

# Market Concentration in Fintech\*

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## Abstract

This paper discusses concentration in consumer credit markets with a focus on fintech lenders and residential mortgages. We present evidence that show 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 regulatory pressure explains about a third of the change in market shares but have a modest impact on concentration. Changes in lender financial technology (interpreted as improvements in quality of loan services) explain more than 50 per cent of the increase in fintech market shares and 43 per cent 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

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\*The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. Any errors or omissions are the responsibility of the authors.

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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.<sup>1</sup> This article 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).<sup>2</sup> Based on previous research, we classify institutions originating loans on this market into three types: (traditional) banks, non-fintech nonbanks and fintech nonbanks.<sup>3</sup> 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 securitization financed with short-term securities.<sup>4</sup> As described by others, fintech lenders have a significant presence online and processes mortgages faster than non-fintech lenders.<sup>5</sup>

The period analyzed 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

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<sup>1</sup>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).

<sup>2</sup>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.

<sup>3</sup>The classification into fintech or non-fintech lender relies on [Buchak, Matvos, Piskorski, and Seru \[2018\]](#). 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.

<sup>4</sup>[Corbae and D’Erasmus \[2021\]](#) 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.

<sup>5</sup>[Fuster, Plosser, Schnabl, and Vickery \[2019\]](#) showed that fintech lenders process mortgage applications 20 per cent faster than other lenders, controlling for observable characteristics. Fintech lenders adjust supply more elastically than other lenders.

lenders. In line with evidence in past research, we find that the market share of nonbanks has almost doubled in the last ten years.<sup>6</sup> There is a significant decline in the loan origination market share for (traditional) 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 per cent of the market.<sup>7</sup> Concentration within the fintech sector is remarkably high, 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 per cent 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 per cent. 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 per cent 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 per cent 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 (i.e., 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 Buchak et al. [2018]. Unlike in that paper, we introduce heterogeneity within each institution type, allowing us to link the model to data on

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<sup>6</sup>See, for example, Buchak et al. [2018] and Fuster et al. [2019].

<sup>7</sup>Corbae and D’Erasmus [2015] studied concentration within the bank sector and the role the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 had on the observed increase in concentration between 1984 and 2018. Corbae and D’Erasmus [2020] also examined the consequences of government policies that promote foreign competition in a concentrated banking industry.

concentration with a particular focus on fintech. The model captures differences in financing costs, lending quality/technology and regulatory pressure.<sup>8</sup> 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, under-occupied and poorly maintained.<sup>9</sup>

In our two main experiments, we focus on how changes in regulatory pressure for banks and changes in quality and technology of financial intermediaries (with a particular attention to fintech nonbanks) affect market shares and concentration in the industry. In our “Regulation” experiment, we show that an increase in regulatory pressure in the banking sector explains about a third of the changes in market shares and modest changes in overall concentration. The estimated increase in regulatory pressure on the banking sector leads to an increase in lending by existing nonbanks (larger for non-fintech) and the entry of new non-bank lenders. This results in a reduction in concentration in the non-bank sector. In the experiment that evaluates changes in lender quality, which capture not only consumer preferences regarding the quality of financial services, but also technological advances in the fintech sector, we show that these changes account for more than 50 per cent of the increase in the fintech market share and 40 per cent of the decline in the bank market share.

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<sup>8</sup>In line with [Buchak et al. \[2018\]](#) and [Fuster et al. \[2019\]](#) 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 (e.g., loan applications that can be completed entirely online and expand access to some borrowers), and the provision of a more comprehensive customer service.

<sup>9</sup>See, for example [Frederic, Marukel, Pradip, and Stephens \[2017\]](#).

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 the overall concentration in the residential mortgage market 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.

**Related Literature.** Our paper is related to previous work on the roles of nonbanks and fintech lenders on credit markets.<sup>10</sup> The most closely related papers are [Buchak et al. \[2018\]](#) and [Fuster et al. \[2019\]](#) that study fintech lending and how technology changes shaped the evolution of the industry after the Great Financial Crisis. 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.<sup>11</sup>

Past research has investigated the connection between bank capital regulation and the prevalence of nonbanks in the US corporate loan market ([Irani, Iyer, Meisenzahl, and Peydró \[2020\]](#)). 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 ([Balyuk, Berger, and Hackney \[2022\]](#)). 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 ([Gopal](#)

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<sup>10</sup>See [Adrian and Ashcraft \[2016\]](#) for a review of the literature on credit intermediation outside the banking sector.

<sup>11</sup>[Jagtiani, Lambie-Hanson, and Lambie-Hanson \[2021\]](#) studied whether the growth of fintech lending in mortgage markets results in expanded credit access. [Buchak, Matvos, Piskorski, and Seru \[2022\]](#) studied technological disruptions in the real estate market and the emergence of iBuyers.

and Schnabl [2022]). Chernenko, Erel, and Prilmeier [2022] provide evidence on the terms for direct lending by nonbanks in the market for business credit. Murfin and Pratt [2018] present evidence on the financing of durable goods through captive finance subsidiaries. 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 data samples used in this paper and present the main facts.

### II.A Sample description

We constructed our main sample using the Home Mortgage Disclosure Act (HMDA) loan origination dataset. 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.<sup>12</sup> An institution (or lender) 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. An updated classification included some fintech banks (i.e., banks that switched from a more traditional application procedure with significant person-to-person interaction to one similar to that of nonbank fintech lenders). Since the adoption of a fintech application procedure among banks is relatively recent, we decided to

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<sup>12</sup>We manually matched lenders in HMDA in year 2019 using lender names to the updated list that Buchak et al. [2018] 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 exist in previous years, but not in 2019). Once lenders were matched, we kept the type of the given lender constant for the length of our sample. Additionally, we classified Better Mortgage Corporation and Sofi as fintech lenders, following the discussion in Jagtiani et al. [2021]. See the updated list from Buchak et al. [2018] here <https://sites.google.com/view/fintech-and-shadow-banks> (accessed 14 June 2022).

continue with the original three-type classification for the analysis in this article.<sup>13</sup>

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). On average, the top 200 lenders accounted for 70 per cent 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 per cent 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.<sup>14</sup> 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).

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<sup>13</sup>See also [Fuster et al. \[2019\]](#) and [Jagtiani et al. \[2021\]](#) for a similar three-type classification.

<sup>14</sup>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 in HMDA)

<b>Fintech Lender Name</b>	<b>Fintech Start</b>	<b>Volume (MM)</b>	<b>Market Share</b>
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%

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 amortizing, 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 in order to analyze 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.

## II.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.

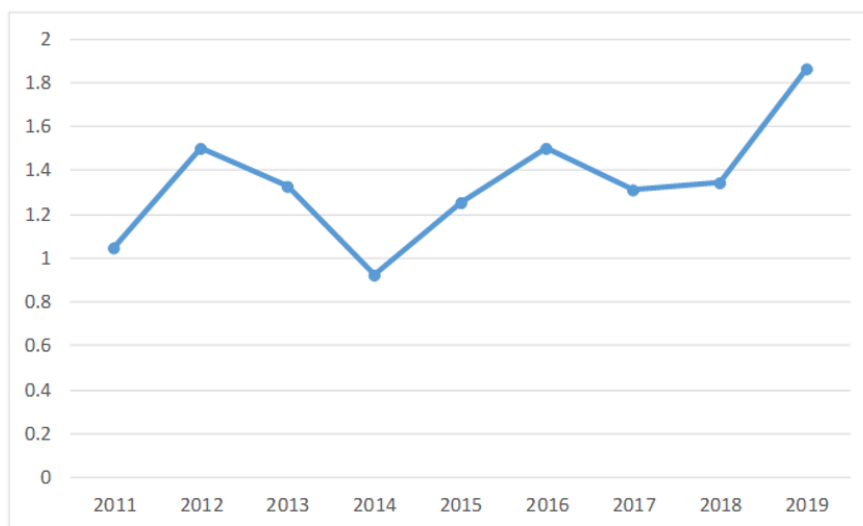


Subsection II.B.3. provides a decomposition of lender concentration to help understand the dynamics.

## II.B.1 Mortgage Market Size and Aggregate Level Concentration

We start by documenting aggregate dynamics in our sample. Our findings are in line with previous research. 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 per cent between 2011 and 2019.

