Nonbank Issuers and Mortgage Credit Supply

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Abstract

We show that a shift from bank to nonbank issuers of mortgage-backed securities (MBS) led to easier credit standards and higher interest rates for Federal Housing Administration (FHA) mortgages and increased lending to riskier borrowers. We estimate these causal, equilibrium effects using a difference-in-differences design that exploits plausibly exogenous geographic variation in the exit of JPMorgan Chase from FHA lending. Our findings highlight that MBS issuers and the industrial organization of securitization markets are crucial for credit supply, and are among the first direct pieces of causal evidence on how bank-nonbank shifts affect equilibrium credit supply in consumer credit markets.

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1 Introduction

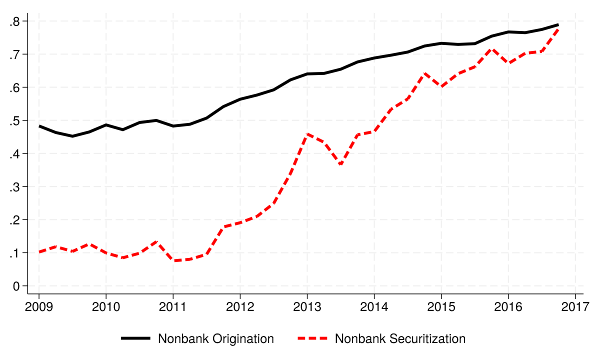
The nonbank share of financial activity has increased significantly since the Global Financial Crisis (GFC), dramatically changing the industrial organization of financial intermediation. The mortgage market is emblematic of this trend — nonbanks originated about 65% of home-purchase loans in 2022 compared with almost 40% in 2008 (Financial Stability Oversight Council, 2024). Although previous studies have explored the rise of nonbanks in the mortgage market (Buchak et al., 2018, 2024; Fuster et al., 2019; Gete and Reher, 2021; Kim et al., 2018) as well as in other financial markets (Lim et al., 2014; Irani et al., 2021; Chernenko et al., 2022; Gopal and Schnabl, 2022), the literature has two shortcomings. First, there is still not much direct causal empirical evidence on how the shift to nonbank financial intermediaries has affected consumer credit supply. Second, for mortgages, the focal product market of many nonbank studies, the literature has overlooked the rise of nonbank issuers of mortgage-backed securities (MBS) as a separate development from the rise of nonbank loan originators.

To address these gaps, we study the rise of nonbank MBS issuers in the Ginnie Mae market, which provides long-term funding for mortgages insured by the Federal Housing Administration (FHA), and empirically test whether the tilt from bank to nonbank loan securitization affected equilibrium credit supply. For causal identification, we design a difference-in-differences estimator that leverages plausibly exogenous geographic variation in exposure to the exit of a large bank issuer from the Ginnie Mae market. We find that bank-issuer exit substantially increased the market share of nonbank issuers, and that the increase in nonbank securitization led to easier credit standards, higher borrowing costs, and increased originations to lower credit score borrowers.

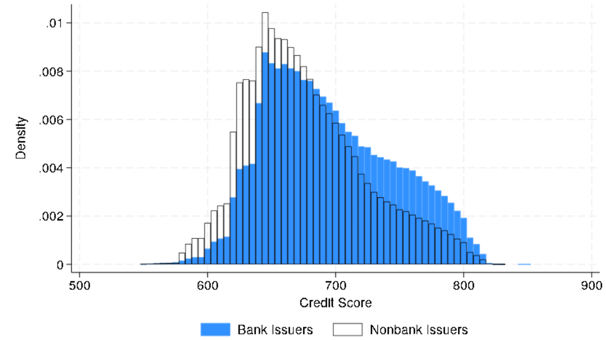
Our contribution is among the first direct causal empirical tests for the equilibrium effects of nonbank financial intermediation in consumer credit markets. Earlier studies have empirically identified the causal determinants of nonbank expansion (Buchak et al., 2018; Irani et al., 2021), without tracing through the causal effects on credit supply. Other work has studied how nonbank lenders can attenuate the effects of monetary policy (Elliott et al., 2019), but does not identify the broader effects of bank-to-nonbank shifts on equilibrium credit supply outcomes. Most empirical evidence on the relationship between nonbanks and consumer credit supply is identified on differences in outcomes between banks and nonbanks (Buchak et al., 2018; Fuster et al., 2019; Gete and Reher, 2021), which sweeps out the equilibrium impacts of nonbank expansion in local markets.

The rise of nonbank issuers in the Ginnie Mae market is a useful setting to study the credit supply implications of bank-to-nonbank shifts. First, the shift is dramatic. By way of background, Ginnie Mae issuers are financial institutions that are approved to issue MBS guaranteed by Ginnie Mae. They either securitize their own loans or act as "aggregators" that securitize loans purchased from "correspondent" lenders. Because of this aggregator role, the nonbank share of securitization can differ from the share of origination. Figure 1(a) shows both this divergence and the sharp rise in nonbank securitization of FHA loans since the GFC.

Figure 1: Nonbank Issuer Market Share and Credit Scores



(a) Share of FHA Home-Purchase Mortgages Originated or Securitized by Nonbanks



(b) Credit Score Distribution for Bank and Nonbank Issuers

Note: Authors' calculations based on HMDA and FHA administrative data.

Second, issuers in the FHA market arguably play a larger role in credit standards than originators. In their role as aggregators, issuers take on the liability for any errors made by the loan originator, and in their role as servicers, they can incur significant unreimbursed costs if borrowers default (Kim et al., 2018). Nonbanks may be more willing to bear these credit risks because they have less franchise value and face a less stringent prudential regulatory regime. As evidence in support of this conjecture, Figure 1(b) shows that the credit-score distribution on FHA mortgages securitized by nonbank issuers lies to the left of the bank-issuer distribution.

Finally, the FHA market is large and important, representing 28% of all owner-occupied home-purchase mortgage originations from 2009 to 2017, a total of \$1.3 trillion. Borrowers who obtain FHA mortgages generally have lower credit scores and may have difficulty qualifying for other types of mortgages. Credit standards in the FHA market can affect the extensive margin of whether a borrower gets a mortgage at all.

We begin with descriptive evidence that MBS issuers play an important and distinct role from loan originators in determining credit standards. Using regressions that control for loan characteristics, time-varying heterogeneity across local markets, and the type of originator and issuer, we estimate that FHA home-purchase loans originated to borrowers with low credit scores (below 640) are equally likely to be originated by a bank or nonbank but 14 percentage points (pp) more likely to be securitized by a nonbank than bank issuer. To establish that this result reflects an expansion of credit in the lower tail of the credit score distribution, we construct a measure of the minimum credit score at which firms are willing to originate and securitize mortgages, and show that nonbank issuers are associated with a much lower minimum credit score (19 points) than nonbank originators. These findings suggest that the importance of nonbank mortgage securitization has been overlooked in prior studies such as Buchak et al. (2018) and Gete and Reher (2021).

We then estimate the causal effects of the shift to nonbank issuers on equilibrium credit supply. This exercise is more difficult because broader market developments since the GFC might have simultaneously determined credit supply outcomes as well as influenced the relative incentives of nonbanks and banks to expand and withdraw. Identification must isolate the effects of increased nonbank market share from the effects of these confounding factors.

Our difference-in-differences (DID) identification strategy rests on variation in cross-county exposure to the nationwide exit of JPMorgan Chase (Chase) from the FHA market in 2013. In the aggregate, Chase was the issuer for more than 10% of FHA home-purchase loans in Ginnie Mae pools in 2012, but its market share in individual counties ranged from 0% to 37%. We compare outcomes over time across counties where Chase had large and small market shares before its exit. This variation captures equilibrium effects of the shift from bank to nonbank issuers on local markets, while purging confounding secular trends and thereby providing cleaner identification than approaches relying solely on cross-sectional comparisons.

We begin by showing that nonbank issuers filled the void resulting from the Chase exit. Looking at the post-exit period as a whole, we find that nonbank issuers replaced 70%–80% of Chase's pre-exit market share as an issuer; toward the end of the exit period, the confidence intervals encompass, or nearly encompass, 100% nonbank replacement. Evaluated at the average exit exposure, the average effect of Chase's exit on counties exposed to the exit (the average treatment effect on the treated or ATT) is a 7 pp increase in the share of FHA originations securitized by nonbanks. About 75% of the increase came from nonbank aggregators who, like Chase, purchased loans from correspondents. The rest had a different business model: nonbank integrated originators that securitized their own originations.

We next show that Chase's exit led to a significant expansion in the credit available to borrowers with lower credit scores, consistent with our earlier descriptive regressions, with timing that closely tracks the rise of nonbank issuers. The DID estimates indicate that if Chase's county-level market share fell from 100% to 0%, the average borrower would obtain an FHA mortgage from a lender with a minimum credit score 87 points lower. The ATT is a 7.9 point decline, about 33% of the standard deviation of the minimum credit score. In line with this easing of standards, if Chase's county-level market share fell from 100% to 0%, the fraction of FHA loan originations to borrowers with credit scores below 640 would increase by 13 pp. The ATT is an 1.2 pp increase, about 8% of the average share of those borrowers.

The easing of credit standards after the rise in nonbank securitization appears attributable to two channels. The first channel is that nonbank issuers have greater overall tolerance for risk. Underwriting appears to have eased on standards other than credit scores: most notably, debt-to-income ratios rose. The fraction of loans that entered 60-day delinquency within three years of origination also increased, even after controlling for observable loan-level underwriting characteristics, suggesting that standards also eased on criteria that are less easily observable. The second channel is equilibrium responses by incumbent nonbank issuers, who eased their own credit standards as the market shifted from bank to nonbank securitization.

We next show that Chase's exit increased interest rates. Our estimates indicate that if Chase's securitization share fell from 100% to 0%, mortgage interest rates would increase about 18 basis points, controlling for observed risk factors like credit scores, loan-to-value ratios, and debt-to-income ratios. For a representative FHA loan in our study period, a 100 pp decline in Chase's share causes more than $1,500 in additional interest expense borne by the borrower over the average life of FHA loans (7 years).

Increased interest rates after the rise in nonbank securitization might be attributable to several forces. One mechanism is nonbanks' higher cost of funds. Our estimates suggest that if bank securitizations fell from 100% to 0%, then funding costs per loan would increase by about 7 basis points (in units of an annual mortgage interest rate), nearly 40% of the increase in mortgage rates. Another possible mechanism is compensation for increased credit risk as underwriting standards eased. Although we control for observed risk factors to estimate the effect on interest rates, we cannot rule out pricing on unobserved risk. Finally, the evidence suggests that equilibrium forces also played a role. Existing bank issuers increased their own interest rates as the market shifted from bank to nonbank securitization.

Last we examine aggregate quantity outcomes, as easier credit standards and higher costs of credit have potentially countervailing effects on borrower welfare. The shift from bank-to-nonbank issuers led to an increase in FHA loan originations to low credit score borrowers. Our results suggest that a 100 pp decline in Chase's share would lead to a 68% increase in originations to borrowers with credit scores below 640, with the ATT equal to a 6.5% increase. Moreover, we find no robust evidence suggesting that the shift to nonbank securitization affected the overall volume of lending or whether higher-score borrowers obtained mortgages.

We consider several threats to identification. Foremost, we estimate specifications with propensity score matching to establish that our results for nonbank industrial organization (IO) outcomes, credit standards, cost of credit, and lending quantities for low credit score borrowers are not driven by systemic differences in the characteristics of counties with greater exposure to Chase's exit.

We also consider evidence on the exclusion restriction – whether other changes in market structure correlated with or brought about Chase's exit might be the causal mechanism behind these effects on credit supply, rather than the shift from bank to nonbank securitization. The estimates do not reject the hypothesis that nonbank issuers almost fully replaced Chase toward the end of our study period, however, the causal effects of Chase's exit might also operate outside of changes in the issuer space. For example, although Chase originated far fewer FHA loans than it securitized as an aggregator, its exit from FHA origination might have distinct effects on the outcomes we study. We rule this out with evidence from the propensity score specification, which includes Chase's originator market share as a match characteristic. We also rule out the possibilities that our results are driven by (i) increased nonbank originations, (ii) increased fintech lending, (iii) changes in market concentration and competition, (iv) shifts in the composition of originators, (v) the impact of increased securitization from vertically integrated originators, (vi) Chase's withdrawal from other lending businesses such as mortgages eligible for sale to Fannie Mae or Freddie Mac (or GSE mortgages), auto lending, and small business lending, and (vii) other big banks' withdrawal from FHA aggregation.

