Diverging Trends in National and Local Concentration' (2021) 35 *NBER Macroeconomics Annual* 115 (http://dx.doi.org/10.1086/712317).

[37] Fig 4 shows three measures of concentration at the national level. Fig 9, below, shows that these dynamics were consistent with data aggregated from smaller markets (county level). In that respect, the evidence for mortgage origination appears to show a different pattern than any of those described in Rossi-Hansberg et al. (n 33) for other industries.

Figure 4: National level concentration (all loans/all lender types).



Note: Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance, as well as non-conventional loans). Classification was based on an existing classification system.[38] The Herfindahl-Hirschman Index (HHI) equals $\sum_{i=1}^{N} s_i^2$, where s_i corresponds to the market share of lender i. $C3$ refers to the market share of the top three lenders in the market. Top 10 % corresponds to the market share of the top 10 percent lenders when sorted by originations (since we studied the top 200 lenders, this corresponds to the top 20 lenders).

Table 2 presents the changes in market share by lender type. Most of the gain in the nonbank sector is accounted for by the largest lenders (non-fintech and fintech). In the bank sector, most of the decline is accounted for by banks in the top three of the loan distribution. This suggests that concentration has declined in the bank sector and increased in the nonbank (fintech and non-fintech) sector. Next, we will study the dynamics of lender concentration.

Table 2: Changes in market shares (by lender type).

	market share changes 2011-2019			
Lender Type	Largest	2nd Largest	3rd Largest	Non-top 3 Rep.
Banks	-12.67%	-4.61%	-2.70%	-0.03%
Nonfintech Nonbanks	4.99%	1.60%	1.49%	0.10%
Fintech Nonbanks	4.81%	1.03%	0.74%	0.17%

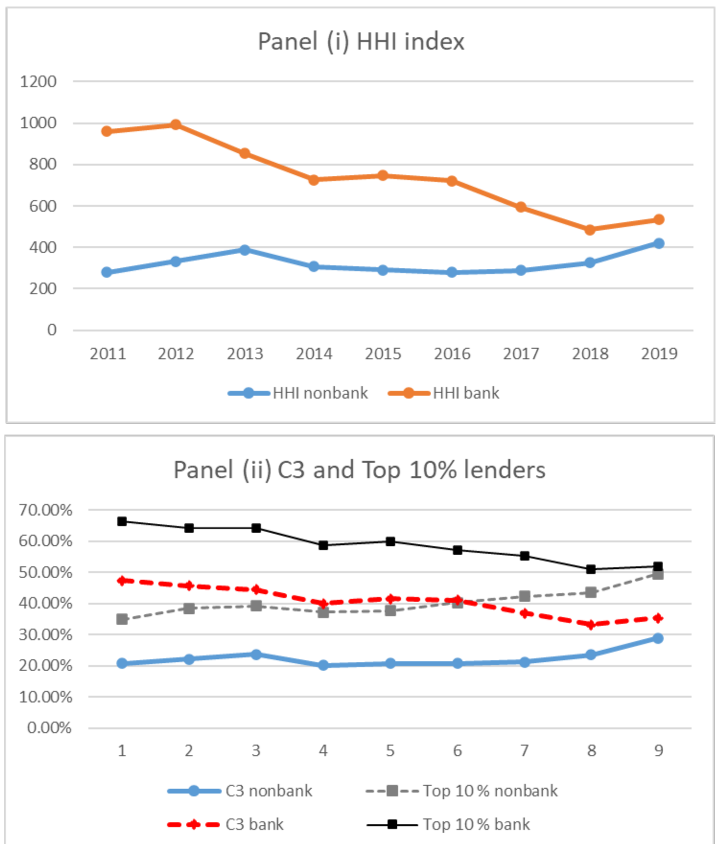
Note: Loan level data from HMDA. We included all loans (both purchase and refinance as well as non-conventional loans). Classification was based on an existing classification system.[39] Market share changes correspond to the percentage point change in overall market share for a given lender type between 2011 and 2019. The 'non-top three rep.' refers to the change in market share for the representative non-top three lender in the relevant group.

2. Fintech concentration

[38] Buchak et al. (n 4).
[39] ibid.

We start this subsection by exploring how the compositional changes in the industry affected the evolution of market concentration. Figure 5 shows the HHI (panel (i)), C3, and the market share of the top 10 percent lenders (panel (ii)), when separating lenders by whether they are a bank or not. Both panels show consistent trends. The bank sector appears to be more concentrated than the nonbank sector on average, but differences decrease towards the end of the period. The HHI for bank lenders is 2.5 times larger than that of nonbank lenders in 2011, but only 25 percent larger in 2019. A similar dynamic can be observed for C3 and the market share of the top 10 percent lenders. The dynamics of concentration conditional on bank status are explained by a significant reduction in concentration in the bank sector (recall also the decline in banks' overall market share), together with an increase in concentration in the nonbank sector. For example, the HHI for the nonbank sector increased by more than 50 percent between 2011 and 2019, while the HHI for banks declined by 44 percent during the same period. This increase in concentration in the nonbank sector derives from significant growth at the very top of the distribution.

Figure 5: Concentration by bank status



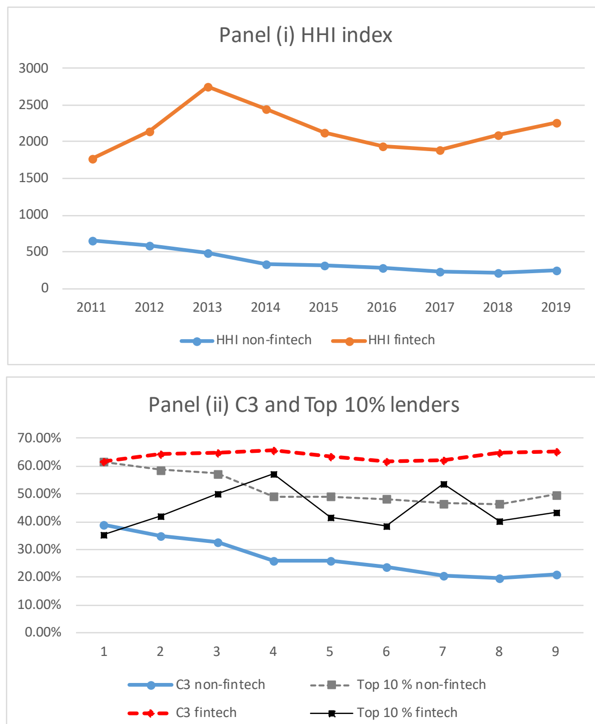
Note: Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans). Classification based on latest version of lender classification data.[40] The Herfindahl-Hirschman Index (HHI) equals $\sum_{i=1}^{N} s_i^2$, where s_i^2 corresponds to the market share of lender i. $C3$ refers to the market share of the top three lenders in the market. Top 10 % corresponds to the market share of the top 10 percent lenders when sorted by originations (since we studied the top 200 lenders, this corresponds to the top 20 lenders).

Next, we focus on market concentration by fintech status. Figure 6 shows the HHI (panel (i)), C3, and market share of the top 10 percent lenders (panel (ii)) when separating lenders into fintech and non-fintech

[40] ibid.

(banks and nonbanks). Fintech lenders were significantly more concentrated that non-fintech lenders. The HHI for fintech lenders was 2–7 times larger than that of non-fintech lenders. The number of fintech lenders in the sample (top 200 lenders in HMDA) was 16–20. The HHI and C3 reflect the fact that most lending by fintech lenders was done by a handful of institutions (C3 was 62–66 percent), while lending in the non-fintech sector was more equally distributed across more institutions (between 180 and 184 entities). The decline in concentration for non-fintech lenders derived from the decline in the bank sector. The market share of the top 10 percent lenders appeared to be lower for fintech than for non-fintech. It is relevant to note that lending by the top 10 percent lenders in the case of non-fintech lenders corresponded to around 18 lenders, while this corresponded to two lenders at most for fintech lenders. Thus, while the top 10 percent lenders accounted for a similar fraction of lending in both sectors towards the end of the period, the non-fintech sector needed 5–6 times more lenders to achieve the same market share.

Figure 6: Concentration by fintech status.