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

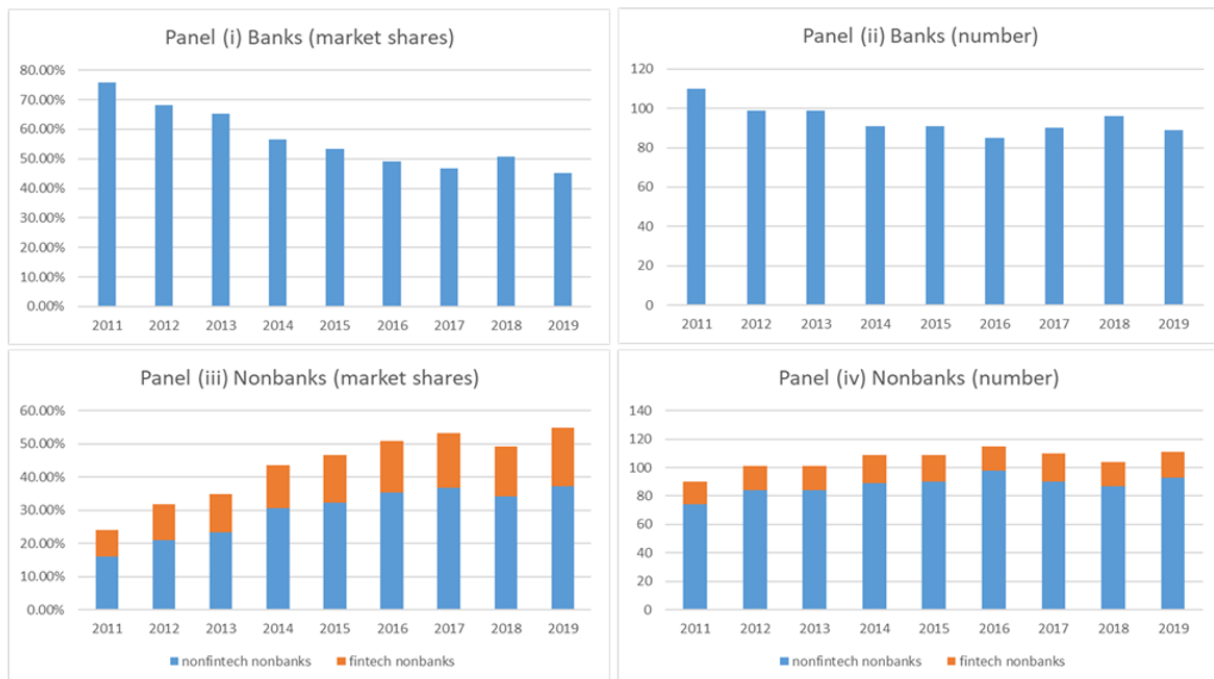


**Note:** Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans).

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 per cent (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 per cent 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 per cent, while fintech nonbanks’ market share

increased from 8 to over 17 per cent. 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 per cent. 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.

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



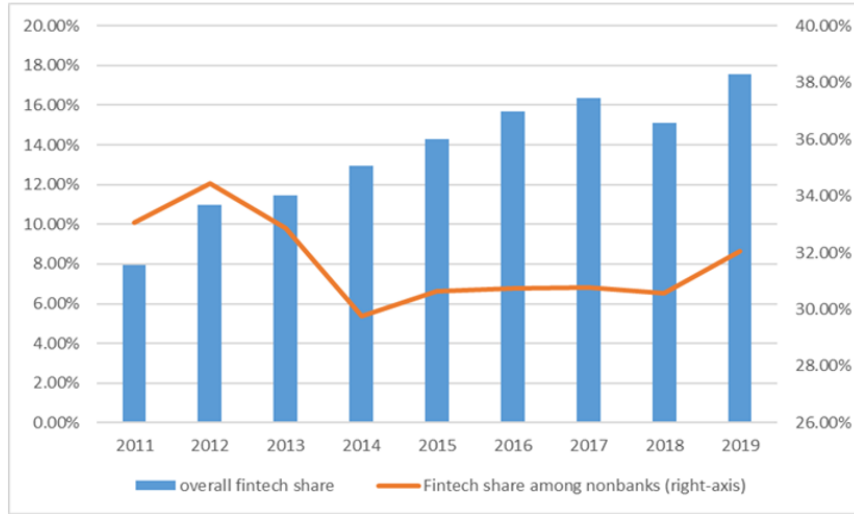
**Note:** Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans). Classification was based on the latest version of lender classification data. Market shares corresponded to shares of originations among the top 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 per cent on average (see Table 1, panel B). In the case of nonbanks, the average is 7.5 per cent, with non-fintech lenders at 6.8 per cent and fintech lenders at 10.5 per cent. 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 per cent of loans originated in this sector

were financed by some underlying government guarantee.

Figure 3 focuses on fintech lending during the period. The market share of fintech lenders increased from close to 8 to more than 17 per cent. 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.

Figure 3: Fintech lending market shares



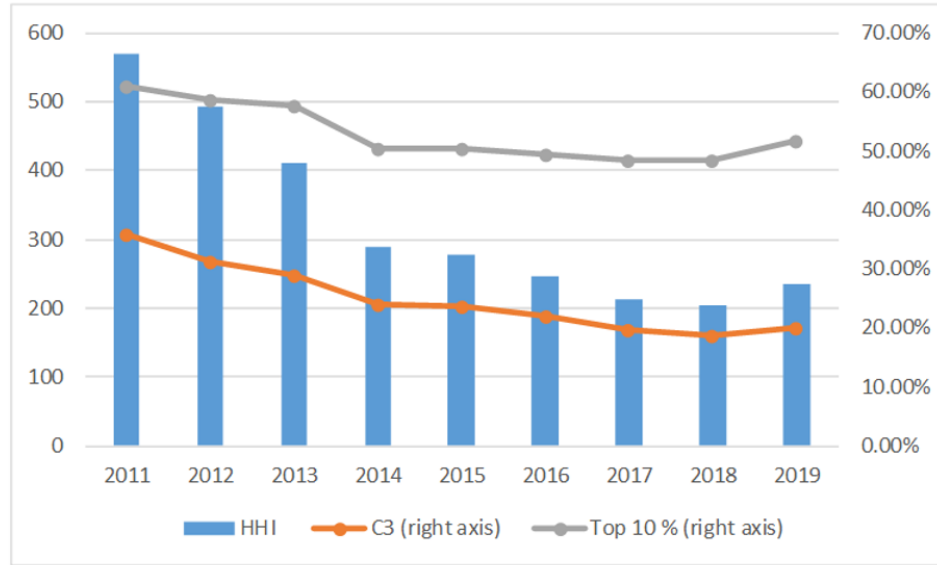
**Note:** Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans). Classification was based on the latest version of lender classification data. “Overall fintech share” refers to the share of fintech lending in 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 presents the evolution of three measures of market concentration at the national level: the Herfindahl-Hirschman Index (HHI),<sup>15</sup> the market share of the top three lenders (C3), and the market share of the top 10 per cent lenders (when sorted by originations).<sup>16</sup>

<sup>15</sup>The HHI is defined as  $HHI_t = \sum_{i=1}^N s_{i,t}^2$ , where  $s_{i,t}^2$  corresponds to the market share of lender  $i$  (in percentage points) in the period  $t$

<sup>16</sup>The HHI is a widely used measure of market concentration and can assume values between  $[1/N, 10,000]$ , where  $N$  is the number of lenders in the industry. See, for example, Rossi-Hansberg, Sarte, and Trachter [2021].

Figure 4: National level concentration (all loans and 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 based on latest version of lender classification data. 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 per cent corresponds to the market share of the top 10 per cent lenders when sorted by originations (since we studied the top 200 lenders, this corresponds to the top 20 lenders).

Figure 4 shows that there was a decline over time in the degree of overall market concentration (consistent across the three measures).<sup>17</sup> The overall HHI dropped from 570 in 2011 to 236 in 2019 (an almost 60 per cent decline). The market share of the top three lenders ( $C3$ ) declined from 36 to 20 per cent. There was also a (less pronounced) decline in the market share of the top 10 per cent lenders (when sorted by originations), from 61 to 52 per cent. 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,

<sup>17</sup>Figure 4 shows three measures of concentration at the national level. Figure 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. [2021] for other industries.

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.