As additional evidence that our results are not driven by other factors related to Chase's exit, we look at the changes in credit supply after Bank of America (BOA) exited the FHA aggregation business in 2010. Like Chase, BOA's market share varied across counties, but its exit was more seismic: BOA was the issuer for nearly 40% of FHA home-purchase loans in Ginnie Mae pools in 2010. Our identification strategy is not as clean for BOA's exit, because BOA also exited the market for GSE mortgages at the same time. Nonetheless, most results are qualitatively the same as for Chase's exit, even though BOA's exit happened at a different time period and affected different counties. Nonbank issuers increased their market share, credit standards eased, mortgage interest rates rose, and mortgage originations to borrowers with low credit scores increased.

Our findings on credit supply suggest that the shift to nonbank issuers had heterogeneous effects on borrower welfare. Some lower credit score borrowers appear better off, as credit standards eased and loan originations to these borrowers expanded. Higher delinquency rates, however, suggest that some of these borrowers were not successful in retaining their homes, and thus on net may not be better off. Higher credit score borrowers may also be worse off, since they bear the costs of higher interest rates without the benefit of increased access to credit. Since we do not find robust evidence of a decline in loan originations among these borrowers, though, any negative welfare effects are likely small. In addition, the shift to nonbank issuers might have welfare effects from financial stability that are beyond the scope of our analysis (Kim et al., 2018, 2022; Financial Stability Oversight Council, 2024; Begley and Srinivasan, 2022).

Our paper relates to the literature on the rise of nonbanks in the mortgage origination market (Buchak et al., 2018, 2024; Fuster et al., 2019; Gete and Reher, 2021; Jiang, 2023; Sarto and Wang, 2023; Frame et al., 2024). Some of these studies (Jiang, 2023; Bosshardt et al., 2023; Fuster et al., 2019) show a relationship between increased nonbank origination market share and higher costs of credit. Frame et al. (2024) find that the departure of large banks from the FHA origination market reduced low-income borrowers' access to credit. In contrast, our paper provides causal estimates of the role of nonbank issuers in mortgage credit supply.

Our paper also sheds light on aggregators and MBS issuers, an under-studied component of the mortgage market intermediation chain. The existing literature on aggregators is relatively small (Stanton et al., 2014, 2018; Lewellan and Williams, 2021; Becker et al., 2023; Zheng, 2024). Of these papers, Zheng (2024), which examines the effect of changes in capital regulations after the GFC on bank aggregator mortgage purchases, is the closest analog to our work. Clark et al. (2021) note that, although many lending markets rely on secondary markets for long-term funding, there is still not much evidence on how the industrial organization of loan securitization impacts credit supply.

Our paper also relates to literature on how the constraints and organizational form of mortgage market intermediaries affect mortgage market outcomes. Buchak et al. (2024) show that a bank's option (unlike a nonbank) to fund a loan either on balance sheet or through securitization affects how policy changes manifest in mortgage credit supply. Buchak et al. (2023a) show that firms that combine the origination and servicing function are more likely to refinance their own borrowers and to charge lower fees. Aiello (2022), Cherry et al. (2022), Kim et al. (2024), Cherry et al. (2021), Degerli and Wang (2022), and Hamdi et al. (2023) show that factors such as the capital and liquidity positions of mortgage servicers and whether the servicer is a bank or nonbank affect borrower outcomes in the servicing market. Fuster et al. (2021, 2024) and Sharpe and Sherlund (2016) show that the capacity constraints of mortgage originators affect credit supply. Allen et al. (2023) and Robles-Garcia (2020) show that the incentives of mortgage brokers affect borrower choices and welfare.

2 Financial Intermediation in the FHA Market

To fix ideas, we describe the different roles that banks and nonbanks may play in the origination, funding, and servicing of a mortgage, also shown in Figure 2.

Loan Origination A borrower works with a correspondent originator (Figure 2 - top box, left side) or integrated originator (top box, right side) to obtain a mortgage. Originators can be banks or nonbanks.

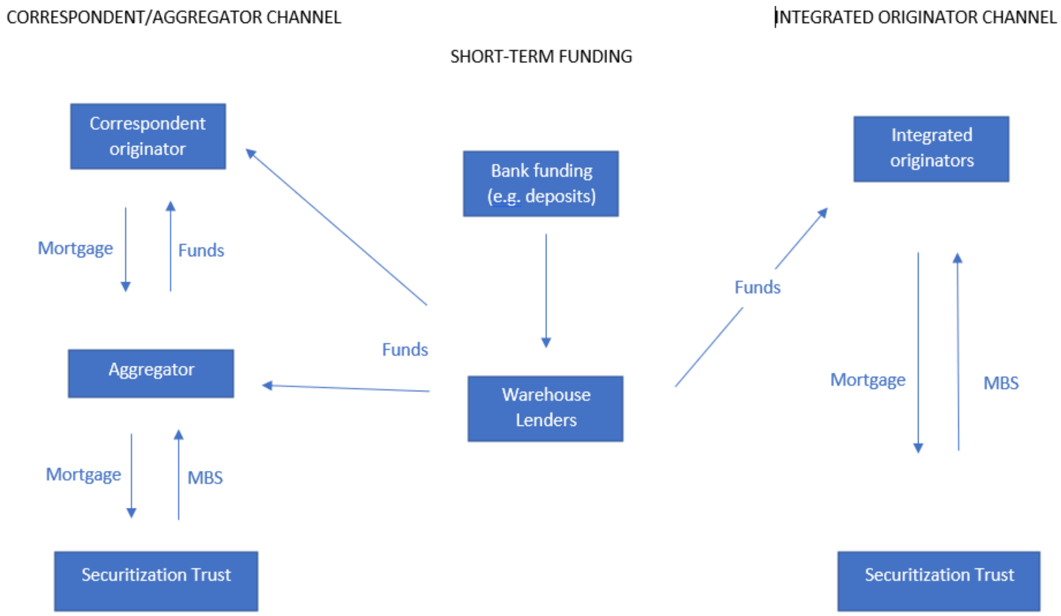
Loan Aggregation Large financial institutions—both bank and nonbank—purchase mortgages from small correspondent originators that lack the scale to securitze mortgages in a cost-effective manner (middle box, left side).

Short-term Funding for Mortgages Bank correspondent originators, integrated originators, or aggregators generally fund their originations with deposits provided by savers (not shown). Nonbank correspondent originators, integrated originators, or aggregators fund their originations with warehouse lines of credit provided by banks (middle of flow chart). Nonbanks also rely on bank lines of credit to fund other corporate expenses.

Loan Securitization When a bank or nonbank integrated originator or aggregator accumulates sufficient mortgages, it obtains long-term funding for the mortgages by selling them to a securitization trust (bottom box) and receives in exchange an MBS guaranteed by Ginnie Mae (for loans insured or guaranteed by the FHA or other government agencies) or Fannie Mae or Freddie Mac (for "conforming" loans that meet these agencies' guidelines), or it receives a "private label" MBS without a government credit guarantee (for loans that are too large or otherwise do not meet the standards of the agencies). A firm that issues an MBS with a Ginnie Mae guarantee is called a Ginnie Mae issuer, while a firm that sells loans to Fannie Mae or Freddie Mac is known as a Fannie Mae or Freddie Mac seller/servicer. Banks have the option of obtaining long-term funding by holding the mortgage on their balance sheet (not shown in the figure), although they also generally fund FHA loans by issuing securitizations guaranteed by Ginnie Mae.

Mortgage Servicing Ginnie Mae issuers are responsible for servicing the mortgages in the MBS that they issue. Those responsibilities include routine payment processing for borrowers who are making their payments and loss mitigation activities for borrowers who are not. Issuers can incur substantial costs from mortgage foreclosure even with the insurance payout from the FHA or other credit guarantor (Kim et al., 2018).

Figure 2: Nonbank Financial Intermediation in the FHA Market



2.1 Bank and Nonbank Incentives in the Mortgage Market

While both banks and nonbanks can originate, aggregate, securitize, and service mortgages, banks and nonbanks operate under a different set of incentives that may influence how they carry out these functions. In particular, nonbanks may have a higher cost of funds and a greater tolerance for risk. In lieu of specifying a formal theoretical framework that encompasses these dimensions, such as in Buchak et al. (2018, 2023b, 2024) and Kim et al. (2022), we summarize some of the insights from those frameworks here.

Nonbanks have a higher cost of funds because they cannot use low-cost government-insured deposits as funding. Deposit funding provides banks with low-cost alternatives to equity and debt financing, and gives banks the option to hold mortgages on their balance sheet instead of relying solely on securitization (Buchak et al., 2024). In contrast, nonbanks primarily finance themselves with lines of credit from banks (on which banks charge a markup over their own deposit funding costs (Jiang, 2023)) as well as equity (Jiang et al., 2024; Kim et al., 2022).

The existing theoretical frameworks derive a greater risk tolerance for nonbanks in two ways. First is the less-stringent regulatory regime for nonbanks (Buchak et al., 2018, 2023b, 2024; Kim et al., 2022). Second are mechanisms that limit nonbanks' exposure to default risk and lower their incentives to screen borrowers (Kim et al., 2022). For example, banks' multiple business lines provide banks with more franchise value and more reasons to be risk-averse (Brander and Lewis, 1986; Demsetz et al., 1996). Banks may not want to jeopardize these other business lines with risks that can emerge from lending to borrowers with low credit scores.

2.2 Post-Crisis Pullback of Banks from the Mortgage Market

In the immediate aftermath of the Global Financial Crisis (GFC), banks dominated all the roles shown in Figure 2, in part because some large nonbanks collapsed during the GFC. In 2010, banks originated 74% of all mortgages, were the issuers for 84% of mortgages funded by Ginnie Mae MBS, and were the seller/servicers for 82% of mortgages sold to Fannie Mae and Freddie Mac (HMDA, 2009-2016).

This picture changed rapidly over the next decade. In 2017, the end of the period that we study, banks originated 46% of mortgages and were the issuers for 25% of mortgages funded by Ginnie Mae MBS and the seller/servicers for 49% of mortgages sold to Fannie Mae/Freddie Mac. Banks continued, however, to provide warehouse credit to nonbanks and hold some originations on balance sheet.

Banks pulled back from the mortgage market for multiple reasons, some of which apply to all mortgages. For example, regulatory changes, including the U.S. implementation of the Basel III capital rules (Hamdi et al., 2023; Agarwal et al., 2024; Zheng, 2024) and the Liquidity Coverage Ratio (Gete and Reher, 2021), made mortgage lending less profitable for banks (Buchak et al., 2018; Kim et al., 2018). Nonbanks were quicker to take advantage of fintech innovations in mortgage origination (Buchak et al., 2018; Fuster et al., 2019). The secular decline in interest rates eroded banks' funding cost advantage relative to nonbanks (Sarto and Wang, 2023).

However, in the FHA market, banks' reassessment of the risk associated with mortgage default was a major factor in their decision to pull back. During and after the GFC, lenders experienced a sharp increase in the cost, uncertainty, and liability associated with originating and servicing loans that subsequently defaulted. Aggregators of FHA mortgages bear substantial default risk because FHA mortgages are originated to borrowers with lower credit scores and a higher probability of default, and because aggregators assume the liability for any errors made by the originator.

Of the costs associated with mortgage default, FHA lenders appeared to find the liability stemming from False Claims Act (FCA) prosecutions for defrauding the government particularly costly (Frame et al., 2024). Sixteen lenders paid around \$6.6 billion in FCA penalties from 2012-17 (DOJ, 2012, 2014, 2015, 2016, 2017). Lenders also incurred reputational costs because they were required to plead guilty under the terms of the settlements. The FCA prosecutions were somewhat of a surprise to lenders because FCA prosecutions historically were focused on the defense and health care industries. However, in the aftermath of the GFC, the Fraud Enforcement and Recovery Act of 2009 and the Dodd-Frank Reform Act of 2010 gave the government a greater ability to use the FCA to pursue fraud claims against financial institutions.