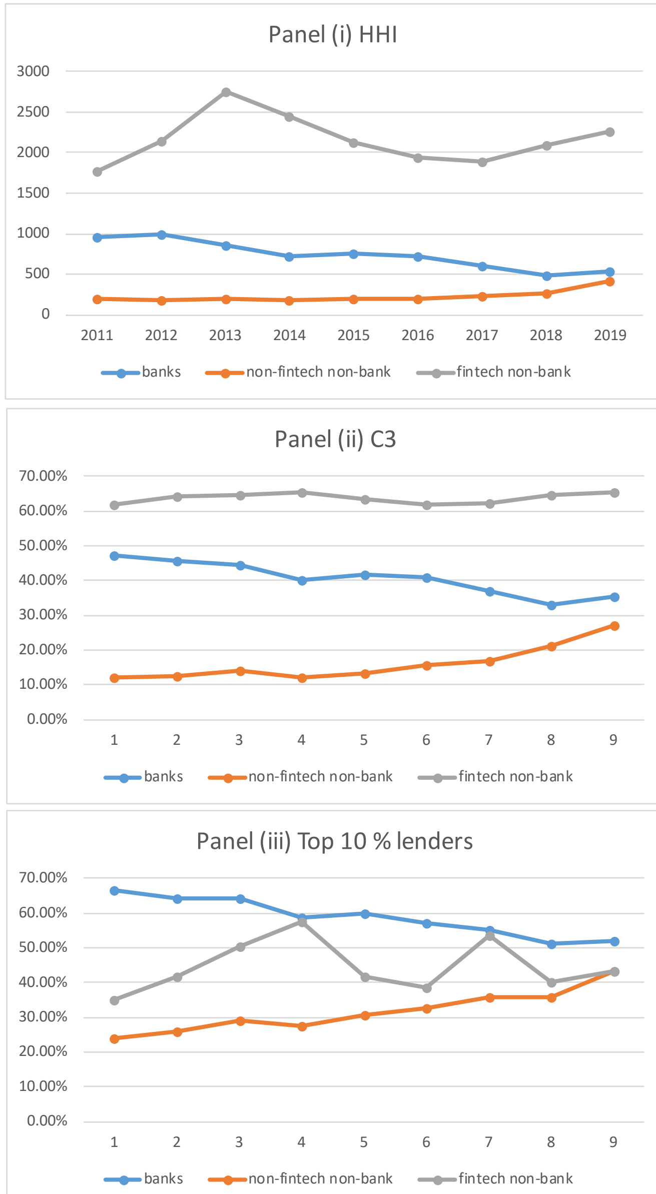
Note: Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans). Classification based on latest version of lender classification data.[41] The Herfindahl-Hirschman Index (HHI) equals $HHI = \sum_{i=1}^{N} s_i^2$, where s_i^2 corresponds to the market share of lender i. $C3$ refers to the market share of the top three lenders in the market. Top 10 percent corresponds to the market share of the top 10 percent lenders when sorted by originations (since we studied the top 200 lenders, this corresponds to the top 20 lenders).

The patterns described in Figures 5 and 6 (higher concentration in the fintech and bank sectors relative to non-fintech and nonbanks, with concentration declining in the bank sector and increasing in the nonbank sector) were also evident when we looked at concentration measures in relation to our three-type classification of lender originators: commercial banks, non-fintech nonbank, fintech nonbank. Figure 7

[41] ibid.

shows the HHI (panel (i)), the market share of the top three lenders (panel (ii)), and the market share of the top 10 percent lenders (panel (iii)).

Figure 7: Concentration by lender type.



Note: Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans). Classification based on latest version of lender classification data.[42]

Figure 7 also helps explain the dynamics of the industry. On the one hand, as the market share of nonbanks increases, the overall level of concentration declines. On the other hand, as the market share of fintech lenders increases, concentration will tend to increase as well. In the period 2011–2019, the shift towards a less concentrated nonbank sector dominated, but the second force appeared to gain strength

[42] ibid.

towards the end of the period, explaining the uptick in overall concentration in 2018 and 2019 (see Figure 4).

3. Market concentration decomposition

We conclude this section by presenting a decomposition of market concentration. This decomposition provides intuition for the pattern described in Figure 7. We decompose the HHI (one of our measures of concentration) as follows

$$HHI_t = (S_t^B)^2\, HHI_t^B + (S_t^{NF})^2\, HHI_t^{NF} + (S_t^F)^2\, HHI_t^F,$$

where S_t^j and HHI_t^j denote the market shares and the HHI, respectively, within type $j \in \{B, NF, F\}$ (ie, when the market is defined using loans from lenders of type j).[43] Expanding the overall HHI in this way shows how changes in concentration in each group contribute to changes in overall concentration. In addition, changes in overall concentration between period t and any period τ can be decomposed into changes between groups (ie, changes derived from redistribution of market shares across types) and changes within groups (ie, changes due to changes in concentration within groups). More specifically, we can write

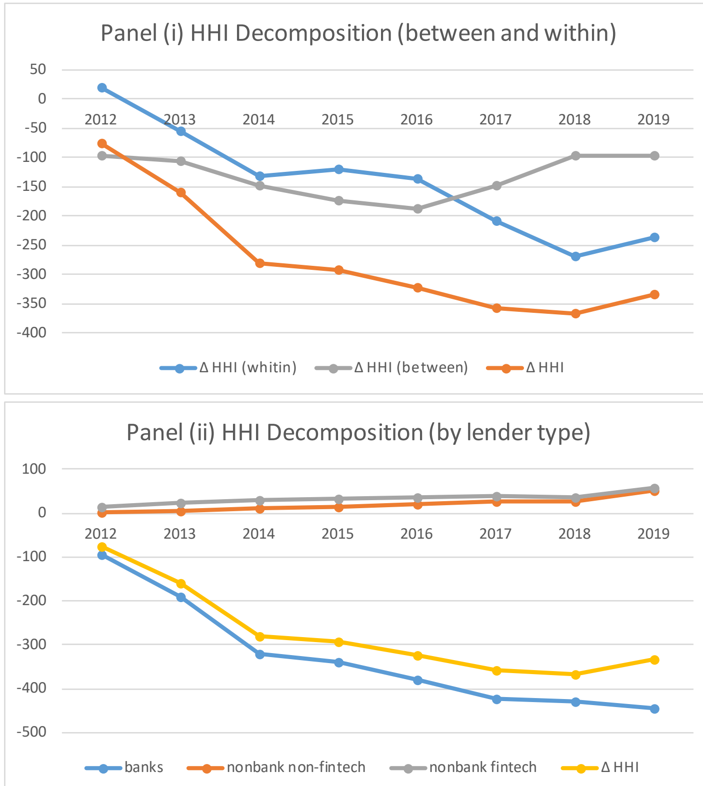
$$\Delta HHI_t = \sum_{j \in \{B,NF,F\}} \Delta\left(S_t^j\right)^2 HHI_t^j - \sum_{j \in \{B,NF,F\}} \left(S_\tau^j\right)^2 \Delta HHI_t^j,$$

where $\Delta HHI_t = \mathrm{HHI_t} - \mathrm{HHI_\tau}$. We call the first term in the previous equation 'ΔHHI_t between' and the second term 'ΔHHI_t within'. Panel (i) in Figure 8 presents the evolution of the overall HHI, 'ΔHHI_t between' and 'ΔHHI_t within' when looking at changes between year t and 2011 (the initial year in our sample). Using this decomposition, we can estimate how much of the overall concentration change is explained by changes in concentration within group. Figure 8, panel (i) shows that most of the change in overall concentration is explained by within-group changes (the contribution is most significant towards the end of the period). In other words, the evolution of the concentration within lender type appears to be the main determinant of concentration in the market for residential mortgages. Within-group changes in the HHI explain 30–75 percent of the overall decline in concentration. For example, in 2019, the overall decline in the HHI was 334 and the decline in 'ΔHHI_t within' was 237 (71 percent of the overall decline). It is possible to show that these dynamics derive mostly from the decline in concentration within the bank sector (see Figure 7).