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)

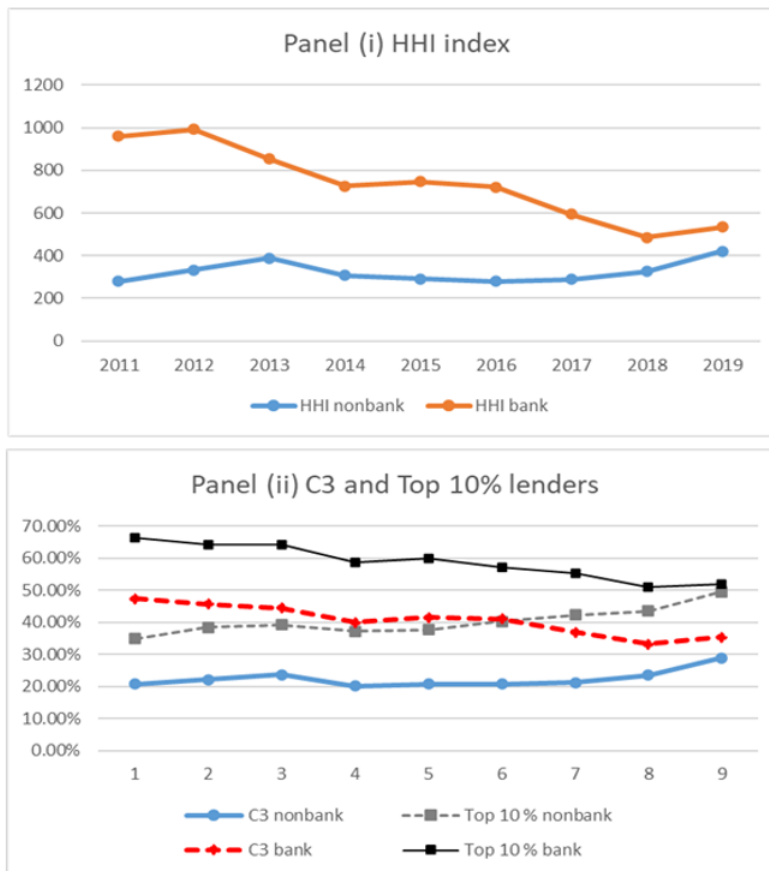
Lender Type	market share changes 2011-2019			
	Largest	2nd Largest	3rd Largest	Non-top 3 Rep.
Banks	-12.67%	-4.61%	2.70%	-0.03%
Nonfintech Nonbanks	4.99%	1.60%	1.49%	0.10%
Fintech Nonbanks	4.81%	1.03%	0.74%	0.17%

**Note:** Loan level data from HMDA. We included all loans (both purchase and refinance as well as nonconventional loans). Classification was based on an existing classification system. 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.

## II.B.2 Fintech concentration

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 per cent lenders (panel (ii)), when separating lenders by whether they are a bank or not.

Figure 5: Concentration by bank status



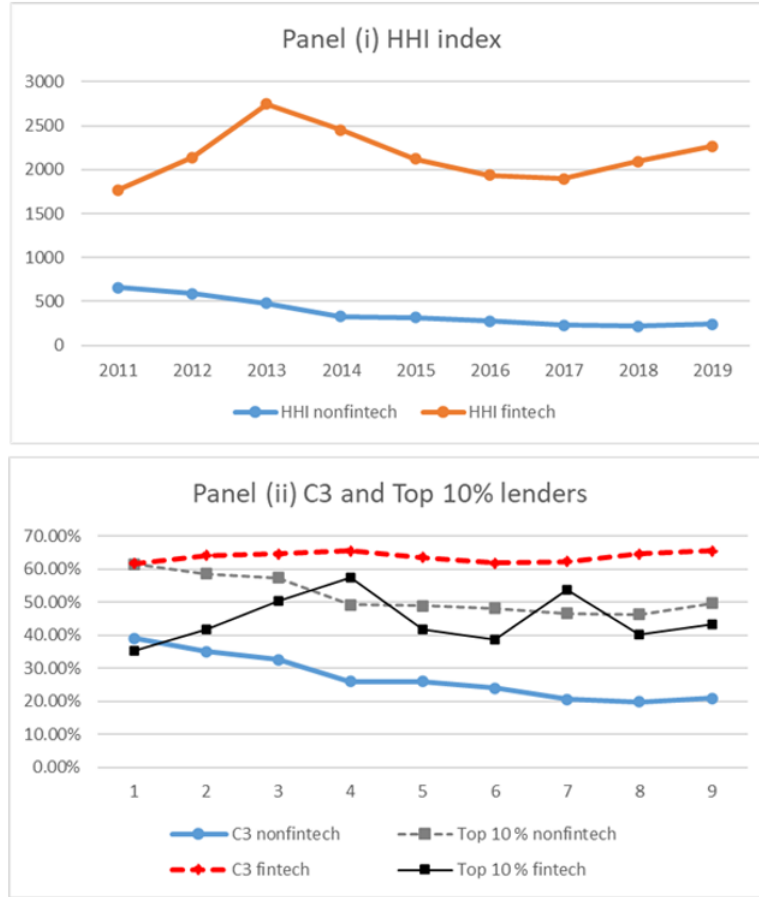
**Note:** Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans). Classification based on latest version of lender classification data. The Herfindahl-Hirschman Index ( $HHI$ ) equals  $\sum_{i=1}^N s_i^2$ , where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

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 per cent larger in 2019. A similar dynamic can be observed for C3 and the market share of the top 10 per cent 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

per cent between 2011 and 2019, while the HHI for banks declined by 44 per cent during the same period. This increase in concentration in the nonbank sector derives from significant growth at the very top of the distribution.

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

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. 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 per cent corresponds to the market share of the top 10 per cent lenders when sorted by originations (since we studied the top 200 lenders, this corresponds to the top 20 lenders).

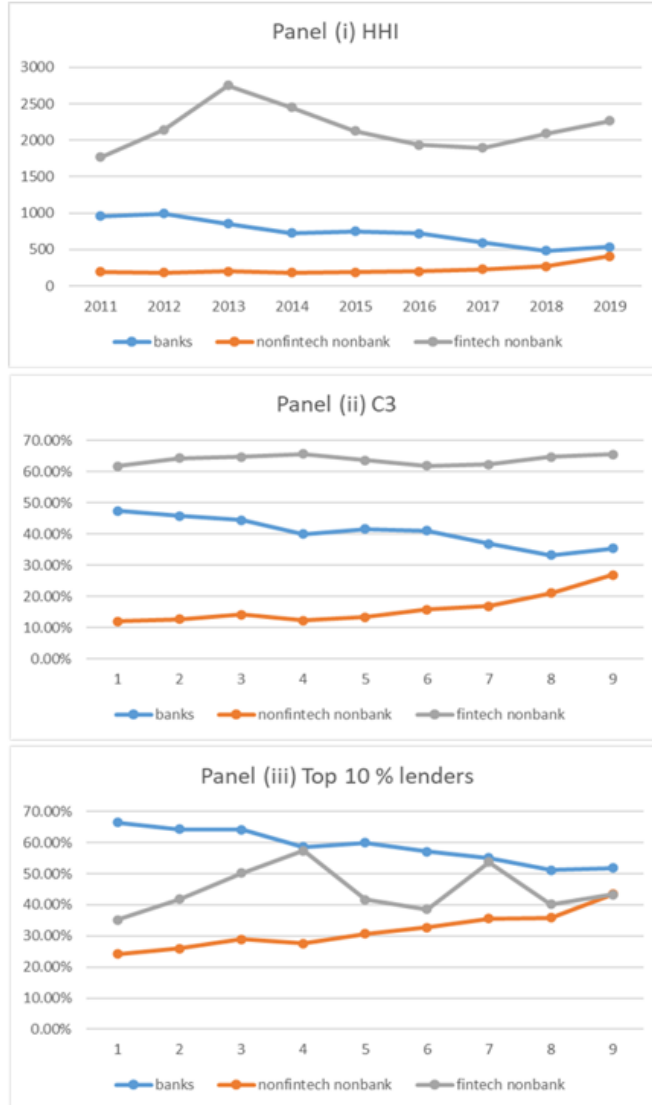
Fintech lenders were significantly more concentrated than non-fintech lenders. The HHI for fintech lenders was 2–7 times larger than that of non-fintech lenders. The number of

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 per cent), 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 per cent lenders appeared to be lower for fintech than for non-fintech. It is relevant to note that lending by the top 10 per cent 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 per cent 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.