Chase CEO Jamie Dimon specifically linked Chase's withdrawal from the FHA market to its February 2014 FCA settlement of $614 million with the Department of Justice. In a July 2014 conference call with investors, Dimon stated that "*Until they come up with a safe harbor or something, we are going to be very, very cautious in that line of business... The real question for me is should we be in the FHA business at all*" (Dimon, 2014). Dimon later stated that the FCA settlement "wiped out a decade of FHA profitability" (Dimon, 2017). From the HMDA data, we observe that the withdrawal was mostly complete by early 2014.

Other bank issuers did not react as strongly as Chase to the FCA settlements. As shown in Appendix Figure A.10, the two banks with the largest FHA servicing portfolios – Wells Fargo and U.S. Bank – did not exit at the same time as Chase even though both banks faced FCA prosecutions. The continued presence of other bank aggregators during Chase's exit allows us exploit geographic variation in exposure to Chase's exit to identify the effects of the shift from bank to nonbank issuers.

3 Data

Our empirical estimates are based on loan-level data collected under the Home Mortgage Disclosure Act (HMDA) and loan-level FHA administrative data. We extract records from both datasets corresponding to 2012–2016. We describe these data in more detail next.

Confidential HMDA Data Financial institutions that meet certain size thresholds and have one or more offices in metropolitan statistical areas are required under the Home Mortgage Disclosure Act (HMDA) to submit information on the mortgage applications that they receive and on the mortgages that they purchase from other firms. The data covered an estimated 90 to 95 percent of FHA loan originations in 2009 (HUD, 2011). For our purposes, the key data fields are the identities of the loan originator or purchaser, whether these firms are banks or nonbanks, information on whether the loan originator sold the loan to an aggregator or securitized the loan directly, and the exact date when a loan is originated or purchased.

We limit our HMDA sample to originations or purchases of FHA-insured home-purchase loans. We focus solely on home purchase originations because of the possible confounding effects of the streamlined refinancing and modification programs in place during this period to manage the backlog of delinquent mortgages. Moreover, the credit supply effects of the shift from bank to nonbank issuers in the FHA market is difficult to capture with FHA refinance loans because many FHA borrowers can refinance into different mortgage products such as GSE loans relatively easily as their credit scores increase and their home equity grows. This substitution to/ from other loan products is less likely for FHA home-purchase borrowers because their low credit scores and small downpayments make it difficult to qualify for other loan products.

FHA Administrative Data Loan-level data on FHA loans provide detailed information on all loans endorsed by FHA, including interest rates, credit scores, loan-to-value ratios, debt-to-income ratios, and origination dates. The HMDA data do not include many of these variables for the years in our sample. However, the FHA data lack information on the loan originator and MBS issuer.

Data Match for Supplemental Analysis Although the confidential HMDA data and the FHA administrative data are used for our main causal analysis, some supplemental analyses require information we can only obtain by matching our main datasets.

HMDA-Originator-Aggregator Data HMDA does not provide a link between an originator and an issuer if an aggregator issuer purchases a loan from a correspondent originator. For analyses that require information on both the originator and the aggregator, we link each loan-purchase record to its corresponding loan-origination record within HMDA based on loan amount, borrower income, borrower race, and census tract. We also impose the restriction that the loan purchase must occur within two months after the loan origination. We match 77 percent of loan purchases to a corresponding HMDA origination.

FHA-HMDA-Originator Data For analyses that require information on the originators and detailed loan characteristics from the FHA data, we create a FHA-HMDA-Originator dataset by matching the loans in the FHA data with origination records in the HMDA data using common fields (see Appendix A.1 for more details). We match about 86 percent of loans in the FHA data with the corresponding HMDA origination record.

FHA-HMDA-Originator-Aggregator Data For analyses that require information on the originator, aggregator, and borrower, we create the FHA-HMDA-Originator-Aggregator data by matching the FHA-HMDA-Originator data with the HMDA-Originator-Aggregator data. In total, we can match 77 percent of the loans in the FHA data to their issuers.

NMLS Nonbanks that hold a state license or state registration through the Nationwide Multistate Licensing System & Registry (NMLS) are required to file a Mortgage Call Report (MCR) with state regulators that includes information on the nonbank's balance sheet and external financing facilities. The Secure and Fair Enforcement for Mortgage Licensing Act of 2008 authorizes the sharing of these data with state and Federal regulatory agencies with mortgage or financial services industry-oversight authority. The MCR data start in 2012 and are available at a quarterly frequency for Ginnie Mae issuers. We use the data on nonbanks' cost of warehouse funding.

4 Nonbank Issuers and Credit Access: Descriptive Analysis

Previous studies on nonbank mortgage companies, for example Buchak et al. (2018) and Gete and Reher (2021), have found that nonbanks have looser credit standards than banks. However, these studies focused only on nonbank originators. Issuers arguably bear more of the costs of loan default in the Ginnie Mae market than originators: issuers service the loans and bear the liability for any mistakes made by the originator, even if the issuer purchased the loan from another institution. While issuers may have the option to seek compensation from the originator for any losses they incur, that option is worthless if the originator declares bankruptcy, as happened during the GFC.

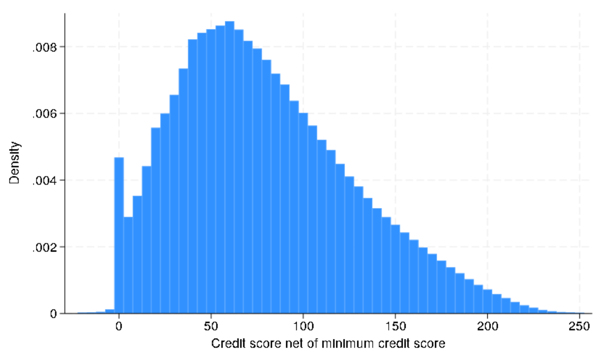
We begin with descriptive evidence that indicates that an issuer's type (bank or nonbank) rather than an originator's type (bank or nonbank) determines credit standards in the FHA market. Our preferred measure of credit standards is the minimum borrower credit score at which an issuer is willing to extend credit. An issuer with a lower minimum credit score is likely to have a looser credit standard. Compared with alternative measures of credit standards such as the fraction of originations to borrowers with low credit scores and average credit scores, the minimum-credit score measure is robust to shifts in the upper end of the credit score distribution, which are not related to changes in credit standards.

We construct the minimum-credit score measure based on the frontier estimation approach used in Anenberg et al. (2019) with the matched loan-level FHA-HMDA-Originator-Issuer data. Because our sample size is not large enough to construct the minimum credit score measure for each issuer at a county×quarter level, we construct the measure for each combination of issuer type I (bank or nonbank), originator type O (bank or nonbank), securitization channel S (integrated originator or aggregator), county c, and quarter t. We thus assign to each borrower the minimum credit score associated with his or her $I \times O \times S \times c \times t$ type. Formally, as described in Appendix B.1, we estimate $E[\min(CreditScore)|I, O, S, c, t]$. So that our sample size is large enough to estimate this statistic, we combine the data from one quarter before and after each quarter for each $I \times O \times S \times c \times t$ combination. To ensure the minimum credit score reflects actual credit standards used, we calculate the measure only for $I \times O \times S \times c \times t$ combinations with at least 100 observations.

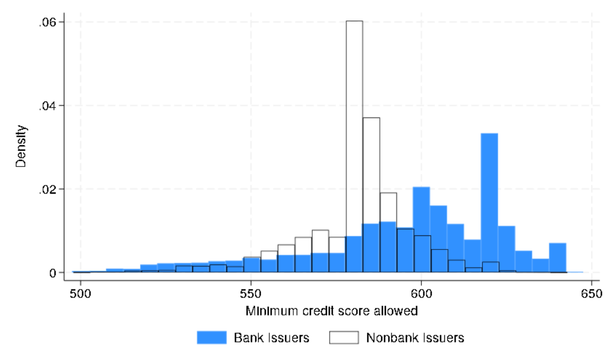
As evidence in support of our assertion that the minimum credit score measure reflects credit standards, Figure 3(a) shows the loan-level distribution of the difference between the credit score on a loan origination and the minimum credit score measure for that borrower's $I \times O \times S \times c \times t$ type. This difference is greater than zero for almost all mortgage originations, with a pronounced spike in the density at zero. Because loan demand is unlikely to drop to near-zero for borrowers with credit scores below the estimated minimum, this spike in the density is attributable to a credit supply decision not to extend loans to borrowers with credit scores below that threshold.

Figure 3(b) plots the distribution of the estimated minimum credit score across $I \times O \times S \times c \times t$ types and shows that nonbank issuers tend to have lower minimum credit scores than bank issuers. The figure also shows that there is wide variation in the estimated minimum credit score both across and within bank and nonbank issuers. Our results from Figure 3(a) suggest that these differences should be attributed to different credit standards across bank and nonbank issuers rather than borrowers sorting into a particular type of issuer.

Figure 3: Minimum Credit Score



(a) Distribution of Credit Score Net of Minimum Credit Score



(b) Minimum Credit Score by Issuer Type

Note: Panel (a) shows the distribution of credit scores across loans net of the minimum credit score conditional on the issuer type, the originator type, the securitization channel type, the county, and the quarter of each loan. Panel (b) shows histograms of the minimum credit score allowed for bank issuers and nonbank issuers. The distributions of minimum credit score allowed conditional on a vector X, described in detail in the text, is weighted by the number of observations for each X. Source: the FHA-HMDA-Originator-Aggregator data.

To examine differences in credit standards across originator and issuer types more systematically, we estimate regressions of the following form:

$$y_i = \beta_1 NonbankOriginator_i + \beta_2 NonbankIssuer_i + \beta_3 IntegratedOriginator_i + X_i\gamma + \xi_{g(i)} + \epsilon_i \quad (1)$$

where the dependent variable y_i is (i) our minimum credit score measure and (ii) a dummy variable for whether the credit score is below 640 for each loan i. Our use of 640 as the cutoff point is in line with an FHA credit performance metric introduced during this time period.[1]

The two main regressors—*NonbankOriginator* and *NonbankIssuer*—are dummy variables that equal one if a loan is originated by a nonbank and is securitized by a nonbank, respectively. For loans originated in the integrated-originator channel, *NonbankOriginator* and *NonbankIssuer* have the same value. Thus, β_1 and β_2 can only be estimated separately because there are loans originated in the correspondent-aggregator channel—for example when a nonbank originator sells loans to a bank issuer.

We include loan-level characteristics X_i so that we can interpret the coefficients on *NonbankOriginator* and *NonbankIssuer* as differences in credit standards for otherwise similar loans. These include whether a loan is originated in the integrated-originator channel (as opposed to the correspondent-aggregator channel), dummy variable bins of the loan-to-value (LTV) ratio and borrower debt-to-income (DTI), whether a borrower is a first-time home buyer, and log loan size. $\xi_{g(i)}$ notates fixed effects. We include fixed effects for each county $\times$ origination month to control for heterogeneity in the evolution of local mortgage market conditions over the sample period. We also estimate a more saturated specification where $\xi_g(i)$ includes originator fixed effects as well, in which case the *NonbankOriginator* coefficient is absorbed and the *NonbankIssuer* coefficient is estimated off differences across loans with the same originator. In each regression, standard errors are clustered at the originator level, the issuer level, and the county $\times$ origination month level. Panel (a) of Table 1 presents the summary statistics of our sample.

As shown in columns (1) and (4) of Panel (b) of Table 1, when *NonbankIssuer* is omitted from the regression, we find that nonbank originators allow lending to borrowers with credit scores almost 13 points lower than bank originators and that nonbank originators are about 7 pp more likely than bank originators to originate a loan to a borrower with a credit score below 640. However, when *NonbankIssuer* is included, the minimum credit score associated with a nonbank originator is only 2.6 point lower than for a bank originator (column (2)), and a loan with a credit score below 640 is no longer more likely to be originated by a nonbank (column (5)). In contrast, *NonbankIssuer* is associated with a 19.4 point lower minimum credit score, nearly as large as its standard deviation, and a 14 pp increase in the probability of securitizing loans to lower credit score borrowers, about the same magnitude as the unconditional mean. The large association between *NonbankIssuer* and low-credit score originations still holds when we include originator fixed effects

[1] The FHA's Supplemental Performance Ratio, used to gauge the credit performance of an issuer's loans relative to its peers, segments mortgages into three credit score buckets: less than 640, 640-680, and greater than 680. See FHA's Office of Single Family Housing, 2015.