To explore this further, panel (ii) in Figure 8 shows the evolution of the individual terms $\left(S_t^j\right)^2 HHI_t^j - \left(S_\tau^j\right)^2 HHI_\tau^j$ for $j \in \{B, NF, F\}$. We observed that changes associated with the bank sector explained the total change in the overall HHI. Concentration within the nonbank sector has increased, with fintech increasing slightly more than non-fintech.

[43] Rossi-Hansberg et al. (n 33). See Appendix VII.A for the derivation of this decomposition.

Figure 8: HHI decomposition.



Note: Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans). Classification based on latest version of lender classification data.[44] In panel (i), 'ΔHHI_t between' equals $\sum_{j\in\{B,NF,F\}} \Delta\left(S_t^j\right)^2 HHI_t^j$ and 'ΔHHI_t within' equals $\sum_{j\in\{B,NF,F\}} \left(S_\tau^j\right)^2 \Delta HHI_t^j$ with τ equal to 2011. In panel (ii), each of the lines plots the corresponding value of $[\left(S_t^j\right)^2 HHI_t^j - \left(S_\tau^j\right)^2 HHI_\tau^j]$ for $j \in \{B, NF, F\}$ (banks, non-fintech nonbanks, fintech nonbanks, respectively).

To complete the analysis of concentration and to complement the insights we gathered from looking at the HHI, we computed C3 and the market share of the top 10% lenders. We also created a Lorenz curve (a measure of lending inequality) using originations from all lenders and conditional on lender type. Lorenz curves are one of the main ways in which household income and wealth inequality are measured. Like the HHI, the Lorenz curve allows us to look at the entire distribution. Figure 9 presents the comparison of Lorenz curves for 2011 and 2019. Panel (i) shows that concentration has declined, when all lenders are included (a shift of the curve towards the 45-degree line implies a reduction in concentration). This is consistent with the evidence presented in Figures 4 and 8. Interestingly, panels (ii)–(iv) show that while concentration declined for banks, it increased for non-fintech and fintech nonbanks.

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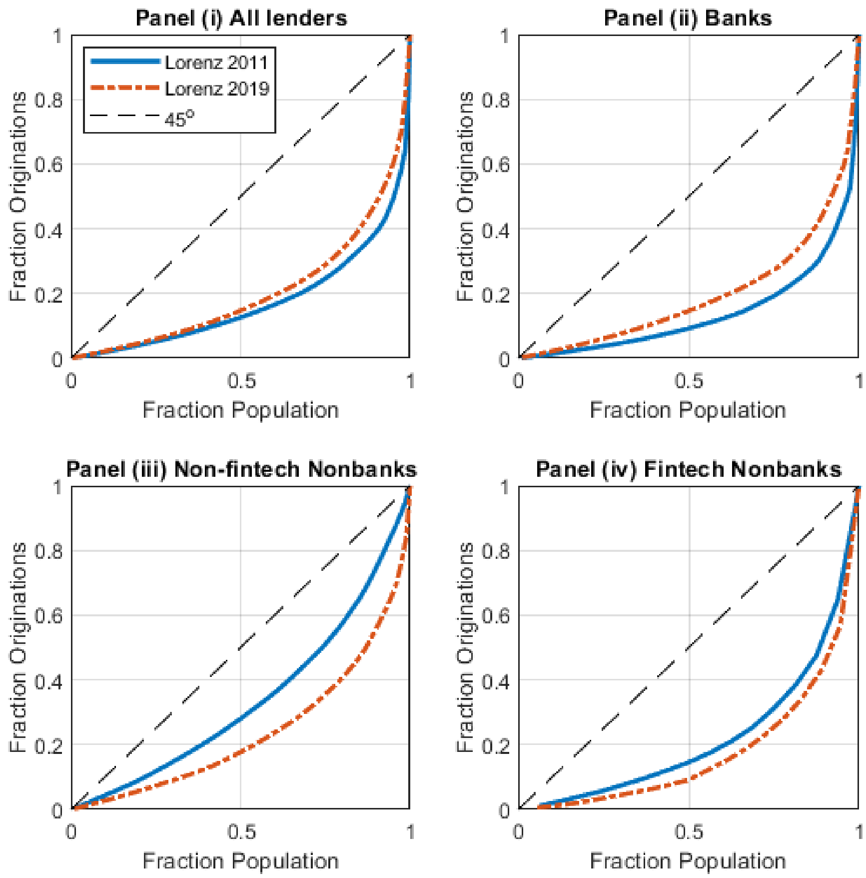
[44] Buchak et al. (n 4).

Figure 9: Lorenz curves loan origination



Note: Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans). Classification based on latest version of lender classification data.[45]

We also studied the evolution of market concentration using the HHI at the county level. Figure 10 shows the (loan-weighted) average of the US county level HHI for all lenders ('all lenders') and within bank type. As in the case of the national level estimates, we found that there was a decline in concentration during the period and that the fintech sector was significantly more concentrated than the non-fintech nonbanks and banks. There was significant heterogeneity across counties, with some counties serviced completely by traditional banks and some completely by fintech lenders. [46] Other researchers have found that having a zip code level HHI greater than 625 (the 90th percentile value) is associated with a 3.7 percentage point greater fintech loan share.[47]

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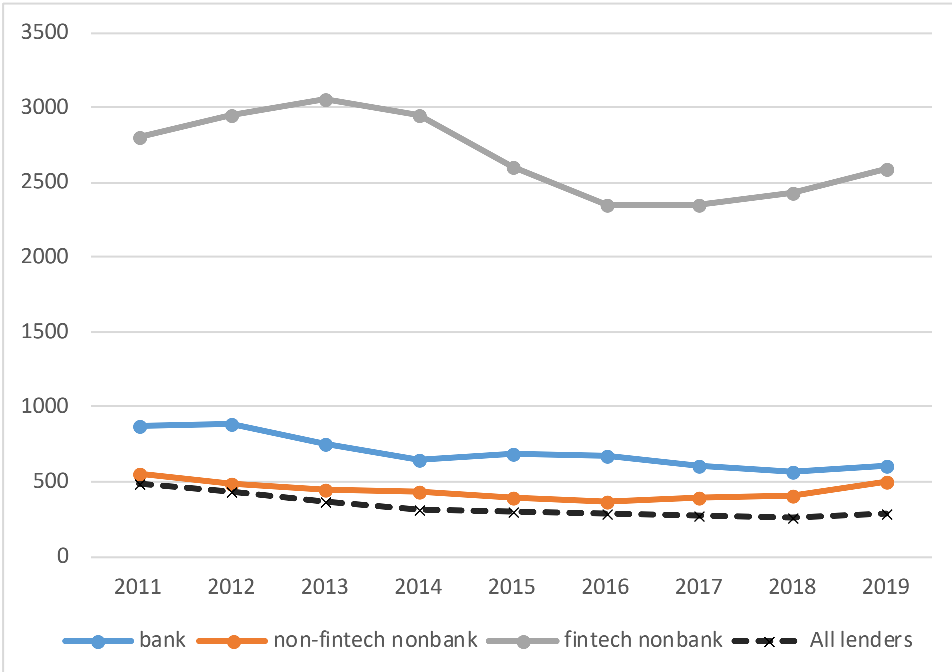
[45] ibid.

[46] For example, in 2016 Boyd County of Nebraska was completely serviced by fintech lenders while Hooker County of the same state was completely serviced by traditional banks.

[47] Jagtiani et al. (n 14) also show that loans originated in census tracts that are included in fewer than ten banks' Community Reinvestment Act (CRA) assessment areas are more likely to be fintech compared with loans originated in tracts with more assessment areas.

Figure 10: Local market concentration (overall and by lender type).



Note: Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans). Classification based on latest version of lender classification data.[48] 'All lenders' refers to the HHI computed using all lender types. 'Bank', 'fintech nonbank' and 'non-fintech nonbank' correspond to the HHI within lenders classified as banks, fintech nonbanks and non-fintech nonbanks, respectively. The figure shows the loan-weighted average of the county level HHI.