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 shows the HHI (panel (i)), the market share of the top three lenders (panel (ii)), and the market share of the top 10 per cent lenders (panel (iii)). 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 towards the end of the period, explaining the uptick in overall concentration in 2018 and 2019 (see Figure 4).



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.

### II.B.3 Market concentration decomposition

We conclude Section II 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:

$$HHI_t = (S_t^B)^2 HHI_t^B + (S_t^{NF})^2 HHI_t^{NF} + (S_t^F)^2 HHI_t^F \quad (1)$$

where  $S_t^j$  and  $HHI_t^j$  denote the market shares and the HHIs, respectively, within lender type  $j \in \{B, NF, F\}$  (i.e., when the market is defined using loans from lenders of type  $j$ ).<sup>18</sup> 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  $\tau$  can be decomposed into changes between groups (i.e., changes derived from redistribution of market shares across types) and changes within groups (i.e., changes due to changes in concentration within groups). More specifically, we can write

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

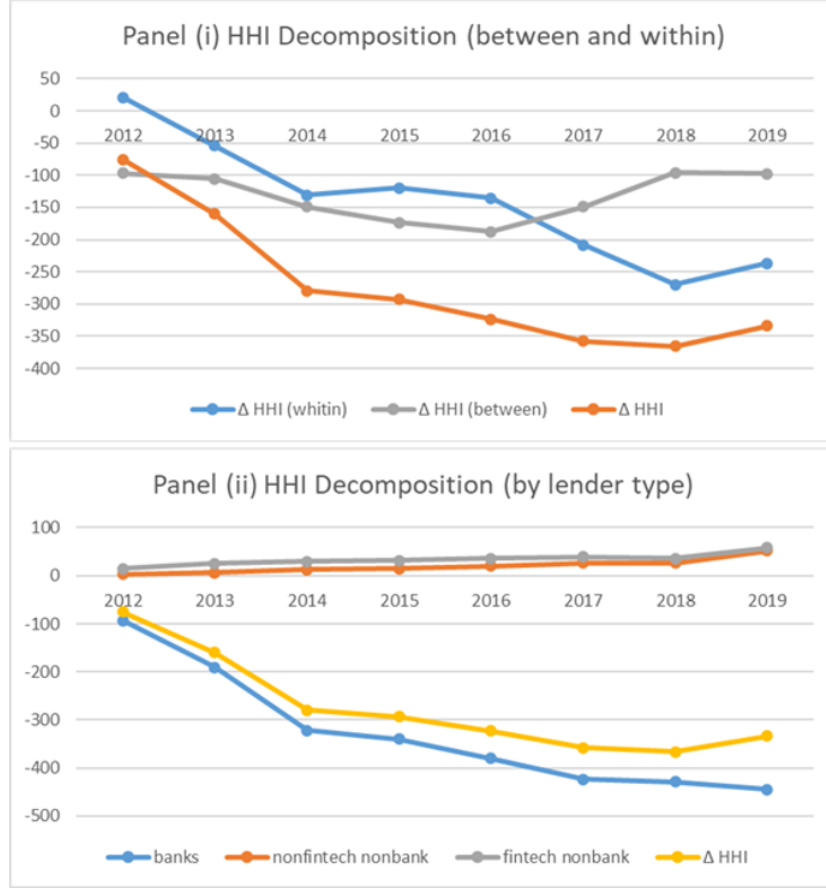
where  $\Delta HHI_t = HHI_t - HHI_\tau$ . We call the first term in the previous equation “ $HHI_t$  between” and the second term “ $HHI_t$  within”. Panel (i) in Figure 8 presents the evolution of the overall  $HHI$ , “ $HHI_t$  between” and “ $HHI_t$  within” when looking at changes between year  $t$  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 per cent of the overall decline in concentration. For example, in 2019, the overall decline in the HHI was 334 and the decline in “ $HHI_t$  within” was 237 (71 per cent 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,

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<sup>18</sup>See Appendix A for the derivation of this decomposition.

panel (ii) in Figure 8 shows the evolution of the individual terms  $(S_t^j)^2 HHI_t^j - (S_\tau^j)^2 HHI_\tau^j$  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.

Figure 8: HHI decomposition

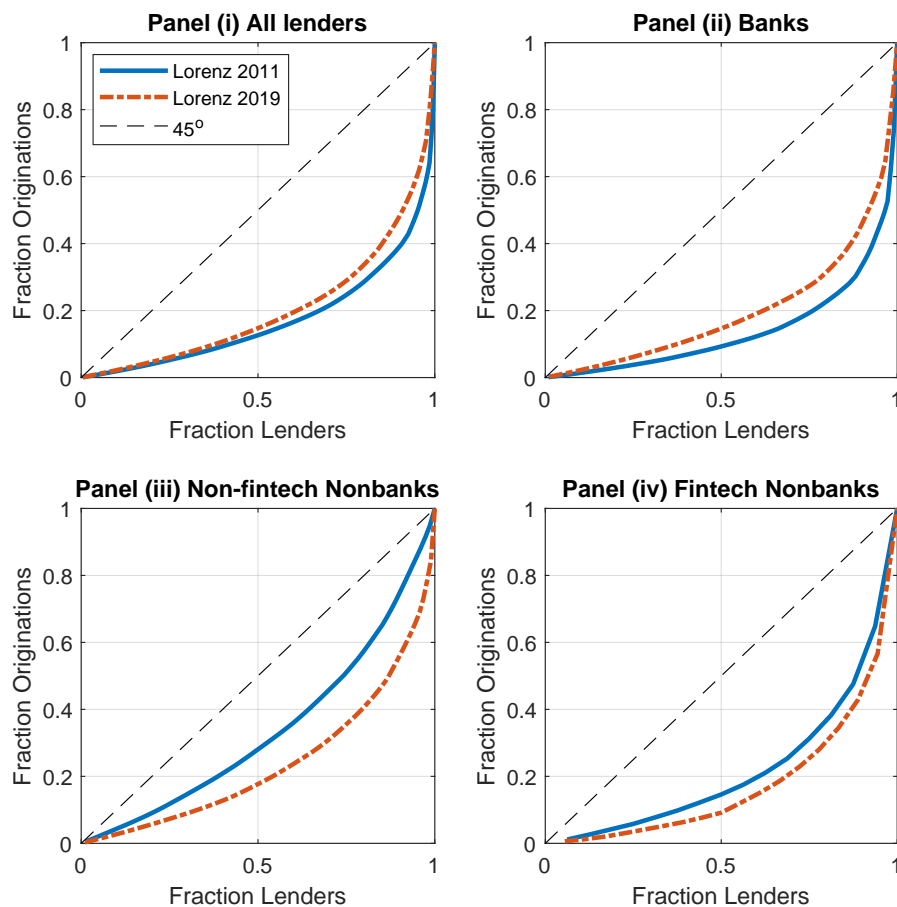


**Note:** Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans). Classification based on latest version of lender classification data. In panel (i), “ $\Delta HHI_t$  between” equals  $\sum_{j \in \{B, NF, F\}}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