Table 1: Differences in credit standards by originator and issuer types

(a) Summary Statistics

	Mean	Std. Dev.
Originated by Nonbank Originator (%)	66.1	47.3
Securitized by Nonbank Issuer (%)	48.1	50.0
Origination in Integrated Originator Channel (%)	45.7	49.8
Credit Score	684.4	46.0
Share of Loans with Credit Score $\leq$ 640 (%)	14.6	35.3
Minimum Credit Score Allowed	603.7	23.7
DTI (%)	40.4	9.2
Loan Amount ($1000)	182.6	94.1
LTV (%)	97.0	4.4
First-Time Home Buyer (%)	79.4	40.5
Number of Observations	2,018,120	

(b) Descriptive Regression Estimates

	Min. Credit Score			1[Credit Score $\leq$ 640]		
	(1)	(2)	(3)	(4)	(5)	(6)
Originated by Nonbank Originator	-12.866***	-2.642*		0.069***	-0.002	
	(1.842)	(1.442)		(0.013)	(0.011)	
Securitized by Nonbank Issuer		-19.386***	-21.345***		0.139***	0.153***
		(1.531)	(1.153)		(0.029)	(0.034)
Origination in Integrated Originator Channel	-25.904***	-20.161***	-18.686***	0.115***	0.076***	0.070**
	(2.604)	(0.552)	(0.565)	(0.018)	(0.019)	(0.032)
County × Month FE	Y	Y	Y	Y	Y	Y
Originator FE			Y			Y
Loan-Level Controls	Y	Y	Y	Y	Y	Y
N. Obs.	1,866,880	1,866,880	1,866,826	1,992,683	1,992,683	1,992,634
Adj. R^2	0.67	0.75	0.77	0.07	0.09	0.13

Note: Panel (a) presents summary statistics of the estimation sample, and panel (b) presents estimates of equation (1). Standard errors are clustered at the originator level, the issuer level, and the county × origination month level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Source: Authors' calculations based on the FHA-HMDA-Originator-Aggregator data from 2012:q1 to 2016:q2.

to control for originator-level heterogeneity (columns (3) and (6)).

The regression results also indicate that loans issued through the integrated originator channel are more likely to be extended to borrowers with low credit scores than loans issued through the aggregator channel. The coefficients are large and statistically significant, corresponding to a nearly 20 point lower minimum credit score and an about 7 pp higher chance of originating a mortgage to a borrower with a credit score below 640. Combining coefficients indicates that the lowest credit scores are associated with a nonbank integrated originator. Integrated originators might be more willing than aggregators to securitize mortgages to lower credit-score borrowers because integrated originators have more full information on borrower credit risk.

This evidence suggests that the type of issuer and whether the mortgage is originated through an integrated originator channel matters much more for credit access than whether the originator is bank or nonbank. Accordingly, a shift on these dimensions might have important consequences for credit supply.

However, this descriptive regression is not causal evidence that the shift from bank to nonbank issuers expanded credit access. Whether a loan is originated by a nonbank or securitized by a nonbank issuer depends on borrowers' choices of originators as well as originators' choices of issuers. Although the regression (1) includes an extensive set of controls, we remain concerned about endogeneity. Moreover, even if estimates from equation (1) are unbiased, they do not capture the equilibrium effects resulting from the shift from bank to nonbank issuers. This change could entail large equilibrium responses from incumbent bank issuers, and these equilibrium forces might have also affected credit supply. As described in the next section, the identification strategy for our main analysis addresses these concerns.

5 Identification and Estimation

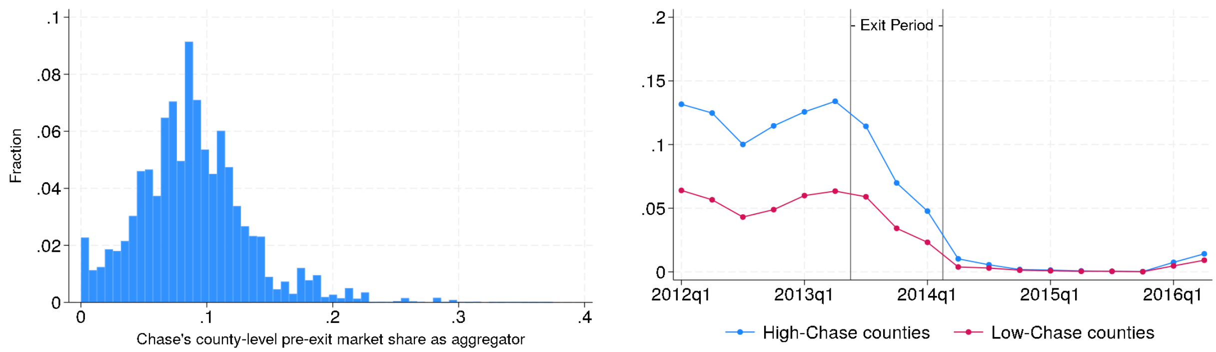
Identifying the causal effects of the shift from bank to nonbank issuers on credit supply must encompass the equilibrium responses of existing issuers while isolating the effects of confounding secular trends. During our sample period, as described in 2.2, the mortgage market was in the midst of significant changes that affected the incentives of borrowers to choose nonbank originators, the incentives of originators to sell loans to bank aggregators, and the decisions of banks and nonbanks to operate in the mortgage space more broadly.

We adopt an empirical strategy that leverages plausibly exogenous variation from Chase's 2014 exit from issuing MBS collateralized by FHA mortgages. Chase was the issuer for more than 10% of FHA home-purchase loans in Ginnie pools in 2012. Chase primarily acted as an aggregator, purchasing 84% of FHA loans that it securitized from other lenders.

Our identification is based on county-level variation in the size of this exit shock. Figure 4(a) plots the cross-county variation in pre-exit market shares for Chase for the period prior to its exit (2012:q1 to 2013:q2) and shows that its county-level footprint ranged from zero to over 30%. To ensure that we are only capturing the effects of Chase's exit from MBS issuance and not mortgage origination, we calculate these shares only for mortgages that Chase purchased as an aggregator.

Figure 4(b) illustrates the evolution of Chase county market shares, split into counties with above- and below-median pre-exit market shares. The vertical lines mark the beginning and end of Chase's exit, which

Figure 4: Exposure to Chase's Exit from FHA Lending



(a) Cross-County Variation in Exposure to Chase Exits

(b) Timing of Chase's Exit, by Exposure Level

Note: Panel (a) plots histograms of county-level market shares of Chase as an aggregator over the period from 2012:q1 to 2013:q2 for FHA home-purchase loans. Panel (b) display conditional averages of Chase's pre-exit county aggregator market shares over time. High-Chase counties are counties where Chase pre-exit market shares were above the distribution median (8.2%). Source: Authors' calculations based on HMDA data.

was gradual given its large presence. Since Chase did not formally announce the beginning of its exit, we pick 2013:q3 as the start because Chase's market share started to decline at that date in the data. During the exit period, Chase's local market share converged toward zero in high and low exposure counties.

This type of variation suggests a difference-in-differences (DID) identification strategy to estimate the effects of Chase's exit. As Chase pulled back nationally, some counties experienced the abrupt exit of a dominant issuer, while other counties experienced insignificant changes in market structure. Comparing otherwise similar markets, the effect of the bank issuer exit is identified off differences in outcomes over time across counties with high and low pre-exit Chase market shares.

This identification strategy contrasts with approaches used in related papers that typically estimate loan-level or lender-level differences in credit outcomes between banks and nonbanks (Buchak et al., 2018; Fuster et al., 2019; Gete and Reher, 2021). Even if these studies' estimates are unbiased, cross-sectional comparisons of banks and nonbanks sweep out the equilibrium effects on local mortgage markets and thus are less informative about effects on credit in aggregate. In comparison, our design preserves the equilibrium effects of the shift to nonbanks on the aggregate credit outcomes in local markets.

We implement the DID strategy in a regression framework, with separate regressions for each exit event.

$$y_{ict} = \sum_{\tau=t^*-6}^{t^*+11} \alpha_\tau S_c 1[\tau = t] + X_{ict}\gamma + \delta_c + \delta_t + \epsilon_{ict} \tag{2}$$

For loan-level (i) outcomes y, we notate the county (c) where the property is located and the quarter (t) when the loan was originated. Each regression includes county δ_c and quarter δ_t fixed effects. Where appropriate for the outcome, regressions also include a rich set of controls X. The exit start quarter (t^*) is 2013:q3. The sample is 18 quarters, 6 pre-exit quarters and 12 quarters after the beginning of the exit (2012:q1–2016:q2).

The treatment exposures are notated S_c, and corresponding DID estimates are α_τ. We measure S_c by calculating the county-level share of FHA home-purchase loans purchased and securitized by Chase as an aggregator in the six quarters prior to the beginning of the exit period (2012:q1 to 2013:q2) using HMDA. The event study DIDs are flexible enough to show how market outcomes evolved over time. This flexibility may be important in our setting because Chase's gradual exit, as shown in figure 4(b), likely affected relevant market outcomes gradually. In addition to event study regressions, we also estimate specifications that pool α_τ in pre-periods ($t < t^*$), exit periods, and post-periods, the latter yielding a single DID estimate for the outcome.

Threats to Identification As noted in Section 2, the mortgage market experienced significant changes during our sample period other than Chase's exit from FHA lending. This could threaten identification if the effects of these other shocks were correlated with variation in exposure to Chase's exit across locations.

To address whether our strategy inaccurately attributes mortgage market outcomes to Chase's exit when other factors were the cause, we first note that contamination from secular changes occurring uniformly across the country is directly purged by the DID design. Examples of such events include the implementation of bank capital and liquidity rules as well as the Ability to Repay rule and other mortgage market regulations made by the Consumer Financial Protection Bureau in 2014. Throughout this period, the GSEs also pursued lenders for larger-than-expected loan putbacks. To the extent that any of these changes were applied homogeneously across local areas, their contribution to the regression residual will not be correlated with Chase's FHA market share in a particular county, and will therefore be swept out of the DID estimator.

Systematic differences in characteristics of counties exposed to Chase's exit shock could still threaten identification, for example if one of the above secular trends interacted with county-specific factors. In general, counties with above-median exposure to Chase's exit have similar characteristics as counties with below-median exposure, as shown in columns (1) and (2) of Table 2. In particular, pre-exit shares of nonbank issuers and nonbank originators are similar between high- and low-exposure counties, helping to alleviate concerns that changes such as the implementation of the bank regulations might be correlated with Chase's exit.

However, some variables are more imbalanced. For example, tract-level median family income and the number of FHA home-purchase loan originations are both higher in counties with high exposure to Chase's exit. Additionally, counties with high exposure tend to have higher local unemployment rates and lower foreclosure rates in 2012.

Our main approach to address the potential identification threat from imbalance is to control for differences across counties using propensity score matching. As detailed in Appendix C, we group counties with similar treatment propensity (Chase's pre-exit share as an aggregator) as predicted by county-level characteristics from Table 2. We do not match on variables in Table 2 that are outcomes to be studied, such as the nonbank issuer/ originator shares and loan characteristics. But we do match on characteristics of the housing market and the local economy, as well as Chase's pre-exit share as an integrated originator. Matching on Chase's integrated originator share helps isolate the effects of Chase's exit as an issuer from its exit as an originator.

Removing variation between propensity score groups improves balance across treatment/control counties. Comparing above- and below-median exposure counties in columns (3) and (4) of Table 2, median income and the number of FHA originations are nearly identical. Throughout the paper, we use propensity score versions of our main specifications as a robustness check.

For additional robustness to these and related identification threats, we provide evidence from another, distinct bank issuer exit shock. As detailed in Appendix I, Bank of America (BOA) exited FHA lending on a national level in 2010, and had substantial cross-county variation in its pre-exit market share as an aggregator. Section 11 shows that credit supply outcomes after BOA's exit are similar to those after Chase's exit, despite the different timing of their exits and the different geographical patterns of the counties where BOA and Chase had large market shares.