We now turn to the analysis of mortgage interest rates. Using the Fannie Mae and Freddie Mac loan data for 2011–2019, we tested differences between the interest rates charged by different bank types. We extended an existing approach to include dummies for the largest banks in each sector and focus on the conforming loan sample reporting FICO scores.[49] We estimated the following regression:

$$rate_{ijzt} = \beta_1 FintechB_j + \beta_2 NonFintechNB_j + \beta_3 FintechNB_j + \beta_4 Largest_j + \beta_5 2nd\ Largest_j + \beta_6 3rd\ Largest_j + Z_j'\Theta + X_i'\Gamma + \delta_{zt} + \epsilon_{ijzt},$$

where an observation is a mortgage *i,* originated by lender j, in zip code *z,* in quarter *t*. The dependent variable $rate_{ijzt}$ is the mortgage rate in percentage points. $Fintech\ B_j$ corresponds to a dummy variable that takes value 1 if the lender is a fintech bank. Similarly, $NonFintech\ NB_j$ takes value 1 if the lender is a non-fintech nonbank, and $Fintech\ NB_j$ if the lender is a fintech nonbank. The rank dummies $Largest_j$, $2nd\ Largest_j$ and $3rd\ Largest_j$ represent whether lender j is the largest, second largest or third largest by loan amount in its sector, respectively. The vector Z_j' contains interacting terms between lender type dummies and lender rank dummies. We included borrower (mortgage) characteristics in X_i' and zip-time fixed effects in δ_{zt}.

[48] Buchak et al. (n 4).
[49] ibid.

Table 3 shows our results. The base group in the regressions in columns (1) and (2) is (traditional) banks, so the coefficients reported in these columns are relative to banks. For instance, the coefficient of the dummy 'nonbank' in column (1) shows that interest rate in a loan originated by a nonbank lender was, on average and after controlling for borrower and regional differences, 3.93 basis points higher than that of a traditional bank. Thus, nonbank lenders charged slightly higher interest rates than banks. When looking within this group along the lines of our lender classification (as in column (2)), we found that fintech lenders charged higher interest rates than non-fintech nonbanks, which charged higher interest rates than banks. This is consistent with previous evidence.[50] There is no evidence that fintech lenders originated riskier mortgages, suggesting that risk does not play a role in interest rate differentials.[51] The base group in columns (3) and (4) is non-top three banks, so coefficients in these columns are relative to this group. We found that interest rates increased with bank size, with the top three banks charging higher interest rates than others, but decreased with nonbank lender size, with lenders in the top three charging lower interest rates than banks and other nonbanks (column (3)). Column (4) shows that this was driven mostly by non-fintech nonbanks, while there was also evidence of fintech nonbanks charging lower interest rates. Focusing on size differences among nonbanks, column (6) shows that fintech lenders at the very top appeared to charge higher rates than non-fintech and smaller fintech lenders.

[50] ibid. A different sample that includes Federal Housing Administration loans shows that nonbank lenders charge higher interest rates on conventional loans but lower rates on Federal Housing Administration loans (see Buchak et al. (n 4) and Fuster et al. (n 6).

[51] Fuster et al. (n 6).

Table 3: Interest rates by lender type.

	interest rate					
Lenders	All lenders				Non-Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Bank	0.0393***		0.0563***			
	(0.0011)		(0.0015)			
Non-Fintech Non-Bank		0.0176***		0.0628***		
		(0.0013)		(0.0015)		
Fintech Non-Bank		0.0606***		0.0325***	0.0403***	-0.0235***
		(0.0013)		(0.0024)	(0.0014)	(0.0019)
Largest			0.0279***	0.0277***		-0.0445***
			(0.0012)	(0.0012)		(0.0022)
Second Largest			0.0619***	0.0618***		-0.0234***
			(0.0014)	(0.0014)		(0.0026)
Third Largest			0.0331***	0.0323***		0.0137***
			(0.0034)	(0.0034)		(0.0019)
Nonbank×Largest			-0.0042**			
			(0.0019)			
Nonbank×2nd Largest			-0.0617***			
			(0.0021)			
Nonbank×3rd Largest			-0.0289***			
			(0.0037)			
Non-fintech Nonbank×Largest				-0.0799***		
				(0.0022)		
Non-fintech Nonbank×2nd Largest				-0.0851***		
				(0.0031)		
Non-fintech Nonbank×3rd Largest				-0.0206***		
				(0.0037)		
Fintech Nonbank×Largest				0.0518***		0.1138***
				(0.0029)		(0.0033)
Fintech Nonbank×2nd Largest				-0.0232***		0.0614***
				(0.0027)		(0.0032)
Fintech Nonbank×3rd Largest				-0.0223***		-0.0098***
				(0.0044)		(0.0029)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Zip - Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.7051	0.7055	0.7058	0.7068	0.7087	0.7101
Within Adj R2	0.4644	0.4652	0.4658	0.4675	0.4556	0.4581
Period	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019
Num Observations	6,947,858	6,947,858	6,947,726	6,947,726	2,448,142	2,448,142

Note: Loan level data from Fannie Mae and Freddie Mac. Our sample period was 2011–2019. This sample included conforming loans only. Classification based on latest version of lender classification data.[52] Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[52] Buchak et al. (n 4).

III. A SIMPLE MODEL

In this section, we present a simple model that allowed us to analyse the role of technology in explaining the concentration dynamics that we described in the previous section. The model environment closely follows the environment described elsewhere.[53]

A. Environment

There are three types of lenders that compete for a mass B of mortgage borrowers: (traditional) banks b, non-fintech nonbanks n and fintech nonbanks f. There are N_b number of banks, N_n non-fintech nonbanks, and N_f fintech nonbanks. Within each type, there are four heterogeneous lenders. The first three lenders of a type correspond to the largest, second largest and third largest lender, by loan amount, of that type in the data. We think of the fourth lender within a type as representative of the non-top three institutions. We denote lender types by $\tau \in \{b, n, f\}$ so that the number of the non-top three representative lenders of each type is equal to $N_\tau - 3$.

A.1. Demand

Lenders in the model are indexed i and offer mortgages at interest rate r_i. Borrower b's utility from choosing a mortgage from lender i is

$$u_{ib} = -\alpha r_i + q_i + \epsilon_{ib} \quad . \qquad (1)$$

Borrower utility declines with the mortgage rate with $\alpha > 0$ measuring interest rate sensitivity. Borrowers also derive utility from nonprice attributes of lenders: $q_i + \epsilon_{ib}$. We think of q_i as the quality of financial services provided by lender i (eg, technological innovations that affect processing times, customer accessibility, the clarity of information provided to the customer, and the provision of a more comprehensive customer service). The rest of a borrower's utility from lender i is captured by ϵ_{ib}, an independent and identically distributed taste shock that we assume follows a type one extreme value distribution.

A.2. Supply

Lenders differ in quality of service q_i and in the marginal costs of providing a mortgage ρ_i, which can reflect their external finance costs. Operating within a market entails a fixed entry cost c_i, such as the cost of basic regulatory registrations, offices, and support staff. Note that lenders within a type τ are also heterogeneous, so that the lender side of the economy is parameterised by each type's qualities $\{q_{\tau 1}, q_{\tau 2}, q_{\tau 3}, q_{\tau 4}\}_{\tau=b,n,f}$, funding costs $\{\rho_{\tau 1}, \rho_{\tau 2}, \rho_{\tau 3}, \rho_{\tau 4}\}_{\tau=b,n,f}$, and fixed entry costs $\{c_{\tau 1}, c_{\tau 2}, c_{\tau 3}, c_{\tau 4}\}_{\tau=b,n,f}$.

In addition to changing a bank's marginal cost, regulatory burdens may also reduce traditional banks' activities on the extensive margin. For example, binding capital requirements raise the cost of making loans. Our model captures this type of regulatory burden through parameter γ_b. If lender i is a bank, its probability of lending to a specific borrower is scaled by a factor γ_b. A higher γ_b captures a relatively unconstrained bank, a lower γ_b captures a relatively constrained bank. Throughout the model, we assume

[53] ibid.

that nonbanks are not subject to such regulatory burdens, so we set $\gamma_n = 1$ and $\gamma_f = 1$. If the market share a bank would have obtained without regulatory burdens is s_i, then the actual market share is $\gamma_b s_i$.

Conditional on being present in a market, a lender sets its interest rate r_i to maximise its expected profit:

$$\pi_i = (r_i - \rho_i)\gamma_i s_i F - c_i \qquad (2),$$

where F is the total face value of loans in the market (ie, size of the mortgage market). A lender only operates in a market as long as $\pi_i \geq 0$.