Figure 9: Lorenz curves for loan origination

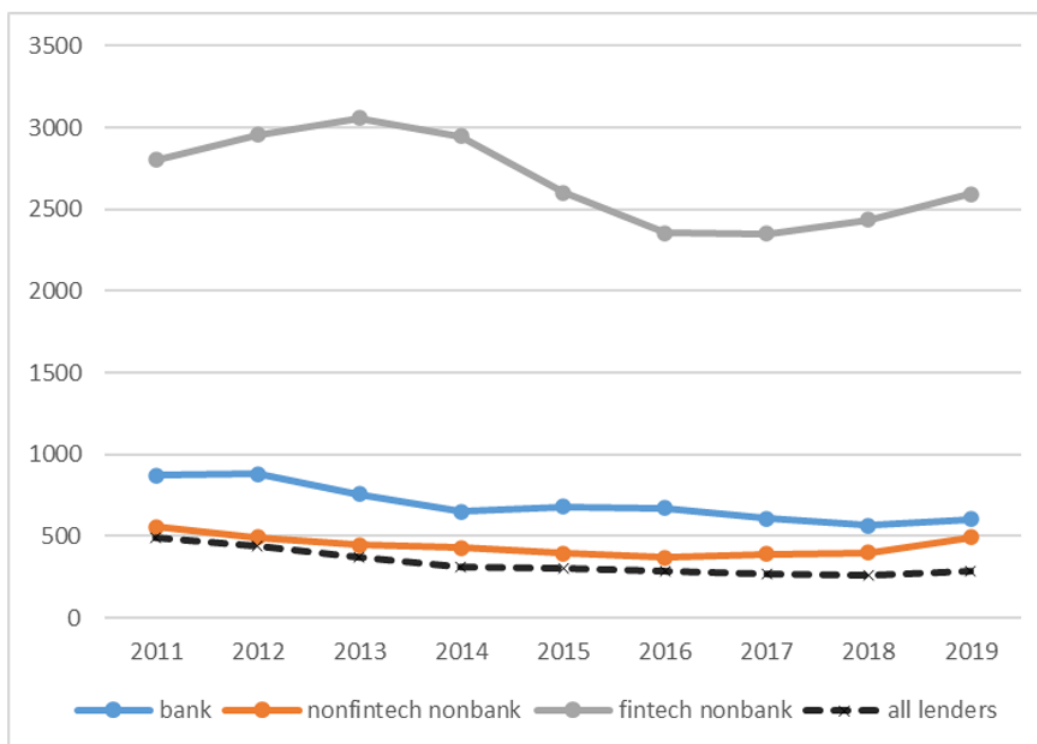


**Note:** Loan level data from HMDA. Our sample period was 2011–2019. We included all loans (both purchase and refinance as well as non-conventional loans).

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.<sup>19</sup> 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.<sup>20</sup>

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. “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.

<sup>19</sup>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.

<sup>20</sup>Jagtiani et al. [2021] 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.

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. We estimated the following regression:

$$\begin{aligned} rate_{ijzt} = & \alpha + \beta_1 FintechNB_j + \beta_2 NonFintechNB_j + \beta_3 Largest_j + \beta_4 2nd Largest_j \\ & + \beta_5 3rd Largest_j + Z'_j \Theta + X'_i \Gamma + \delta_{zt} + \epsilon_{ijzt} \end{aligned} \quad (3)$$

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.  $\alpha$  is the regression constant.  $FintechNB_j$  corresponds to a dummy variable that takes value 1 if the lender is a fintech nonbank. Similarly,  $NonFintechNB_j$  takes value 1 if the lender is a non-fintech nonbank. The rank dummies  $Largest_j$ ,  $2ndLargest_j$  and  $3rdLargest_j$  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  $\delta_{zt}$ .

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. There is no evidence that fintech

lenders originated riskier mortgages, suggesting that risk does not play a role in interest rate differentials. 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.

### III A simple model

In this section, we present a simple model that allowed us to analyze the role of technology in explaining the concentration dynamics that we described in the previous section.

#### III.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  $N_\tau - 3$ .

Table 3: Interest rate regressions

	interest rate					
Lenders	All lenders				Non-Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Bank	0.0393*** (0.0011)		0.0563*** (0.0015)			
Non-Fintech Non-Bank		0.0176*** (0.0013)		0.0628*** (0.0015)		
Fintech Non-Bank		0.0606*** (0.0013)		0.0325*** (0.0024)	0.0403*** (0.0014)	-0.0235*** (0.0019)
Largest			0.0279*** (0.0012)	0.0277*** (0.0012)		-0.0445*** (0.0022)
2nd Largest			0.0619*** (0.0014)	0.0618*** (0.0014)		-0.0234*** (0.0026)
3rd Largest			0.0331*** (0.0034)	0.0323*** (0.0034)		0.0137*** (0.0019)
Nonbank×Largest			-0.0042** (0.0019)			
Nonbank×2nd Largest			-0.0617*** (0.0021)			
Nonbank×3rd Largest			-0.0289*** (0.0037)			
Nonfintech Nonbank×Largest				-0.0799*** (0.0022)		
Nonfintech Nonbank×2nd Largest				-0.0851*** (0.0031)		
Nonfintech Nonbank×3rd Largest				-0.0206*** (0.0037)		
Fintech Nonbank×Largest				0.0518*** (0.0029)		0.1138*** (0.0033)
Fintech Nonbank×2nd Largest				-0.0232*** (0.0027)		0.0614*** (0.0032)
Fintech Nonbank×3rd Largest				-0.0223*** (0.0044)		-0.0098*** (0.0029)
Borrower and loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Zip - Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj $R^2$	0.7051	0.7055	0.7058	0.7068	0.7087	0.7101
Within Adj $R^2$	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. Standard errors in parentheses.  $*p < 0.10$ ,  $**p < 0.05$ ,  $***p < 0.01$ .



### III.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:

$$u_{ib} = -\alpha r_i + q_i + \epsilon_{ib} \quad (4)$$

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  $i$  (e.g., 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  $\epsilon_{ib}$ , an independent and identically distributed taste shock that we assume follows a type one extreme value distribution.

### III.A.2 Supply

Lenders differ in quality of service  $q_i$  and in the marginal costs of providing a mortgage  $\rho_i$ , 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  $\tau$  are also heterogeneous, so that the lender side of the economy is parameterized by each type's qualities  $\{q_{\tau 1}, q_{\tau 2}, q_{\tau 3}, q_{\tau 4}\}_{\tau=b,n,f}$ , funding costs  $\{q_{\tau 1}\rho_{\tau 2}, \rho_{\tau 3}, \rho_{\tau 4}\}_{\tau=b,n,f}$ , 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  $\gamma_b$ . If lender  $i$  is a bank, its probability of lending to a specific borrower is scaled by a factor  $\gamma_b$ . A higher  $\gamma_b$  captures a relatively unconstrained bank, a lower  $\gamma_b$  captures a relatively constrained bank. Throughout the model, we assume 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 maximize its expected profit:

$$\pi_i = (r_i - \rho_i) \gamma_i s_i F - c_i \quad (5)$$

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

### III.A.3 Equilibrium

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

1. Borrowers maximize utility in equation (4), taking market structure and pricing as given;
2. Lenders set interest rates to maximize profits, taking market structure and the pricing decisions of other lenders as given;
3. There is free entry: the number of firms of each type  $N_\tau$  is set such that profits of all firms are zero. (Eq. (5) equals zero for all lenders  $i$ ).

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

$$s_i(r_i, q_i; \{r_{-i}, q_{-i}\}) = \frac{\exp(-\alpha r_i + q_i)}{\sum_{\iota=1}^N \exp(-\alpha r_\iota + q_\iota)} \quad (6)$$

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

Given regulatory burdens  $\gamma_i$ , the actual market shares of a lender  $i$  of type  $\tau$  is given by

$$\hat{s}_{\tau i}(r_i, q_i; N_\tau, N_{-\tau}) = \frac{\gamma_\tau \exp(-\alpha r_{\tau i} + q_{\tau i})}{\sum_{\tau \in \mathcal{T}} \sum_{i=1}^{N_\tau} \gamma_\tau \exp(-\alpha r_{\tau i} + q_{\tau i})}, \forall \tau \in \mathcal{T} \quad (7)$$

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

$$S_\tau = \sum_{i=1}^{N_\tau} \hat{s}_{\tau i}(r_i, q_i; N_\tau, N_{-\tau}) \quad (8)$$

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

$$r_{\tau i}^*(N_\tau, N_{-\tau}) - \rho_{\tau i} = \frac{1}{\alpha} \frac{1}{1 - \hat{s}_{\tau i}(r_i, q_i; N_\tau, N_{-\tau})} \quad (9)$$

Equation (9) makes it clear that the more inelastic/insensitive demand is to interest rates (i.e., the smaller is  $\alpha$ ) the higher the markup, and the greater the market share of a particular lender of type  $\tau$  (i.e., the higher the  $\hat{s}_{\tau i}$ ) the higher the markup of the bank (i.e., the higher the  $(r_{\tau i}^*(N_\tau, N_{-\tau}) - \rho_{\tau i})$ ). Finally, zero-profit conditions pin down the number of banks of each type  $\tau$ .

$$\pi_i(N_\tau, N_{-\tau}) = (r_{\tau i}^*(N_\tau, N_{-\tau}) - \rho_{\tau i}) \hat{s}_{\tau i}(r_i, q_i; N_\tau, N_{-\tau}) F - c_{\tau i} \quad (10)$$

### III.B Calibration

In order to quantify the contribution of lender quality to changes in market share and concentration in the industry we need to calibrate the parameters of the model. We allow the parameters to change from year to year to give the model enough degrees of freedom to match exactly the data on interest rates, market shares, the size of the market, and the number of lenders by lender type. More specifically, we use the data we presented in Section

II to obtain values for the sequence of parameters  $q_{i\tau}, \rho_{i\tau}, c_{i\tau}, \alpha$ , and  $\gamma_b$  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 in [Buchak et al. \[2018\]](#) and make the following identifying assumptions.<sup>21</sup>

**Assumption 1:** funding costs are measured relative to 10-year U.S. treasury yield (i.e.,  $\tilde{\rho} = \rho - r^{10}$ ).