There are also theoretical econometric threats to identification and to interpretation of estimates from equation (2) as an average treatment effect. DIDs with continuous treatment require strong parallel trends across local markets that had different degrees of exposure to the exit shocks (Callaway et al., 2021). Figure 4(b) shows that above- and below-median Chase county-level market shares evolved in parallel before the exits. DID estimates α_τ for pre-exit periods also generally support the parallel trends hypothesis. For the regression estimator to be interpreted as a population average treatment effect on the treated (ATT), it is also important that the empirical distribution of exit exposure aligns with the distribution of weights in the two-way fixed effects specification. Appendix Figure A.1 shows that Chase's pre-exit market share and the regression weights from Callaway et al. (2021) have similar densities.

Table 2: Summary Statistics for Treatment/Control Group Balance

	(1) Below-Median Chase Exposure (raw)	(2) Above-Median Chase Exposure (raw)	(3) Below-Median Chase Exposure (propensity score)	(4) Above-Median Chase Exposure (propensity score)	(5) $\frac{m_a - m_b}{\sigma}$
Nonbank Issuer Share (%)	27.0	23.3	26.6	23.7	-0.30
Nonbank Originator Share (%)	61.0	62.6	61.5	62.1	0.04
1[Credit Score < 640] (%)	14.2	14.6	13.9	14.9	0.27
Credit Score	684.7	684.6	685.3	684.0	-0.22
LTV Ratio (%)	97.0	96.9	96.9	97.0	0.06
DTI Ratio (%)	40.4	40.9	40.6	40.7	0.07
Mortgage Interest Rate (%)	3.9	3.9	3.9	3.9	0.25
log(Number of FHA Originations)	7.4	7.6	7.5	7.5	-0.01
Tract-Level Median Family Income (1000)	65.5	71.9	69.0	68.4	-0.04
Chase's Share as Integrated Originators (%)	1.6	2.1	1.8	1.9	0.06
House Price Growth in 2012 (%)	-0.2	-0.9	-0.5	-0.6	-0.05
Unemployment Rate in 2012 (%)	8.5	7.6	8.2	8.0	-0.11
60+ Day Delinquency Rate in 2012 (%)	7.2	7.6	7.3	7.5	0.04
Forclosure Rate in 2012 (%)	2.7	3.3	2.9	3.1	0.05
N. Obs.	2,208	1,006	1,872	855	

Note: Columns (1) and (2) present conditional means by above/below median county-level exit exposure during pre-exit period (2012q1-2013q2). Columns (3) and (4) present conditional means of the same variables within propensity score bins. The measure $\frac{m_a - m_b}{\sigma}$ in column (5) gives the significance of the difference in conditional means $m_a = \mathbb{E}(x|\text{above-median exposure})$ from column (3) and $m_b = \mathbb{E}(x|\text{below-median exposure})$ from column (4) relative to the standard deviation of the characteristic $\sigma = \sqrt{\mathbb{V}(x)}$. Authors' calculations based on the FHA administrative data and the HMDA data.

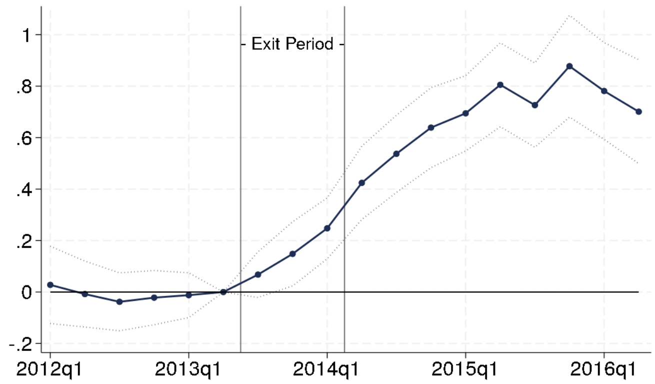
6 Effects on Industrial Organization of the FHA Mortgage Market

6.1 Nonbanks Expand their Presence as Ginnie Mae Issuers

We first examine whether nonbanks increased their market share as Ginnie Mae issuers for FHA home-purchase loans after Chase's exit. We estimate equation (2) with the dependent variable being an indicator variable for whether the loan was securitized by a nonbank issuer. We include county fixed effects and quarter fixed effects but do not include other variables as controls.

The estimates indicate significant substitution between bank and nonbank issuers. Figure 5 graphs the quarterly event-study DID coefficients α_τ, interpreted as the change in the outcome variable relative to 2013:Q2 if the share of loans issued by Chase went from 100% to 0%. Toward the end of the post-exit period, the α_τ are close to 1, and standard errors cannot reject the hypothesis of an almost 1-for-1 shift from bank to nonbank issuers. On average in the post-exit period, accounting for gradual shifts in market structure, every 1 pp of decline in Chase's market share was replaced by roughly 0.8 pp of nonbank market share in the same county in 2016. Chase's pre-exit market share as an FHA aggregator in 2012 was 9% on average in the six quarters prior to the beginning of its exit, meaning that Chase's exit from the FHA market led to a 7 pp increase in the nonbank share of Ginnie Mae issuance.

Figure 5: Effects of Chase's Exit on Market Share of Nonbank Issuers



Note: Estimates and 95% confidence intervals from equation (2) for the effects of a 100 pp decline in Chase's market share on whether a loan is securitized by a nonbank Ginnie Mae issuer. Standard errors clustered at the county level. Source: Authors' calculations based on HMDA data.

6.2 Growth of Nonbanks with Different Business Models

As detailed in Section 2, issuers encompass both aggregators and vertically integrated originators. To parse out which types of nonbanks underlie the rise in nonbank Ginnie Mae issuer market share after Chase's exit, we estimate equation (2) with outcome variables for whether the loan was purchased and securitized by a nonbank aggregator and for whether the loan was originated and securitized by a nonbank integrated originator.

Table 3: Effects of Chase's Exit on Nonbank Ginnie Mae Issuer Market Shares, by Business Model

	(1) Nonbank issuer (aggregator or integrated originator)	(2) Nonbank aggregator	(3) Nonbank integrated originator
Exit Period ×			
Pre-exit County-level Share (S_c)	0.150***	0.116***	0.034
	(0.051)	(0.040)	(0.038)
Post Exit ×			
Pre-exit County-level Share (S_c)	0.704***	0.541***	0.164***
	(0.073)	(0.064)	(0.051)
Avg. Treatment Effects on Treated	0.064	0.049	0.015
County FE	Y	Y	Y
Quarter FE	Y	Y	Y
N. Obs.	2,883,508	2,883,508	2,883,508
Adj. R^2	0.87	0.77	0.73

Note: Estimates and standard errors from equation (2) for the effects of a 100 pp decline in Chase's market share. Standard errors clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Source: Authors' calculations based on HMDA data.

The results indicate that both types of issuers increased their market shares (Table 3). Column (1) reports estimates for all issuers and is the pooled-DID estimates corresponding to the event study results in Figure 5. After Chase's exit shock, nonbank aggregators (column 2) made up about 77% (= 0.541/0.704) of nonbank issuer growth, and nonbank integrated originators (column 3) accounted for around 23%. The fact that some of the bank aggregator market share was replaced by nonbank integrated originators suggests that Chase's exit led to a net reduction in the share of mortgages that flowed through the aggregator channel.

6.3 Robustness: Propensity Score Matching

To examine robustness to the threat of covariate imbalance, we analyze these same IO outcomes using a propensity-score matching approach outlined in Appendix C. Although the shift in nonbank loan securitization and lack of pre-trends does suggest that the estimates in Figure 5 and Table 3 measure a causal effect, DIDs based on between-county variation might include confounding effects from other determinants of mortgage market IO that are correlated with Chase's pre-exit market share. Chase's market share of FHA originations was very small, for example, but did vary across counties and thereby pose a threat to identifying the causal effect of Chase's exit from the issuer market. Forming DIDs off counties that had similar Chase origination shares but different Chase aggregator shares is an arguably cleaner experiment. Our propensity score strategy thus confines the estimator to variation across counties within groups that have similar observable characteristics, ensuring that the DID reflects issuer exit exposure and not other systematic differences. The primary cost of propensity score matching is the potential reduction in statistical power, since by construction it removes some variation in treatment exposure across counties.

The rise of nonbank issuers after Chase's exit is robust to balancing treatment/control groups on observed characteristics. The results in Table A.2 and Figure A.2 presented in Appendix D.1 indicate that Chase's exit caused a 53% increase in nonbank securitization, a bit lower than the 70% increase estimated in our main specification. As in the main specification, most of this growth came from nonbank aggregators rather than integrated originators.

6.4 Robustness: Originator Fixed Effects

The credit standards and cost structures of loan originators may also affect credit supply. If Chase's exit led to a different mix of originators, this compositional shift might explain the credit supply changes that we observe. To rule out this explanation, we repeat our main analysis with the addition of fixed effects for originators. Using within-originator variation does not substantively change our results for whether loans were securitized by nonbank issuers or the type of business model of the issuer (Appendix Table A.3). The evidence thus favors the hypothesis that our results are driven by a shift from bank to nonbank issuers rather than changes at the originator level of the intermediation chain.

6.5 Alternative Identification: Variation in Originators' Exposure to Chase

If county-level exposure to Chase's exit is correlated with unobserved county-level characteristics or trends that attracted nonbank issuers, the rise in nonbank securitization might stem from these factors rather than from Chase's exit. As a robustness exercise, we use a different identification strategy: variation across originators in the share of loans that they sold to Chase. As detailed in Appendix D.3, some originators sold a large share of their originations to Chase before its exit, while others did not. We design a alternative DID estimate that contrasts outcomes for originators with high- and low-exposure to the exiting bank issuer, including within-county originator-level variation that is robust to county-level threats to identification.

Mirroring the between-county DID results, we find that most originators responded to Chase's exit either by selling their loans to other nonbank aggregators or by securitizing their own originations directly (Appendix Figure A.4). The first response corresponds to the growth of nonbank aggregators (column 2 in Table 3), and for nonbank originators the second response corresponds to the growth of nonbank integrated originators (column 3 in Table 3). As shown in Appendix D.3.2, some of the growth in integrated originators came from former correspondent lenders who responded to Chase's exit by switching to an integrated business model. In particular, we find that only large former correspondent lenders switched their business model, suggesting that being an issuer is not very cost-effective for small lenders. As this distinct originator-level variation yields DID estimates consistent with our main results, the evidence suggests that the causal shift from bank to nonbank issuers on Chase's exit is robust to bias from unobserved county-level trends.

7 Easing of Credit Standards

We next explore how Chase's exit affected credit supply, beginning with credit standards. Although originators engage directly with borrowers, MBS issuers face the possibility of significant liability for underwriting errors from the loan guarantor (FHA in this case) and of significant servicing costs if a loan defaults. Issuers control these costs in part by limiting the scope of borrower credit risks that they are willing to assume when purchasing loans as an aggregator or when originating loans as a vertically integrated issuer. To the extent that nonbanks are more willing than banks to bear mortgage credit risk, as described in Section 2.1, a shift toward nonbank issuers may have implications for access to credit.

We estimate the effects of Chase's exit on mortgage credit characteristics and ex-post delinquency outcomes in loan-level FHA administrative data using equation (2). The main results are presented in Table 4 and Figure 6, with supplemental results provided in Appendix E. As in the preceding section, the regression coefficient gives the change in the outcome attributable to Chase's market share falling from 100% to 0%.