A.3. Equilibrium

An equilibrium is a market structure comprising the number of lenders of each type N_τ, the pricing decisions of lenders $r_{\tau i}$ and the market shares of lenders $s_{\tau i}$ such that:

1. Borrowers maximise utility in equation (1), taking market structure and pricing as given;
2. Lenders set interest rates to maximise profits, taking market structure and the pricing decisions of other lenders as given; and
3. There is free entry: the number of firms of each type N_τ is set such that profits of all firms are zero. (Eq. (2) equals zero for all lenders *i*).

Given the type one extreme value distribution of idiosyncratic taste shocks ϵ_{ib}, consumers' optimal choices result in standard logistic market shares:

$$s_i(\mathrm{r}_i, \mathrm{q}_i; \{\mathrm{r}_j, \mathrm{q}_j\}) = \frac{\exp(\alpha\, \mathrm{r}_i + \mathrm{q}_i)}{\sum_{j=1}^{N} \exp(\alpha\, \mathrm{r}_j + \mathrm{q}_j)},$$

where N is the total number of lenders in the economy. That is, $N = N_b + N_n + N_f$.

Given regulatory burdens γ_i, the actual market shares of a lender *i* of type τ is given by

$$\hat{s}_{i\tau}(\mathrm{r}_{i\tau}, \mathrm{q}_{i\tau}; \mathrm{N}_\tau, \mathrm{N}_{-\tau}) = \frac{\gamma_\tau \exp(\alpha\, \mathrm{r}_{i\tau} + \mathrm{q}_{i\tau})}{\sum_\tau \sum_{j=1}^{N_\tau} \gamma_\tau \exp(\alpha\, \mathrm{r}_j + \mathrm{q}_j)}.$$

The total market share of a type τ is the sum of individual lenders' market shares within the type, which is given by

$$S_\tau = \sum_{i=1}^{N_\tau} \hat{s}_{i\tau}(\mathrm{r}_{i\tau}, \mathrm{q}_{i\tau}; \mathrm{N}_\tau, \mathrm{N}_{-\tau}).$$

The solution to the lender's profit-maximisation problem over interest rate choice gives the standard expression for markup over funding costs as a function of market share.

$$r_{i\tau}^*(\mathrm{N}_\tau, \mathrm{N}_{-\tau}) - \rho_{i\tau} = \frac{1}{\alpha}\, \frac{1}{1-\hat{s}_{i\tau}(\mathrm{r}_{i\tau}, \mathrm{q}_{i\tau}; \mathrm{N}_\tau, \mathrm{N}_{-\tau})} \qquad (3)$$

Equation (3) makes it clear that the more inelastic/insensitive demand is to interest rates (ie, the smaller the α), the higher the markup, and the greater the market share of a particular bank of type τ (ie, the higher the $\hat{s}_{i\tau}$), the higher the markup of the bank (ie, the higher the $(r_{i\tau}^*(\mathrm{N}_\tau, \mathrm{N}_{-\tau}) - \rho_{i\tau})$). Lastly, zero-profit conditions pin down the number of banks of each type τ,

$$\pi_i(\mathrm{N}_\tau, \mathrm{N}_{-\tau}) = (r_{i\tau}^*(\mathrm{N}_\tau, \mathrm{N}_{-\tau}) - \rho_{i\tau})\hat{s}_{i\tau}(\mathrm{r}_{i\tau}, \mathrm{q}_{i\tau}; \mathrm{N}_\tau, \mathrm{N}_{-\tau})F - c_{i\tau} = 0.$$

B. Calibration

In order to quantify the contribution of lender quality to changes in market share and concentration in the industry, we needed to calibrate the parameters of the model. We allowed the parameters to change from year to year to give the model enough degrees of freedom to exactly match the data on interest rates, market shares, the size of the market, and the number of lenders by lender type. More specifically, we used the data presented in section II to obtain values for the sequence of parameters $q_{i\tau}, \rho_{i\tau}, c_{i\tau}, \alpha$, and γ_b between 2011 and 2019. For each year, we observed the number of lenders by type $N_{i\tau}$, the market share of each lender $\hat{s}_{i\tau}$, the loan interest rates $r_{i\tau}$ and the total size of the market F. We used a strategy similar to that described elsewhere and made the following identifying assumptions:[54]

Assumption 1: funding costs are measured relative to 10-year US treasury yield (i.e., $\tilde{\rho} = \rho - r^{10}$).
Assumption 2: quality and funding costs are relative to non-top 3 banks (a normalisation): $\tilde{\rho}_{4b} = q_{4b} = 0$.
Assumption 3: $q_{4b} - q_{4n}$ is constant. That is, the difference in service quality between non-top three banks and non-top three non-fintech nonbanks is constant.
Assumption 4: in the first year in our sample (i.e., 2011), $\gamma_b = 1$.

Table 4 shows the calibrated values for 2011 and 2019 by lender type.[55] Our calibrated parameters imply that in 2011, top lenders offered higher quality services than lenders not in the top three, with the top banks having the highest quality, followed by fintech and non-fintech nonbanks. The ranking was similar across lenders not in the top three, with non-fintech nonbanks offering the lowest quality lending services. The data show that between 2011 and 2019, quality improved for most lenders (except top banks) and that the largest gains were in the top non-fintech nonbanks, followed by fintech nonbanks. The changes are significant, but not large enough to reverse the original ranking completely, with the top fintech moving from fourth place to second place in the ranking. We linked the estimated reduction in bank quality to the reduction in the fraction of consumers that expressed a preference for the person-to-person and branch-based interaction that is at the core of the (traditional) bank business model. Technology and advertising make consumers more aware of more options and more likely to search and find better alternatives.[56] The increase in estimated fintech quality can be associated with fintech technological innovations that reduce the cost of applying for a loan and involve no human loan officer. The experiments presented in the following section study the role of these quality changes in explaining the changes in lender market shares and the dynamics of concentration.

Table 4 shows that there is a relatively homogeneous decline in funding costs (with the smallest decline for the top bank and the largest for the top fintech and non-fintech nonbanks). As stated in identifying Assumption 2 above, we normalised the funding cost spread for non-top 3 banks to zero, so changes in funding costs for this group displayed in Table 4 correspond one-to-one to changes in the 10-year US treasury yield. That means that the table also reveals a significant variation in terms of entry costs. In 2011, top lenders (across all types) showed the highest cost, with entry into banking being more costly than entry into fintech and non-fintech nonbanking. In 2019, in line with changes in market shares, the top

[54] ibid. See Appendix VII.B for more details on the calibration strategy.
[55] Appendix VII.B presents the full time series of the estimated parameters by lender type.
[56] E Honka, A Hortaçsu, and MA Vitorino, 'Advertising, Consumer Awareness, and Choice: Evidence from the US Banking Industry', (2017) *The RAND Journal of Economics* 611 (http://dx.doi.org/10.1111/1756-2171.12188).

fintech lender showed the highest entry cost. All lenders except the top bank had an increase in entry costs between 2011 and 2019, with the largest increase happening at the very top of the distribution of nonbanks.

Table 4: Calibrated parameters (2011 and 2019).

	Lender	q			ρ (%)			c (bn $)		
	Type	2011	2019	Δ	2011	2019	Δ	2011	2019	Δ
B	Largest	3.97	2.99	-0.98	2.52	2.03	-0.49	3.02	2.64	-0.38
B	Second largest	3.27	2.66	-0.61	2.72	2.11	-0.61	1.29	1.82	0.53
B	Third largest	3.00	2.62	-0.38	2.72	2.08	-0.64	0.99	1.77	0.78
B	Non-top three	0.00	0.00	0.00	2.78	2.14	-0.64	0.05	0.13	0.08
N	Largest	0.78	2.36	1.58	2.79	2.04	-0.75	0.10	2.27	2.16
N	Second largest	0.49	1.40	0.91	2.82	2.14	-0.67	0.07	0.82	0.75
N	Third largest	0.42	1.34	0.92	2.85	2.18	-0.67	0.07	0.76	0.69
N	Non-top three	-0.57	-0.57	0.00	2.84	2.20	-0.64	0.03	0.11	0.09
F	Largest	2.10	2.68	0.58	2.86	2.10	-0.77	0.36	3.03	2.67
F	Second largest	1.36	1.51	0.15	2.84	2.17	-0.67	0.18	0.91	0.73
F	Third largest	0.72	1.01	0.29	2.82	2.16	-0.66	0.09	0.55	0.46
F	Non-top three	-0.46	-0.30	0.16	2.81	2.17	-0.64	0.03	0.15	0.12

Note: Calibrated parameters using loan level data from Fannie Mae and Freddie Mac and HMDA. Our sample period was 2011–2019. This sample includes conforming loans only. Classification based on latest version of lender classification data.[57] Lender type 'B' refers to banks, 'NF' to non-fintech nonbanks and 'F' to fintech nonbanks.