**Assumption 2:** quality and funding costs are relative to non-top3 banks (a normalization):  $\tilde{\rho}_{4b} = q_{4b} = 0$ .

**Assumption 3:**  $q_{4b} - q_{4n}$  is constant. That is, the difference in service quality between non-top 3 banks and non-top 3 nonfintech non-bank is constant.

**Assumption 4:** in the first year of our data sample (i.e., 2011),  $\gamma_b = 1$ .

Table 4 shows the calibrated values for 2011 and 2019 by lender type.<sup>22</sup> 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 ([Honka, Hortacsu, and Vitorino \[2017\]](#)). The increase in estimated fintech quality can be associated with fintech

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<sup>21</sup>See Appendix B for more details on the calibration strategy.

<sup>22</sup>Appendix B presents the full time series of the estimated parameters by lender type.

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 demonstrates 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 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.

## IV Main experiments and results

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

In our first experiment, and to set a baseline, we analyzed the evolution of the industry if the calibrated parameters  $\{\gamma_i, q_i\}$  had remained constant at their 2011 levels and the fixed operating cost  $c_i$  and the funding costs  $\rho_i$  had evolved as shown in Table 4.<sup>23</sup> 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  $c_i$  are partly induced by increased regulatory burdens after the 2010 Dodd-Frank Act (Liu [2022]). The solution

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<sup>23</sup>The parameter that controls the demand elasticity  $\alpha$  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.

Table 4: Calibrated parameters (2011 and 2019)

<b>Panel A: Cost parameters</b>						
Lender	$\rho$ (%)			$c$ (bn \$)		
Type	2011	2019	$\Delta$	2011	2019	$\Delta$
B Largest	2.52	2.03	-0.49	3.02	2.64	-0.38
B Second Largest	2.72	2.11	-0.61	1.29	1.82	0.53
B Third Largest	2.72	2.08	-0.64	0.99	1.77	0.78
B Non-Top3	2.78	2.14	-0.64	0.05	0.13	0.08
NF Largest	2.79	2.04	-0.75	0.10	2.27	2.16
NF Second Largest	2.82	2.14	-0.67	0.07	0.82	0.75
NF Third Largest	2.85	2.18	-0.67	0.07	0.76	0.69
NF Non-Top3	2.84	2.20	-0.64	0.03	0.11	0.09
F Largest	2.86	2.10	-0.77	0.36	3.03	2.67
F Second Largest	2.84	2.17	-0.67	0.18	0.91	0.73
F Third Largest	2.82	2.16	-0.66	0.09	0.55	0.46
F Non-Top3	2.81	2.17	-0.64	0.03	0.15	0.12
<b>Panel B: Technology and regulation parameters</b>						
Lender	$q$			$\gamma$		
Type	2011	2019	$\Delta$	2011	2019	$\Delta$
B Largest	3.97	2.99	-0.98	1.00	0.62	-0.38
B Second Largest	3.27	2.66	-0.61	1.00	0.62	-0.38
B Third Largest	3.00	2.62	-0.38	1.00	0.62	-0.38
B Non-Top3	0.00	0.00	0.00	1.00	0.62	-0.38
NF Largest	0.78	2.36	1.58	1.00	1.00	0.00
NF Second Largest	0.49	1.40	0.91	1.00	1.00	0.00
NF Third Largest	0.42	1.34	0.92	1.00	1.00	0.00
NF Non-Top 3	-0.57	-0.57	0.00	1.00	1.00	0.00
F Largest	2.10	2.68	0.58	1.00	1.00	0.00
F Second Largest	1.36	1.51	0.15	1.00	1.00	0.00
F Third Largest	0.72	1.01	0.29	1.00	1.00	0.00
F Non-Top3	-0.46	-0.30	0.16	1.00	1.00	0.00

**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. Lender type “B” refers to banks, “NF” to non-fintech nonbanks and “F” to fintech nonbanks.

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.<sup>24</sup>

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, with larger differences observed at the very top of the distribution, explaining the changes in market shares and number of lenders. Figure 12 shows changes in concentration for the entire market and by lender type. Changes in overall 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).

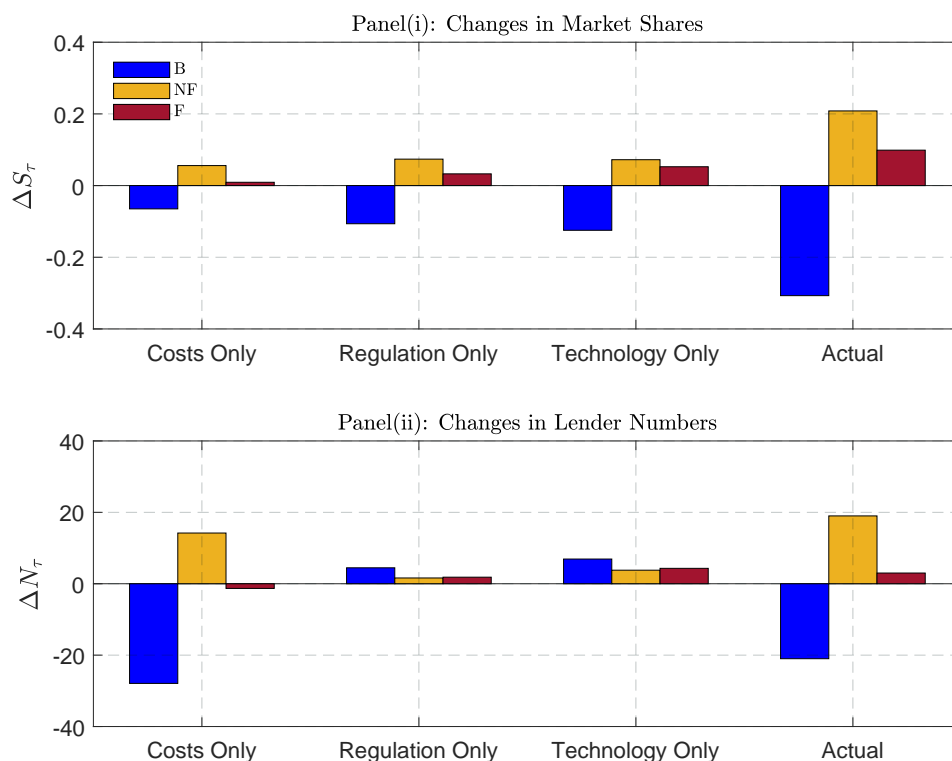
This result hides important heterogeneity within type. Figure 12 also shows that both bank and fintech concentration increased due to changes in costs (non-fintech lenders’ concentration declined slightly). In the case of banks, the increase in concentration derived from the reduction in operating costs 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 per cent 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 demonstrates that the overall change in the HHI in the “costs” experiment was almost null, implying that, in this case, the within-group

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<sup>24</sup>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.

variation was fully compensated by the between-group HHI variation, driven by the decline in the market share of banks.