Table 4: Effects of Chase's Exit on Credit Risk Measures

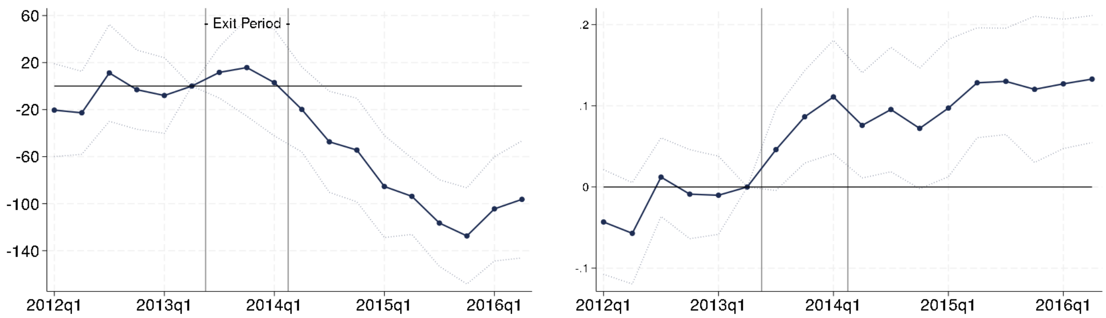
	(1) Min. CS	(2) 1[CS < 640]	(3) Average CS	(4) LTV	(5) DTI	(6) Ever 60+ DQ	(7) Ever 60+ DQ
Exit Period ×							
Pre-exit County-level Share (S_c)	15.463	0.091***	-9.458***	-0.019	1.811***	0.012	-0.009
	(15.889)	(0.020)	(2.950)	(0.278)	(0.535)	(0.015)	(0.014)
Post Exit ×							
Pre-exit County-level Share (S_c)	-86.977***	0.132***	-13.194***	0.287	1.575***	0.088***	0.063***
	(19.416)	(0.031)	(3.702)	(0.365)	(0.601)	(0.025)	(0.023)
Avg. Treatment Effects on Treated	-7.864	0.012	-1.193	0.026	0.142	0.008	0.006
County FE	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y
Loan-level controls							Y
N. Obs.	1,203,288	2,684,506	2,684,506	2,684,506	2,684,506	2,684,506	2,684,506
Adj. R^2	0.28	0.02	0.03	0.01	0.04	0.01	0.06

Note: Estimates and standard errors from regression (2) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in Chase's market share. Loan-level controls in column (7) include log loan size, an indicator for first time homebuyers, and indicator variables defining 11 bins of credit scores, 7 bins of loan-to-value ratios, and 6 bins of debt-to-income ratios. Standard errors in parenthesis, clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Authors' calculations based on the HMDA-FHA matched sample (column (1)) and FHA administrative data (columns (2)–(7)).

The estimates suggest that Chase's exit led to the average FHA borrower obtaining a mortgage from a lender with substantially easier credit standards. Column (1) of Table 4 and Figure 6(a) present results for our minimum credit score measure – the lowest credit score allowed by the borrower's lender type × issuer type × securitization channel in the borrower's county in the same quarter of origination, as described in Section 4. The estimates suggest that the minimum credit score would decline by 87 points if Chase's market share in that county declined from 100% to 0%. Since on average Chase's market share was around 9%, the average treatment effects on the treated (ATT) amounts to an 7.9 point easing of credit standards, about 33% of the standard deviation of the minimum credit score, for borrowers who experienced the exit.

As a consequence of easier credit standards, a larger share of mortgages were originated to borrowers with lower credit scores (Figure 6(b)), and average credit scores declined. This is consistent with our earlier descriptive evidence that nonbank issuers had a higher probability of securitizing loans to borrowers with lower credit scores (Table 1), and complements the literature on the effect of nonbank originators on credit standards (Buchak et al., 2018; Gete and Reher, 2021). The estimates indicate that a shift from 100% to

Figure 6: Effects on Credit Standards



(a) Minimum Credit Score (by lender and market)

(b) Credit Score $\leq$ 640

Note: Estimates and 95% confidence intervals from equation (2) for the effects of a 100 pp decline in Chase's market share on outcome variables for credit standards. Panel (a) presents the estimates for the minimum credit score for each combination of issuer type (bank or nonbank), originator type (bank or nonbank), origination channel type (correspondent origination or integrated origination), county, and quarter. Panel (b) presents the estimates for whether the borrower's credit score is below 640. Standard errors clustered at the county level. Source: Authors' calculations based on the HMDA-FHA matched sample (panel (a)) and on administrative FHA data (panel (b)).

0% Chase issuer share would lead to a 13 pp increase in the share of FHA mortgages extended to borrowers with credit scores less than 640 (column 2, Table 4). Evaluating at the mean exit exposure, the proportion of FHA loans extended to such low credit score borrowers increased 1.2 pp, or an 8% increase relative to the average share of borrowers with credit scores below 640.

If bank issuers are reluctant to securitize loans to borrowers with lower credit scores, why didn't nonbanks securitize loans to such borrowers even before Chase exited? One reason is that being a Ginnie Mae issuer is operationally complex and developing the appropriate infrastructure is more cost effective for larger institutions. Most nonbanks in 2010 were small institutions and preferred to sell their originations to large bank issuers. This calculus changed when those bank issuers departed the market and left an opening for nonbank issuers to fill. As discussed in Section 6.5, we find evidence that an institution's scale matters for the decision to become an Ginnie Mae issuer: only relatively large originators that sold loans to Chase were more likely to become Ginnie Mae issuers themselves after their exits (Appendix D.3.2).

7.1 Other Dimensions of Credit Risk

Nonbank issuers might have been comfortable easing credit standards on the credit score dimension because issuers tightened underwriting on other, offsetting dimensions. However, the results presented in columns (4) and (5) in Table 4 do not support this hypothesis. Average loan-to-value (LTV) ratios held steady, and debt-to-income (DTI) increased. This absence of compensating risk factors suggests that a greater taste for risk underlies the expanded nonbank securitizations of loans to lower credit score borrowers, as discussed in Section 2.1.

7.2 Ex-Post Delinquencies

We can also gauge whether the credit-score expansion is symptomatic of a greater nonbank taste for risk by looking at loan performance after origination. An increase in delinquencies even after conditioning on observable determinants of credit risk (credit score, LTV, DTI) may suggest that nonbanks have eased standards on harder-to-monitor aspects of underwriting as well.

Perhaps not surprisingly, given the evidence on relaxation of credit standards, the share of loans that became 60 or more days delinquent within 3 years of origination rose after Chase's exit, shown in column (6) in Table 4. Including controls for a variety of loan-level risk characteristics reduces the effect of bank issuer exits on delinquency rates, shown in column (7) in Table 4, but the rise in delinquencies remains statistically significant. As measured by the ATT, Chase's exit resulted in a 0.6 pp increase in delinquencies, a 5.4% increase relative to the pre-exit average 60 or more day delinquency rate within there years of 11%. These findings suggest that nonbank issuers have a greater appetite for credit risk, even along dimensions of risk less easily to quantify at origination. Our findings are in line with Bosshardt et al. (2023), who find higher default rates for nonbanks conditional on observed characteristics in the context of GSE mortgages.

7.3 Issuer Equilibrium Responses

So far we have attributed the change in credit standards after Chase's exit solely to the compositional shift from bank to nonbank issuers with greater appetites for risk. But an equilibrium mechanism could also underlie our results if existing issuers eased their own standards in response to nonbank expansion. To provide evidence on compositional vs equilibrium mechanisms, Table A.8 in Appendix E provides estimates of equation (2) for subsamples of loans with bank issuers (excluding Chase) and nonbank issuers separately. We also restrict the subsamples to incumbent issuers who operated in a county before and after Chase's exit. Because the regression was estimated with the subsamples of the same issuer type, these estimates reflect changes in credit standards among remaining issuers, not the effects of the compositional shift from bank to nonbank issuers. We also estimated the same regression with issuer fixed effects in order to hold constant any issuer-specific factors.

We find some evidence that incumbent nonbank issuers eased credit standards in response to nonbank entry. The minimum credit score among nonbank issuers declines by a statistically significant amount when we include issuer fixed effects (column (6)) and the share of loans originated to low credit score borrowers decreases, albeit at a borderline level of significance (column (8)). The credit standards of bank issuers appear unchanged in response to nonbank entry (columns (1)–(4) of Table A.8). This evidence suggests that incumbent nonbank issuers' equilibrium responses may have played a small role in the expansion of credit access after Chase's exit. Our finding that incumbent banks did not ease their credit standards is not unique to our setting. Gissler et al. (2020) find similar results in the context of auto lending.

7.4 Robustness: Propensity Score Matching

As in the preceding section, our first robustness exercise examines whether the results for credit risk outcomes are sensitive to balance concerns. The extent to which credit standards eased is slightly attenuated in the specification with propensity score matching, but qualitatively the same as the main specification for most dependent variables (Figure A.5 and Table A.5 in Appendix E). The one exception is the overall average credit score across FHA originations, which after balancing treatment/control groups on observed characteristics yields a statistically insignificant 4 point decrease rather than the significant 13 point decrease in the main specification.

7.5 Robustness: Originator Fixed Effects

Loan originations must meet the credit standards of both the originator and the issuer. If Chase's exit led to a different mix of originators, this compositional shift might explain the credit standard changes that we observe. To explore this possibility, we repeat our main analysis with fixed effects for originators (Appendix Table A.6). Including originator fixed effects slightly weakens the relationship between Chase's exit and easier credit standards, indicating that changes at the originator level may have played a small role in the easing of credit standards. The minimum credit score declines by 69 points in the originator fixed effects specification, for example, compared with 87 points in the main specification. However, the overall story remains intact, indicating that the shift from bank to nonbank issuers is the primary driver of the easier credit standards.

7.6 Controlling for the Integrated Originator Channel

While the primary effect of Chase's exit on the industrial organization of the FHA market was an increase in the market share of nonbank issuers, there was also an increase in the share of mortgages that were securitized through the integrated originator channel (Section 6). MBS issuers that are also the mortgage originators may be more willing to extend credit to borrowers with low credit scores, for example, if they have more or better information from the underwriting process compared with aggregators who purchase loans originated by other firms. Indeed, our descriptive regressions in Section 4 suggested a relationship between easier underwriting standards and the integrated originator channel.

To parse the nonbank issuer effect from the integrated originator mechanism, Table A.7 in Appendix E repeats the analysis from Table 4 with an additional control variable for the integrated originator channel added to the specification. The results corroborate our finding from Section 4 that credit standards are looser for loans in the integrated originator channel. However, the effects of Chase's exit on credit standard outcomes are essentially unchanged after the addition of the integrated originator control variable. This finding indicates that our results are not due to the fact that the integrated originator channel increased somewhat along with the rise in nonbank securitization.

8 Increased Costs of Credit

We test whether the shift from bank to nonbank MBS issuers affected the costs of financial intermediation by analyzing interest rates and funding cost outcomes using equation (2). To ensure that our estimates can be interpreted as treatment effects on otherwise similar loans, each regression in this section includes indicator variables defining 11 bins of credit scores, 7 bins of loan-to-value ratios, 6 bins of debt-to-income ratios, log loan size, and whether the borrower is a first-time homebuyer as control variables. As before, the regression estimate is interpreted as the causal effect on the outcome variable attributable to Chase's market share falling from 100% to 0%.

The shift from bank to nonbank issuers significantly increased mortgage interest rates (Figure 7(a)). The results suggest that moving from a 100% to a 0% Chase market share would increase the average mortgage interest rate by 18 bps (Table 5, column 1). The ATT experienced by the representative borrower during Chase's exit is a smaller 1.6 bps, roughly 2.4% of the in-sample standard deviation (68 bps).

For perspective, consider a 30 year loan of about the average size ($175,000) and about the average interest rate (3.65%) within our study period. Assuming the borrower stays in the loan for 7 years, about the average life of an FHA home purchase loan, shifting Chase's market share from 100% to 0% leads to the borrower incurring an additional $1,500 in interest expense over the 7 years. Scaling by Chase's pre-exit aggregator share of 9%, the ATT amounts to an additional $135 over 7 years for a typical loan in the data.

Figure 7: Effects of Chase's Exit on Interest Rates and Funding Costs

(a) Mortgage Interest Rate

(b) Funding Cost per Loan

Note: Estimates and 95% confidence intervals from equation (2) for the effects of a 100 pp decline in Chase's market share on interest rates at loan origination (panel a) and issuer funding cost for each loan (panel b). Both regressions include loan-level controls for: log loan size, indicator variables for 11 bins of credit scores, indicator variables for 7 bins of loan-to-value ratios, indicator variables for 6 bins of debt-to-income ratios, and an indicator for first time homebuyers. Panel a is calculated from the FHA administrative data. Panel b is from the matched FHA-HMDA-Originator-Aggregator subsample with NMLS or bank call report data. Funding costs per loan are converted to units of annual mortgage interest rates. Standard errors clustered at the county level.