IV. MAIN EXPERIMENTS AND RESULTS

We used the model to perform our main experiments. The goal was to understand the impact of technology (lender quality) and costs on the dynamics of lender market shares and concentration.

In our first experiment, and to set a baseline, we analysed the evolution of the industry if the calibrated parameters $\{\gamma_j, q_j\}$ had remained constant at their 2011 levels and the fixed operating cost c_j and the funding costs ρ_j had evolved as shown in Table 3.[58] We called this experiment 'costs', as it captures the effect of changes in the estimated lenders' cost structure. As pointed out by others, changes in the fixed operating cost c_j are partly induced by increased regulatory burdens after the 2010 Dodd-Frank Act.[59] The solution to this experiment provides a path of interest rates, market shares and number of banks consistent with a counterfactual world where only costs change between 2011 and 2019.[60]

We found that changes in costs explained about a quarter of the increase in the market share of non-fintech nonbanks and only a tenth of the increase in fintech lending (Figure 11). Changes in funding costs were relatively homogeneous among nonbanks, with an average and median reduction of 68 basis points. They were about 10 to 25 basis points smaller for banks than for nonbanks, with larger differences observed at the very top of the distribution, explaining the changes in market shares and number of lenders. Figure 10 shows changes in concentration for the entire market and by lender type. Changes in overall

[57] Buchak et al. (n 4).

[58] The parameter that controls the demand elasticity α also evolves in step with the calibrated values. We assume that entry costs for top lenders of each type adjust so there is at most one lender as the largest, one as the second largest and one as the third largest for each type.

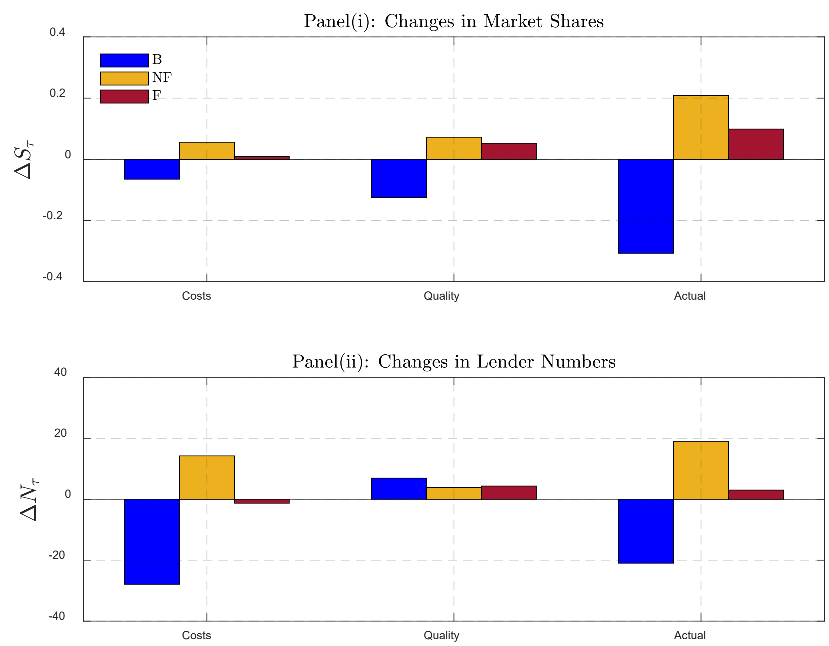
[59] K Liu, 'The Impact of the Dodd-Frank Act on Small U.S. Banks', (2022) *mimeo*, available at https://ssrn.com/abstract=3419586 (http://dx.doi.org/10.2139/ssrn.3419586).

[60] The solution sets a baseline, as our second experiment incorporates changes in quality in addition to changes in costs. The effects of changes in quality correspond to the differential effect between the result of that experiment and this baseline.

concentration were significant in the data (and our calibration), but almost none of those changes derived from changes in costs (as the overall change in HHI under 'costs' was negligible).

This result hides important heterogeneity within type. Both bank and fintech concentration increased due to changes in costs (non-fintech lenders' concentration declined slightly). In the case of banks, the increase in concentration derived from the reduction in operating costs for the very top bank (versus an increase for all other bank lenders, which saw operating costs more than double between 2011 and 2019). This led to a significant decline in market share for banks not in the top three (about 70 percent of their overall reduction in lending between 2011 and 2019) and a decline in the number of non-top three banks (28 banks exited the market in the counterfactual experiment). In the case of fintech nonbanks, the increase in concentration derived from the larger reduction in funding costs, mitigated to some extent by the increase in operating costs for the top nonbanks that resulted in an increase in market share for top fintech lenders. In this experiment, our measure of within-group HHI variation was positive, as there was an increase in the HHI for banks and fintech nonbanks. Figure 12 shows that the overall change in the HHI in the 'costs' experiment was almost null, implying that, in this case, the within-group variation was fully compensated by the between-group HHI variation, driven by the decline in the market share of banks.

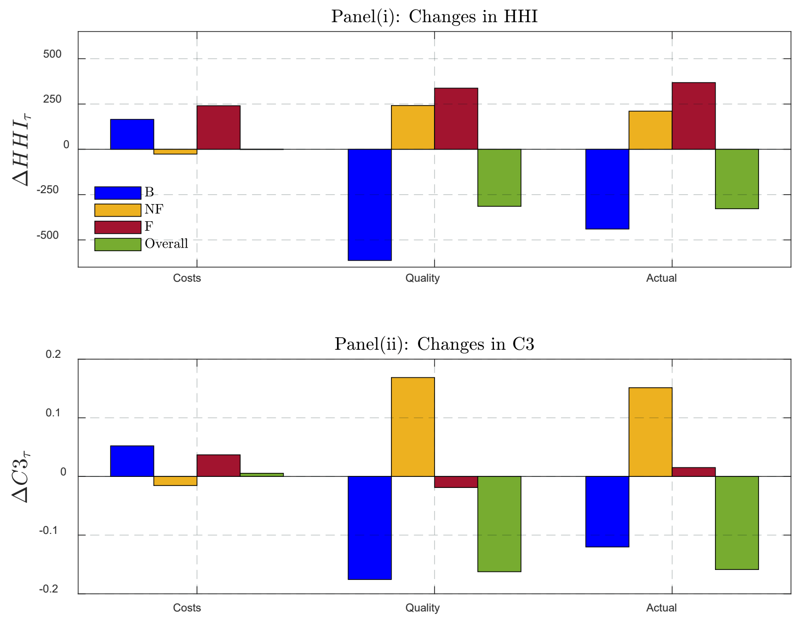
Figure 11: Changes in market shares and number of lenders.



Note: Counterfactuals for the change in lender market shares and number of lenders implied by our model. 'Costs' refers to the counterfactual that evaluates changes to operating and funding costs only. 'Quality' refers to the counterfactual that evaluates changes to the lender quality parameters only. 'B' refers to banks, 'NF' to non-fintech nonbanks and 'F' to fintech nonbanks.

In our second experiment, we analysed how changes in lender quality (technology) affected the equilibrium outcome. We called this experiment 'quality' and it captured changes in consumer preferences toward nontraditional lenders as well as fintech technological innovations that reduced friction in mortgage lending.[61] In particular, we solved the equilibrium of the model keeping the value of γ_j constant at the calibrated value in 2011 and used the calibrated sequence of $\{c_j, \rho_j, q_j\}$. The difference between the outcomes in this experiment and that in the baseline experiment ('costs') allowed us to quantify the impact of lender quality and technology.