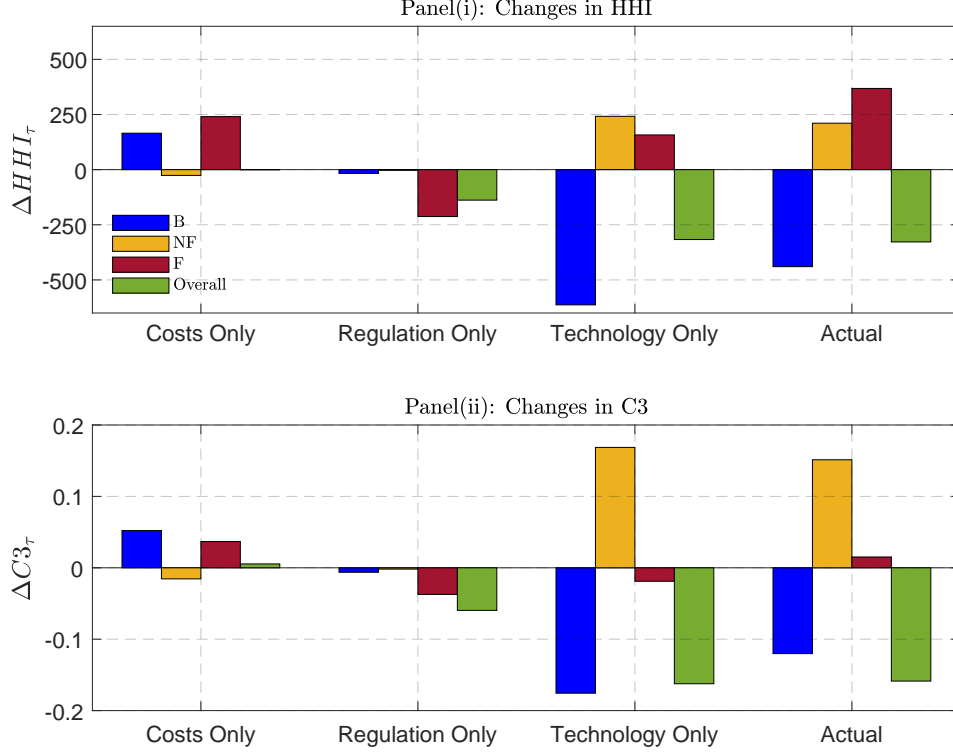
Figure 11: Changes in market shares and number of lenders



**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. “Regulation” refers to the counterfactual that evaluates changes to the regulatory pressure parameters only. “Technology” refers to the counterfactual that evaluates changes to the lender technology parameters only. “B” refers to banks, and “NF” to non-fintech nonbanks.



Figure 12: Changes in market concentration (HHI and C3)



**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. “Regulation” refers to the counterfactual that evaluates changes to the regulatory pressure parameters only. “Technology” refers to the counterfactual that evaluates changes to the lender technology parameters only. “B” refers to banks, “NF” to non-fintech nonbanks, “F” to fintech nonbanks, and “Overall” to aggregate levels.

In our second experiment, we analyzed how changes in regulatory pressure on commercial banks impacted market shares and concentration. We called this experiment “regulation”. To implement this experiment, we solve the equilibrium of the model with the calibrated sequence of  $\{c_j, \rho_j, \gamma_b\}$  but keeping the value of  $q_j$  constant at its value in 2011. The difference between the outcomes in this experiment and that in the baseline experiment (“costs”) allowed us to quantify the impact of regulatory pressure. Figure 11 shows that regulation explains about a third of the change in market shares for all industry participants. While this experiment explains a larger fraction of the change in market shares for banks and nonbanks, changes in regulatory pressure for the bank sector had a similar effect on market shares to that of the estimated changes in costs (as the decline in costs for nonbanks was relatively

larger than that of banks). Figure 12 shows that regulatory changes had a significant effect on overall and nonbank fintech concentration. As regulatory pressure for banks increases and their market share declines, that opens some space for nonbanks to take over via new lending (intensive margin) and new participants (extensive margins). This change in the composition of lending in the industry results in a decline in concentration in the nonbank sector, with a significantly larger effect for fintech lenders. This decline in concentration in the fintech sector (together with the shift in market shares presented in Figure 11) leads to the observed decline in overall concentration. Regulatory changes explains about 40 percent of the decline in overall concentration in the industry during this period.

In our third experiment, we analyzed how changes in lender quality (technology) affected the equilibrium outcome. We called this experiment “technology” and it captured changes in consumer preferences toward non-traditional lenders as well as fintech technological innovations that reduced frictions in mortgage lending.<sup>25</sup> In particular, we solved the equilibrium of the model keeping the value of  $\gamma_j$  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 11 shows that changes in quality explained 40 per cent of the decline in bank market shares, 35 per cent of the market share gain of non-fintech nonbanks, and more than 50 per cent 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 per cent 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 per cent. 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

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<sup>25</sup>Buchak et al. [2018] and Fuster et al. [2019] both document that fintech lenders process mortgages faster than traditional lenders and that fintech lenders respond more elastically to changes in mortgage demand.

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 consistent with previous results.<sup>26</sup> 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 technology have important implications for overall and within-group lender concentration. This experiment explained 97 per cent of the overall change in the overall 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 “technology” experiment more than explained the total change in concentration within the nonfintech nonbank sector (as measured with both the HHI and C3).

In summary, we found that regulatory changes explained about a third of the variation in market shares and concentration but that most of the observed changes can be assigned to technology improvements in the nonbank sector. In the case of market shares, regulation explained between 33 and 36 percent of the changes in market shares while technology explained between 35 and 53 percent.<sup>27</sup> In the case of concentration (when measured using the HHI), regulation explains about 40 percent of the change for the industry but with minor effect on bank and non-fintech nonbank concentration. “Technology” explained large portions of variations in market concentration for banks and non-fintech nonbanks, and

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<sup>26</sup>For example, Buchak et al. [2018], Fuster et al. [2019].

<sup>27</sup>More specifically, ‘regulation’ explains 34 percent, 35 percent and 33 percent of the change in market shares of banks, non-fintech nonbanks, and fintech nonbanks, respectively. “Technology” explains 40 percent, 35 percent, and 53 percent of the change in market shares for banks, non-fintech nonbanks and fintech nonbanks, respectively.

fintech nonbanks.<sup>28</sup> 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, technology (quality) explained 43 per cent of the changes in fintech concentration. While there are important changes in technology at the top of the distribution, we estimated technology 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 article 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 analyzing 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 technology, which reflects that consumers derive higher benefits from their borrowing activity. On the other hand, a shift towards a lender sector (fintech nonbank) 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 (i.e., 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.

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<sup>28</sup>In the cases of banks and non-fintech nonbanks, technology explained more than the total variation in concentration observed in data. 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 technology changes.

The focus of this paper has been concentration in the fintech industry and the role of changes in lender technology and regulatory pressure. 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 and its associated moral hazard problem, similar to deposit insurance. This business model is prevalent among nonbanks and, especially, fintech lenders.

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## VI Appendix

### VI.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 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:

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

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

$$\begin{aligned} \Delta HHI_t &= HHI_t - HHI_\tau = \sum_{j \in \{B, NF, F\}} (S_t^j)^2 HHI_t^j - (S_\tau^j)^2 HHI_\tau^j \\ &= \sum_{j \in \{B, NF, F\}} \Delta (S_t^j)^2 HHI_t^j - \sum_{j \in \{B, NF, F\}} \Delta (S_\tau^j)^2 HHI_\tau^j \end{aligned}$$

We call the first term of the last line above “ $\Delta HHI_t$  between” and the second term “ $\Delta HHI_t$  within”.



## VI.B Calibration details

In this appendix section, we present further details of the calibration strategy. Our strategy is an extension of [Buchak et al. \[2018\]](#) to a model with bank heterogeneity. For completeness, we repeat the assumptions we presented in the main text:

**Assumption 1:** funding costs are measured relative to 10-year U.S. treasury yield (i.e.,  $\tilde{\rho} = \rho - r^{10}$ ).

**Assumption 2:** quality and funding costs are relative to non-top3 banks (a normalization):  $\tilde{\rho}_{4b} = q_{4b} = 0$ .

**Assumption 3:**  $q_{4b} - q_{4n}$  is constant. That is, the difference in service quality between non-top 3 banks and non-top 3 nonfintech non-bank is constant.