Table 5: Effects of Chase's Exit on Cost of Credit

	Mortgage Interest Rate				Funding Cost Per Loan
	(1) Full Sample	(2) CS < 640	(3) 640 ≤ CS < 680	(4) CS ≥ 680	(5)
Exit Period ×					
Pre-exit County-level Share (S_c)	0.072	0.214**	0.131**	-0.001	0.010
	(0.057)	(0.087)	(0.057)	(0.063)	(0.009)
Post Exit ×					
Pre-exit County-level Share (S_c)	0.178***	0.284***	0.210***	0.136*	0.069***
	(0.066)	(0.095)	(0.070)	(0.073)	(0.010)
Avg. Treatment Effects on Treated	0.016	0.026	0.019	0.012	0.006
County FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y
Loan-level controls	Y	Y	Y	Y	Y
N. Obs.	2,684,506	369,949	1,050,996	1,263,447	1,977,568
Adj. R^2	0.38	0.27	0.36	0.34	0.06

Note: Estimates and standard errors from a regression (2) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in Chase's market share on interest rates at loan origination (columns 1–4) and issuer funding cost for each loan (column 5). Columns 2, 3, and 4 present regression results using the subsample of borrowers with credit scores below 640, between 640 and 680, and at least 680, respectively. All regressions include loan-level controls for: log loan size, indicator variables for 11 bins of credit scores, indicator variables for 7 bins of loan-to-value ratios, indicator variables for 6 bins of debt-to-income ratios, and an indicator for first time homebuyers. Columns 1–4 are calculated from the FHA administrative data. Column 5 is from the matched FHA-HMDA-Originator-Aggregator sample with NMLS or bank call report data, excluding loans securitized by Chase. Standard errors in parenthesis, clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

One mechanism for the increase in mortgage rates is that nonbank Ginnie Mae issuers have a higher cost structure, as discussed in Section 2.1. As described in Appendix F.1, we construct a measure of each issuer's funding costs by linking each bank issuer with the cost of its deposits and each nonbank issuer with its cost of warehouse line funding for the matched FHA-HMDA-NMLS subsample of loans. We denominate these short-term funding costs in units of an annual mortgage interest rate, so that estimated effects can be compared directly with effects for interest rate outcomes. The results suggest that nonbanks' higher funding costs can account for about 7 bps, or about 38% of the increase in average mortgage rates after Chase's exit (Figure 7(b) and Table 5, column (5)).

Higher costs in other aspects of their mortgage business may also explain the higher interest rates charged by nonbanks. For example, in the servicing component of their issuer responsibilities, nonbank servicers generally earn less income than banks on escrowed funds, and some nonbanks lack economies of scale in mortgage servicing relative to a large bank issuer such as Chase (Swaminathan et al., 2023). We cannot test these alternative cost hypothesis within our DID framework, as measures of the respective cost outcomes are not in the available data.

Our evidence is inconsistent with mortgage rates increasing as compensation for the increased riskiness of the FHA borrower pool on the *observable* dimensions shown in Table 4. The regressions in Table 5 include a rich set of controls for observable credit risk, which purge the first order compositional effects of underwriting factors on interest rates. The shift from bank-to-nonbank issuers also significantly increased mortgage interest rates within subsamples of observably riskier loans (columns (2) and (3)).

However, we cannot rule out that mortgage rates rose, in part, to compensate for an increase in credit risk *unobserved* in the available data, as hinted at by the delinquency rate results (Table 4, column (7)). Aiello et al. (2023) find, for example, that an influx of new lenders increases the credit risk of the mortgage originations of existing firms, and that these lenders raise interest rates in response. If unobserved risk factors are correlated with credit scores and priced into the loan, then the gradient of the price effect across credit score subsamples may support this hypothesis. Indeed, we find larger increases in rates for lower credit score borrowers than for higher score borrowers that were otherwise observably similar (columns (2)–(4) of Table 5).

The increase in interest rates might overstate the total change in the cost of credit if prices decreased on other, potentially offsetting, dimensions. Mortgage lenders typically offer a menu of rates and origination fees, with "discount points" that borrowers can purchase up-front in exchange for lower mortgage rates. We test whether Chase's exit also led to changes in points using FHA mortgages recorded in the Optimal Blue data from 2013 to 2016.[2] Rather than offsetting the increase in interest rates, Appendix Table A.13 suggests that Chase's exit led to greater discount points purchased by borrowers on average. As in our main data set, Chase's exit results in an increase in mortgage rates in the Optimal Blue sample, and the effect is even larger when we include discount points as an additional control variable. These results suggest that our main estimate of the effect on mortgage rates likely understates, rather than overstates, the extent to which total borrowing costs increased as the market shifted from bank to nonbank securitization.

8.1 Issuer Equilibrium Responses

The increase in cost of credit caused by Chase's exit is consistent with the compositional shift from bank to nonbank issuers, in light of variation in cost structures across these types of financial institutions. But equilibrium forces might also play a role, for example if incumbent issuers reacted to higher interest rates offered by the nonbanks that expanded. For evidence on compositional vs equilibrium mechanisms, Appendix Table A.12 presents estimates for interest rates with and without issuer fixed effects, separately within subsamples of loans securitized by bank and nonbank issuers.

The evidence suggests that equilibrium forces likely played a role in raising interest rates after Chase's exit. Mortgage rates increased significantly within the subsample of incumbent bank issuers after Chase's exit (column (1), Table A.12). Including fixed effects still indicates that bank issuers raised rates in response to the exit (column (2)), although the effect is on the margin of statistical significance. Mortgage rates also increased significantly within the subsample of incumbent nonbank issuers (column (3)), although including issuer fixed effects leaves the estimate statistically insignificant (column (4)). These findings suggest that the increased cost of credit after Chase's exit was driven both by the compositional shift to nonbank issuers as well as by the equilibrium reactions of bank issuers to rising nonbank securitization.

8.2 Robustness: Propensity Score Matching

For robustness, we once again examine whether the effects of shifting from bank to nonbank securitization on costs of credit is sensitive to balancing treatment/control groups on observable characteristics. Estimates for interest rate and funding outcomes in the propensity score design are given in Appendix Table A.9 and Figure A.6. The results suggest a slightly more modest effect on interest rates than the main specification

[2] The Optimal Blue Mortgage Price Data from Optimbal Blue LLC begin in 2013:Q1. This data set covers mainly loans originated by a broker or a correspondent lender, and Bhutta and Hizmo (2021) estimate that the data represent about a quarter of the mortgage market in 2014 and 2015. HMDA reports discount points starting in 2018, after the end of our sample period.

but are qualitatively very similar.

8.3 Robustness: Originator Fixed Effects

Loan originators may have their own pricing incentives that are distinct from the incentives passed-through by MBS issuers. For example, nonbank originators may have a higher cost structure than bank originators, perhaps because of their own higher short-term funding costs. If Chase's exit led to a different mix of originators, these differences might explain the rise in interest rates that we observe. However, when we add originator fixed effects to the regression (Appendix Table A.10), the results are similar to the main specification.

8.4 Controlling for the Integrated Originator Channel

The effects of Chase's exit on interest rates and funding costs could conflate the rise of nonbank issuers with the growth of vertically integrated originators. Originators that securitize their own loans might have different pricing incentives from disintegrated aggregators, for example if their direct access to MBS markets eliminates a margin that aggregators pay to originators when purchasing loans. To parse the nonbank issuer and integrated issuer mechanisms in cost of credit outcomes, we add a control for integrated issuer loans to the regression (Appendix Table A.11). The results indicate that loans securitized by integrated originators had lower interest rates than mortgages securitized by aggregators. Nonetheless, our main result that Chase's exit led to an increase in interest rates remains intact.

9 Lending Quantity

Easier credit standards and higher costs of credit have potentially countervailing effects on borrower welfare, benefiting those who gain access to credit while disadvantaging others who experience higher prices. Inasmuch as aggregate demand is a sufficient statistic for welfare, variation in the market's extensive margin can help resolve this ambiguity. We therefore test whether the shift from bank to nonbank issuers affected the quantity of FHA loan originations and led borrowers to switch to other mortgage products.

For quantity outcomes we estimate county-level regressions that are the aggregate analogue of the loan-level regression (2):

$$Q_{ct} = \sum_{\tau=t^*-6}^{t^*+11} \alpha_\tau S_c 1[\tau = t] + \delta_c + \delta_t + \epsilon_{ct}. \tag{3}$$

The dependent variable Q_{ct} is a measure of lending quantity in county c and in quarter t. To assess changes in quantity in a way that is (i) not confounded by seasonality and (ii) is interpretable as an approximate percent growth within-county, we define Q_{ct} as follows:

$$Q_{ct} = \frac{q_{ct}}{E[q_{ct}|c]} = \frac{q_{ct}}{\sum_{t=2009:q1}^{2016:q4} q_{ct}/32}$$

where q_{ct} is the seasonally-adjusted number of FHA home-purchase loan originations.[3] The denominator scales the number of loan originations by the average number of loan originations in the corresponding quarter in the county from 2009 to 2016. We scale by average originations over the entire sample period, rather than by originations in the pre-exit year only, because the small number of originations in some counties in some quarters in the pre-exit period lead to volatile estimates. As a result, our outcome variable measures percent deviations from the mean. But because DIDs are with respect to the pre-exit quarter, regression estimates are interpretable as the within-county seasonally adjusted percent changes in lending quantity relative to before Chase's exit. To give the county-level regressions a loan-level interpretation in line with our other results, we weight equation (3) by the county's average number of quarterly originations. Standard errors are clustered at the county level.

As before, for robustness we obtain DID estimates with and without propensity score matching. For the results shown in the preceding sections, balancing treatment/control groups on observed characteristics did not significantly alter the results. For quantity outcomes, however, propensity score matching affects our estimates of the quantity outcomes for borrowers with higher credit scores. In this section we therefore present both sets of results side by side.

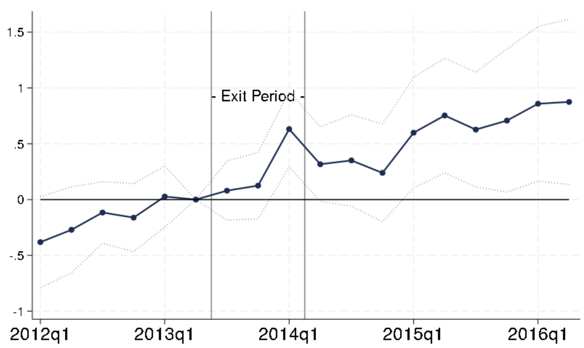
Both sets of results suggest that a complete shift from bank to nonbank securitization would lead to a large and statistically significant increase in the number of FHA mortgages originated to borrowers with credit scores below 640. The increase is 74% in the main specification, Figure 8(a) and Table 6 column (2), and is a similar 68% increase in the specification with propensity matching, Figure 8(b) and Table 6 column (6). Scaling by treatment exposure for an ATT, Chase's exit and the subsequent rise of nonbank issuers

[3]For seasonal adjustment, we calculate the county-level average number of originations of each quarter over the years from 2009 to 2016. Then we normalize the number of origination in a county in each year×quarter by the ratio of the average number of originations in that quarter to the average in the first quarter in that county.

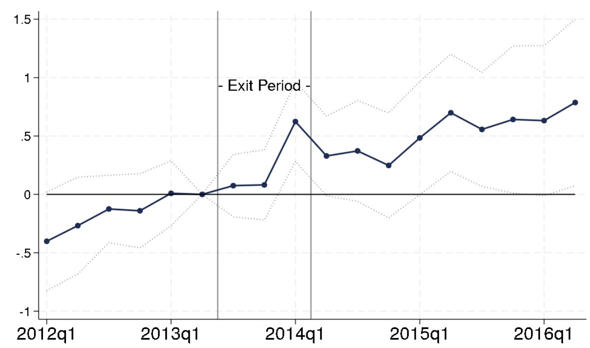
caused the quantity of FHA loans originated to low credit score borrowers to increase by about 6.5%, on average. Given that the share of borrowers with credit scores below 640 is about 15%, the 6.5% increase in the number of originations is consistent with our earlier finding of a 1.2 pp increase in the share of borrowers with credit scores below 640 (Table 4 column (1)).