Figure 12: Changes in concentration (HHI and C).



Note: Counterfactuals for the change in lender market shares and number of lenders implied by our model. 'Costs' refers to the counterfactual that evaluates changes to operating and funding costs only. 'Quality' refers to the counterfactual that evaluates changes to the lender quality parameters only. 'Overall' corresponds to measures of concentration computed using all lenders, 'B' refers to banks, 'NF' to non-fintech nonbanks and 'F' to fintech nonbanks. C3 refers to the market share of the Top 3 lenders.

Figure 11 shows that changes in quality explained 40 percent of the decline in bank market shares, 35 percent of the market share gain of non-fintech nonbanks, and more than 50 percent of the increase in the market share of fintech nonbanks. As described in the previous section, the calibrated parameters showed a significant decline in q_j for banks (a 13–25 percent reduction) and an increase for all nonbanks (slightly more pronounced for non-fintech). These quality dynamics explained the decrease in the bank market share with most of the effect deriving from the intensive margin (i.e., lending activity by incumbent banks) at the top of the distribution. Top banks reduced their lending by up to 10 percent. The number of banks (not in the top three) increased (+7), but the change was not large enough to compensate for the lending reduction by large banks. In the case of nonbank lenders (both non-fintech and fintech), the increase in quality resulted in positive changes along both the intensive and the extensive margin (i.e., changes in the amount of lending by incumbent lenders and changes in the number of lenders, respectively). The portion of the total change explained by quality changes in the fintech sector in our experiment was

[61] As analysed empirically in Fuster et al. (n 6) and Buchak et al. (n 4). Fuster et al. (n 6) document that fintech lenders process mortgages faster than traditional lenders and that fintech lenders respond more elastically to changes in mortgage demand.

consistent with previous results.[62] With a smaller increase in quality, most of the change in fintech lending derived from the extensive margin (the number of fintech lenders almost doubled).

Figure 12 shows that the dynamics of lender quality have important implications for overall and within-group lender concentration. This experiment explained 97 percent of the overall change in the HHI with the reduction in the bank HHI more than explaining the overall change (as previously described, the 'costs' experiment reversed some of this decline). With a completely different outcome, we observed that the increase in quality concentrated in the top nonbanks (fintech and non-fintech) resulted in a large increase in concentration of nonbanks. The results showed that the 'quality' experiment more than explained the total change in concentration within the nonbank sector (as measured with both the HHI and C3).

In summary, we found that quality (or technology) improvements in the nonbank sector explained most of the variation in market shares and concentration observed in the data. In the case of market shares, it explained 40, 35, and 53 percent for banks, non-fintech nonbanks and fintech nonbanks, respectively. In the case of concentration (when measured using the HHI), quality explained almost all of the overall variation. In the cases of banks and non-fintech nonbanks, quality explained more than the total variation in concentration observed in data.[63] As Table 4 shows, this was the result of the significant changes in quality observed at the very top of the distribution in both the bank and the non-fintech nonbank group. Lastly, quality explained 43 percent of the changes in fintech concentration. While there are important changes in quality at the top of the distribution, we estimated quality changes to be more homogeneous among fintech nonbanks.

V. FINAL REMARKS AND DIRECTIONS FOR FUTURE RESEARCH

This paper presents evidence on concentration in the residential mortgage market and the role of fintech lenders. Consistent with previous literature, we find that the industry is shifting towards nonbank lenders. In addition, we describe in this paper that fintech lending is significantly more concentrated than bank and other nonbank lenders. We used our model to show that changes in lender quality and technology play a crucial role in explaining the dynamics of the market and the evolution of concentration over time.

There is a key trade-off to be considered when analysing the observed changes in concentration. On one hand, as we estimate, one of the drivers of the shift towards nonbank fintech lenders (and the implied effect on concentration) is the increase in lender quality, which reflects that consumers derive higher benefits from their borrowing activity. On the other hand, a shift towards a lender sector (nonbank fintech) with higher concentration has negative implications for competition and consumer surplus. Moreover, it is important to consider that nonbanks do not rely on insured deposits. Therefore, their increased participation might not be problematic so long as they do not pose a risk to financial stability (ie, risk to other financial institutions or systemic risk). The model in this paper is not well suited to quantify the relative magnitudes of these effects; thus, we leave this interesting analysis for future research.

The focus of our paper has been concentration in the fintech industry and the role of changes in lender quality and technology. We also leave for future research the role of regulatory changes, such as capital and liquidity requirements. Further, we plan to study the role in promoting market concentration of the originate-to-distribute model that derives from the implicit guarantee that government agencies offer

[62] Buchak et al. (n 4).
[63] This means that changes in quality alone generated a larger change in non-fintech nonbank concentration than what was observed in the data. The changes arising from the 'costs' experiment offset this effect of quality changes.

and its associated moral hazard problem, similar to deposit insurance. This business model is prevalent among nonbanks and, especially, fintech lenders.

VI. APPENDIX

A. HHI decomposition

Let l_i denote loans originated by lender i and L the total value of loans originated. Total loans originated by banks (B) are denoted by L^B, total loans originated by non-fintech nonbank L^{NF}, and total loans by fintech nonbanks L^F. Then, we can decompose the HHI as follows

$$HHI_t = \sum_{i=1}^{N} s_{i,t}^2 = \sum_{i=1}^{N_t} \left(\frac{l_{i,t}}{L_t}\right)^2$$
$$= \sum_{i \in B} \left(\frac{L_t^B}{L_t}\right)^2 \left(\frac{l_{i,t}}{L_t^B}\right)^2 + \sum_{i \in B} \left(\frac{L_t^{NF}}{L_t}\right)^2 \left(\frac{l_{i,t}}{L_t^{NF}}\right)^2 + \sum_{i \in B} \left(\frac{L_t^F}{L_t}\right)^2 \left(\frac{l_{i,t}}{L_t^F}\right)^2,$$
$$= (S_t^B)^2\, HHI_t^B + (S_t^{NF})^2\, HHI_t^{NF} + (S_t^F)^2\, HHI_t^F$$

where S_t^j and HHI_t^j denote the market shares and the HHI, respectively, within type $j \in \{B, NF, F\}$ (ie, when the market is defined using loans from lenders of type j).[64] Expanding the overall HHI in this way shows that changes in overall concentration between periods t and any period τ can be decomposed in changes between groups (ie, changes derived from changes in market shares) and changes within groups (ie, changes derived from changes in concentration within groups). More specifically, we can write

$$\Delta HHI_t = HHI_t - HHI_\tau = \sum_{j \in \{B,NF,F\}} \left(S_t^j\right)^2 HHI_t^j - \left(S_\tau^j\right)^2 HHI_\tau^j$$
$$= \sum_{j \in \{B,NF,F\}} \Delta\left(S_t^j\right)^2 HHI_t^j - \sum_{j \in \{B,NF,F\}} \left(S_\tau^j\right)^2 \Delta HHI_t^j.$$

We call the first term 'ΔHHI_t between' and the second term 'ΔHHI_t within'.

B. Calibration details

In this appendix, we present further details of the calibration strategy. The calibration process is as follows. Using the optimal pricing equation (ie, Eq. (3)) of non-top three banks and data on the average interest rate and market shares of non-top three banks, we pin down α:

$$\alpha = \frac{1}{r_{4b}} \frac{1}{1 - \hat{s}_{4b}}.$$

This gives a common (across-lender) value of α that varies from year to year.[65] To calibrate the service quality of the non-top three non-fintech nonbank, q_{4n}, we first take the ratio of market shares between the non-top three non-fintech nonbank and the non-top three bank in 2011 (when $\gamma_{4b} = \gamma_{4n} = 1$):

[64] As seen in Rossi-Hansberg et al. (n 33).