**Assumption 4:** in the first year of our data sample (i.e., 2011),  $\gamma_b = 1$ .

Recall that, for each year, we observe 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  $F$ . The calibration process is as follows. Using the optimal pricing equation (i.e., equation (9)) of non-top three banks, making use of Assumption 2, and data on the average interest rate and market shares for this group, we pin down  $\alpha$ :

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

This gives a common (across-lender) value of  $\alpha$  that varies from year to year. To calibrate the service quality (technology) 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  $\gamma_{4b} = \gamma_{4n} = 1$  by Assumption 4):

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

Rearranging the terms in this ratio and using Assumption 2 (i.e.,  $q_{4b}=0$ ), we solve for the

value of  $q_{4n}$  in 2011:

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

From Assumption 3,  $q_{4n}$  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  $\gamma_b$  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. (9)), and with the value of  $\alpha$  at hand, we solve for the funding cost spread (over the 10-year treasury rate) for lender  $i$  of type  $\tau$  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— $\gamma_b$ —by taking the ratio of the market share of any bank and the market share of any nonbank. The value of  $\gamma_b$  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. Now we complete the description of our calibration by showing the full time series. Figure A1 shows the value of  $\alpha_t$ . The average value is 0.597, with a minimum of 0.449 and a maximum of 0.832. Figures A2–A4 present the estimated lender qualities ( $q_t$ ), entry costs ( $c_t$ ) and funding costs ( $\rho_t$ ), 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 A1: Demand elasticity

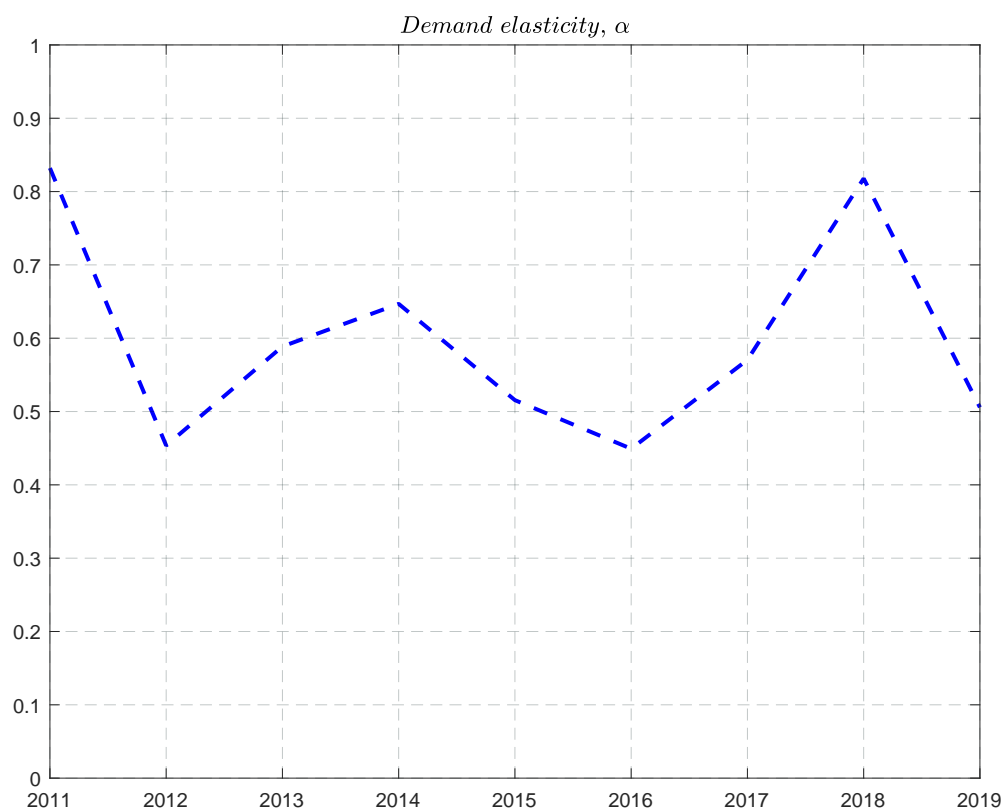


Figure A2: Lender quality/technology  $q_\tau$  (by lender type)

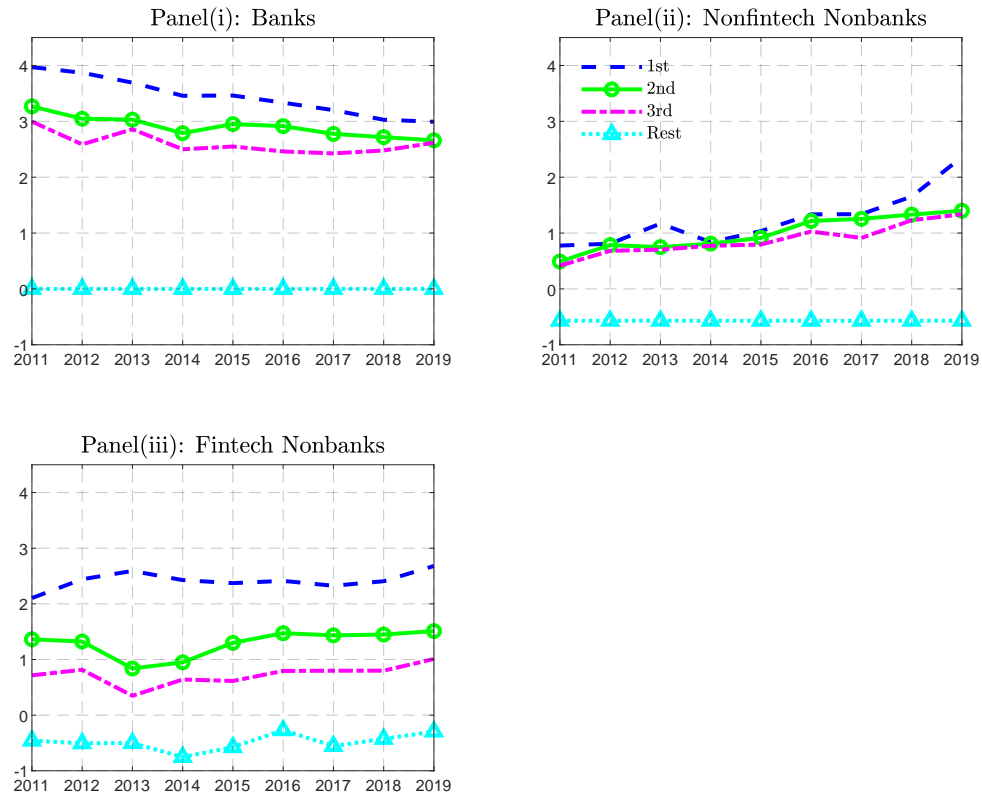


Figure A3: Lender entry cost  $c_\tau$  (in billions \$, by lender type)

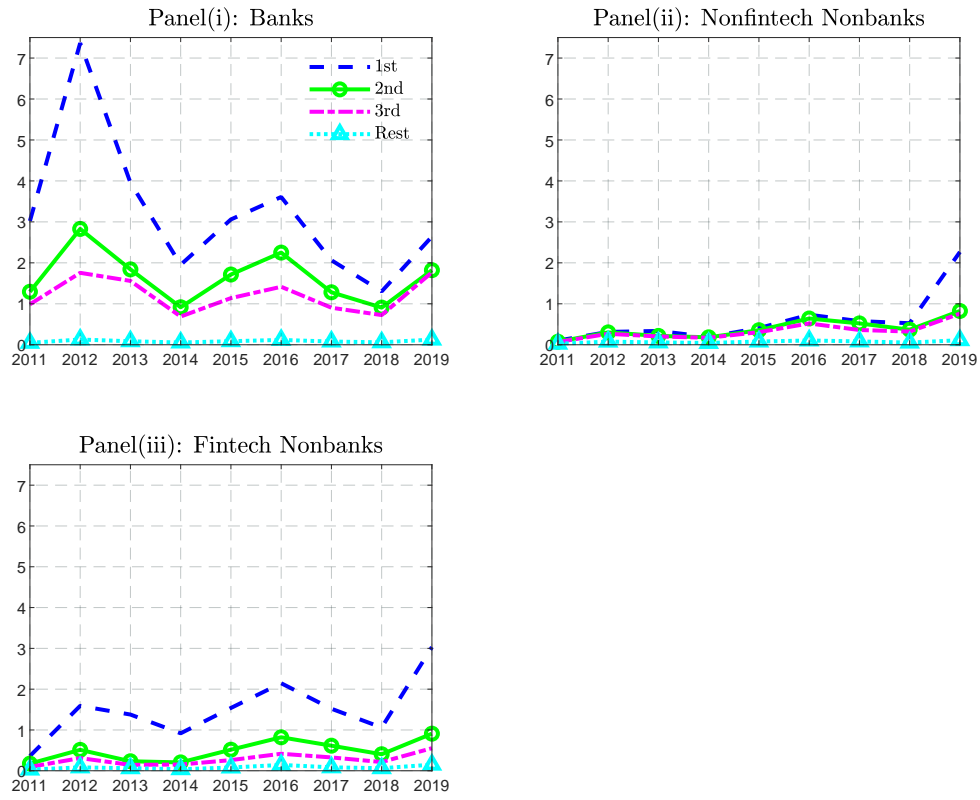


Figure A4: Funding costs  $\rho_\tau$  (in %, by lender type)