[65] Using the optimal pricing equation of non-top three banks is convenient as ρ_{4b} is normalised to zero, so we do not need to set a value for ρ to solve for α.

$$\frac{\hat{s}_{4n}}{\hat{s}_{4b}} = \frac{\exp(\alpha\, r_{4n} + q_{4n})}{\exp(\alpha\, r_{4b} + q_{4b})}.$$

Rearranging the terms in this ratio and using the assumption that $q_{4b} = 0$, we solve for the value of q_{4n} in 2011:

$$q_{4n} = \alpha(r_{4n} - r_{4b}) + \ln\left(\frac{\hat{s}_{4n}}{\hat{s}_{4b}}\right).$$

Based on *Assumption 3* above, q_{4n} stays constant over the sample period. Therefore, once we know q_{4n} in 2011, we also know q_{4n} for all later years. Similarly, we may solve for $q_{i\tau}$ for the top three banks by taking the ratios of their market share to the market share of non-top three banks (since $q_{4b} = 0$ and γ_b is the same across banks, it is straightforward to solve for q_{ib}). Having obtained q_{4n}, we solve for q_{in} and q_{if} by taking the ratios of their market shares to the market share of the non-top three non-fintech nonbanks ($\hat{s}_{4n}$). Using data on interest rates and market shares, we obtain a sequence of $q_{i\tau}$ for every year in the sample.

Next, we calibrate the funding costs for each lender. Inverting the optimal pricing equation (Eq. (3)), and with the value of α at hand, we solve for the funding cost spread (over the 10-year treasury rate) for lender i of type τ at year t as follows:

$$\tilde{\rho}_{i\tau} = (r_{i\tau} - r^{10}) + \frac{1}{\alpha}\,\frac{1}{1 - \hat{s}_{i\tau}}.$$

Having obtained $q_{i\tau}$ for all lenders in all years, we are also ready to solve for the regulatory burden faced by banks – γ_b – by taking the ratio of the market share of any bank and the market share of any nonbank. The value of γ_b is then obtained by rearranging items in that ratio:

$$\gamma_b = \alpha(r_{ib} - r_{in}) + \ln\left(\frac{\hat{s}_{ib}}{\hat{s}_{in}}\right) + q_{in} - q_{ib}.$$

Lastly, we pin down the fixed costs of lenders by solving for $c_{i\tau}$ using the free entry condition:

$$c_{i\tau} = (r_{i\tau} - \tilde{\rho}_{i\tau} - r^{10})\hat{s}_{i\tau}F.$$

Table 4 in the main text presented the value of the estimated parameters for 2011 and 2019. In this appendix, we complete the description of our calibration by showing the full time series. Figure A.1 shows the value of α_t. The average value is 0.597, with a minimum of 0.449 and a maximum of 0.832. Figures A.2–A.4 present the estimated lender qualities (q_τ), entry costs (c_τ) and funding costs (ρ_τ), respectively, by lender type in each year 2011–2019. Panel (i) shows the corresponding values for banks, panel (ii) the values for non-fintech nonbanks and panel (iii) the value for fintech nonbanks.

Figure A.1: Demand elasticity.

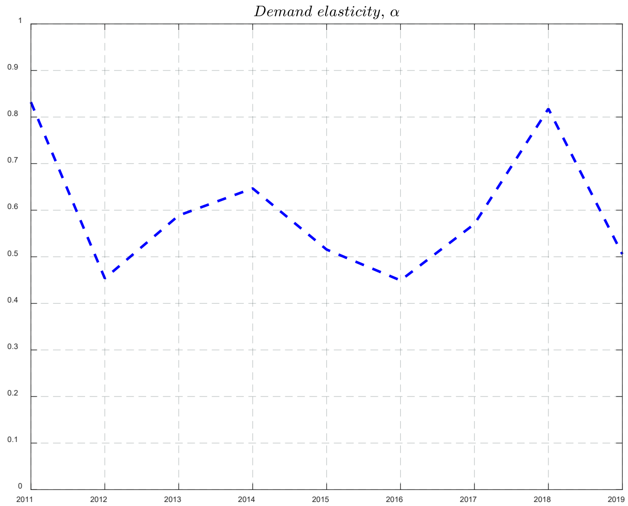


Figure A.2 Lender quality q_τ (by lender type).

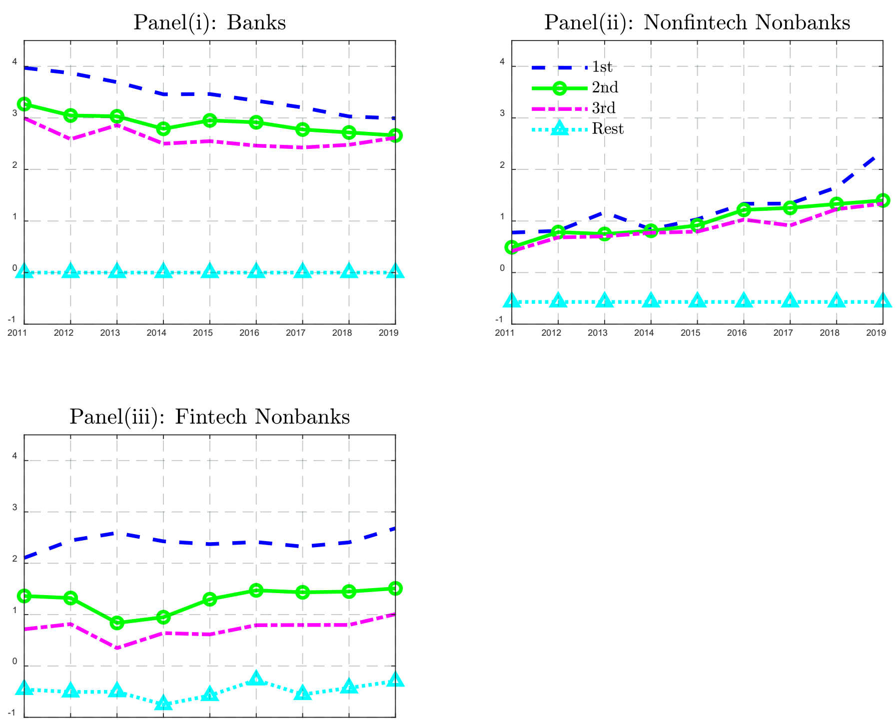


Figure A.3 Lender entry cost c_τ (in billions \$, by lender type).

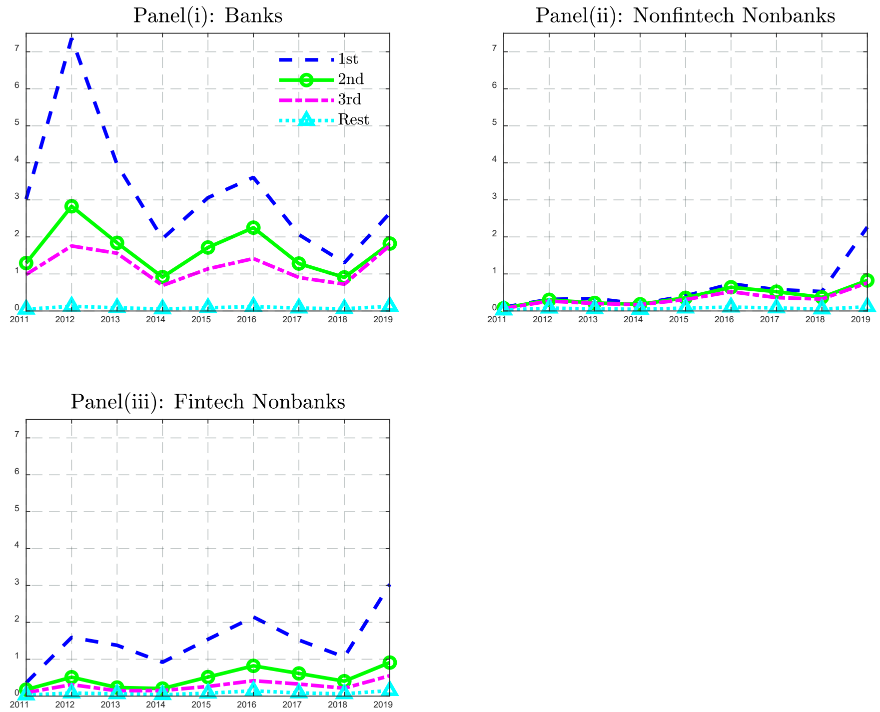


Figure A.4 Funding costs ρ_τ (in %, by lender type).