The results on quantities for borrowers with higher credit scores, and by extension estimates for total lending, are more sensitive to balanced treatment/control groups. The main specification suggests that a 100 pp decline in Chase's pre-exit share would decrease total lending volume by 29% (column (1), Table 6), where increased lending to lower score borrowers is offset by reduced lending for higher score borrowers (columns (3) and (4)). In contrast, estimates from the propensity score specification do not suggest that a shift from bank to nonbank securitization would reduce FHA quantity, either overall nor within credit score buckets (columns (5), (7), and (8)). If anything, total quantity increases in the balanced DID design, albeit by a statistically insignificant amount.

Figure 8: Percent Change in Lending Quantity for Borrowers with Credit Score below 640



(a) No propensity-score matching



(b) Propensity-score matched treatment/control

Note: Estimates and 95% confidence intervals from equation (3) for the effects of a 100 pp decline in Chase's market share on the percentage change in FHA loan originations for borrowers with credit scores below 640. Panel a include county fixed effects and quarter fixed effects. Panel b additionally includes the fixed effects for each of the 20 propensity score bin interacted with each quarter. Standard errors clustered at the county level. Source: Authors' calculations based on administrative FHA data.

Some variation in quantity might reflect substitution by would-be FHA borrowers to outside options. Borrowers with low credit scores likely had to rely on the FHA program for mortgage credit during our time period. But borrowers with higher credit score might have the option to switch to (and from) other mortgage products. To explore this possibility, we expand our sample to include the most likely substitute for FHA mortgages: conventional mortgages sold to the GSEs with loan sizes below the FHA limit and loan-to-value ratios of 95 percent or higher. To accommodate the available geographic information in the

GSE data, market boundaries and exit exposures are taken at the 3-digit zip code level rather than by county. Appendix Table A.14 repeats the main analysis in Table 6 with this broader set of loans.

The results are consistent with our conjecture that borrowers with credit scores below 640 do not use GSE-eligible loans as substitutes for FHA loans. The increase in FHA+GSE mortgages originated to borrowers with credit scores less than 640 is similar to the increase estimated on FHA originations alone (columns (2) and (6), Appendix Table A.14). This finding suggests that the increase in equilibrium mortgage quantity for these borrowers likely reflects increased home ownership in substitution for renting. This result is in line with Gete and Reher (2021), who find that an increase in nonbank credit supply in the FHA market led to an increase in homeownership.

The evidence for borrowers with higher credit scores is less precise, and inconclusive. In the specification without propensity score matching, the decline in mortgage quantity for borrowers with higher credit scores is much smaller and no longer statistically significant in the broader FHA+GSE sample (columns (3) and (4)). While this finding is consistent with substitution from FHA to GSE loans, because of large standard errors the estimates are also not statistically distinguishable from the corresponding estimates in the narrower sample of FHA loans (columns (3) and (4), Table 6). The specification with propensity score matching, as before, indicates that mortgage quantities were almost unchanged for higher-score borrowers after Chase's exit (columns (7) and (8), Appendix Table A.14).

Table 6: Effects of Chase's Exit on FHA Quantity

	Without Propensity Score				With Propensity Score			
	(1) Total Loans	(2) CS $<$ 640	(3) 640 $\leq$ CS $<$ 680	(4) CS $\geq$ 680	(5) Total Loans	(6) CS $<$ 640	(7) 640 $\leq$ CS $<$ 680	(8) CS $\geq$ 680
Exit Period $\times$								
Pre-exit County-level Share (S_c)	-0.162*	0.430***	-0.076	-0.378***	0.090	0.415***	0.086	-0.051
	(0.084)	(0.121)	(0.098)	(0.100)	(0.085)	(0.124)	(0.103)	(0.096)
Post Exit $\times$								
Pre-exit County-level Share (S_c)	-0.286**	0.743***	-0.302**	-0.517***	0.108	0.682***	-0.050	-0.029
	(0.137)	(0.243)	(0.146)	(0.129)	(0.139)	(0.236)	(0.150)	(0.124)
Avg. Treatment Effects on Treated	-0.026	0.067	-0.027	-0.047	0.010	0.062	-0.005	-0.003
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N. Obs.	49,151	45,304	47,725	48,494	48,710	45,107	47,480	48,129
Adj. R^2	0.14	0.37	0.06	0.16	0.47	0.52	0.22	0.44

Note: Estimates and standard errors from (3) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in Chase's market share on the number of loan originations, relative to the average number of loans originated from 2009 to 2016. In addition to county fixed effects and quarter fixed effects, columns (5)–(8) include the fixed effects for each of the 20 propensity score bin interacted with each quarter. Standard errors in parenthesis clustered at the county level ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Source: Authors' calculations based on administrative FHA data.

Another measure of the extensive margin is the probability that a lender approves a mortgage application for a borrower with a given set of characteristics. An ideal test would take a sample of exogenous mortgage applications, and measure whether the shift from bank to nonbank issuers affected equilibrium approval probabilities at different points on the would-be borrower credit score distribution. Unfortunately, data on applications by credit score are not available until 2018, outside our study period. In addition, borrowers decide whether to submit an application in the context of the signals that they receive about the likelihood that their application will be approved. If a shift from bank-to-nonbank securitization was accompanied by an advertising blitz aimed at less credit-worthy borrowers, for example, more such borrowers might apply, leading to a decrease in overall acceptance rates. With these caveats in mind, we show the results of Chase's exit on the overall FHA application acceptance rate in Appendix Figure A.7. The results do not suggest that Chase's exit had significant effects on application approval.

In sum, an equilibrium increase in the number of mortgages for borrowers with credit scores below 640 suggests that at least some borrowers benefited from the shift to nonbank issuers: those who gained access through easier credit standards despite paying higher mortgage rates. In contrast, the shift to nonbank issuers likely made some borrowers with higher credit scores worse off: those whose access was unaffected by looser credit standards but nonetheless faced higher interest rates. That we do not find robust evidence for a decline in mortgage quantity for borrowers with higher credit scores suggests that the potential loss of welfare was not very large, on net.

10 Alternative Explanations

10.1 Chase Withdrew from Lending More Broadly

Chase could have withdrawn from other lending markets at the same time that it exited from FHA aggregation, and impacted counties could have suffered a broader reduction in credit availability that weighed on the local economy. Remaining lenders might have perceived these counties as riskier operations and hiked interest rates to compensate for the additional risk. Appendix H.1 shows, however, that Chase's withdrawal was confined to the FHA market. Chase continued to originate mortgages eligible for sale to the GSEs, auto loans, and small business loans. This finding suggests that a broader contraction in local credit supply is not driving our results.

10.2 Chase was Symptomatic of a Broader Banking Pullback from the FHA Market

Other banks might have responded to the same market developments as Chase and also withdrawn at the same time, in which case our identification strategy may be reflecting other developments than Chase's exit. However, Appendix Figure A.10 shows that the two other largest bank issuers, Wells Fargo and U.S. Bank, remained in the FHA aggregation business over this time period. The participation trends for Wells Fargo and U.S. Bank are near-identical in counties where Chase had high and low market shares, suggesting that any broader pullback of banks from the FHA aggregation market does not confound our estimates.

10.3 Chase's Exit Caused Other Changes in the Industrial Organization of the FHA Market

Chase's exit may have brought about other changes in the industrial organization of FHA lending, beyond the increase in the share of nonbank issuers, which had their own effects on credit supply. We rule out several such explanations next.

10.3.1 Changes in the Nonbank Share of Loan Origination

Chase's exit could have increased the nonbank share of mortgage origination as well as the nonbank share of Ginnie Mae MBS issuance. To explore this possibility, we estimate our main regression specification (Equation (2)) using an indicator variable for "originated by a nonbank" as the dependent variable. The results indicate that the county-level share of nonbank originations did not change after Chase's exit (Figure A.11 in the Appendix).

10.3.2 Fintech Nonbank Issuers

Some "fintech" nonbank lenders harnessed new technologies to increase their market share after the GFC (Buchak et al., 2018; Fuster et al., 2019). However, fintech lenders do not appear to be a factor in our story. To establish this, we classified issuers as "fintech" according to Buchak et al. (2018) and measured their market share. Appendix Figure A.12 shows that fintech nonbank issuers' share changed very little in the counties with greater exposure to BOA and Chase's exits. This result suggests that fintech lenders did not have an advantage over other firms in replacing BOA and Chase as MBS issuers, perhaps because fintech innovations are geared toward the loan origination process rather than loan securitization.

10.3.3 Market Concentration

Chase's exit and the growth of nonbanks might affect competition – either competition between banks and nonbanks, or overall competitiveness at different rungs of the chain of intermediation – and thereby affect credit supply outcomes (Jiang, 2023). To study this possibility, we examine the effects of Chase's exit on FHA market concentration within the originator and issuer markets in Appendix Table A.15. If the increase in interest rates stemmed from a change in competition, we expect market concentration to increase significantly after Chase's exit. However, we find that the Herfindahl–Hirschman Index (HHI) for Ginnie Mae issuers, equal to the sum of squared issuer market shares, is essentially flat after Chase's exit. The HHI for FHA originators inches up slightly in the main specification, but is unchanged in the specification with propensity score matched treatment/control groups, and otherwise remained at very low levels. This weak evidence on market concentration is inconsistent with the effects on credit supply that we observe.

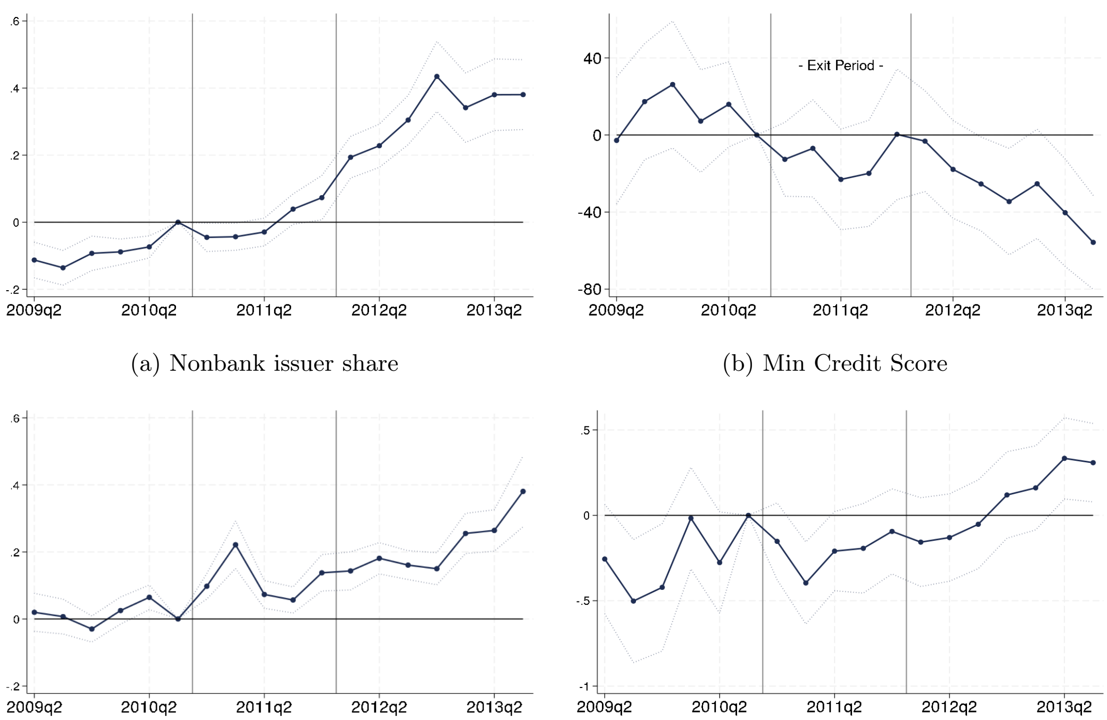
11 Robustness Test: Bank of America's Exit from FHA Lending

As further evidence that we are identifying the effects of a shift from bank to nonbank intermediation, rather than a phenomenon specific to a certain time period or set of counties, we show that the exit of Bank of America (BOA) from FHA aggregation, which occurred nearly two years before Chase's exit and affected a different set of counties, had similar effects on credit supply. BOA announced its exit in October 2011 (Benoir, 2011), one year after it announced that it would stop purchasing loans originated by mortgage brokers (Wotapka, 2010). BOA's pullback had an enormous effect on the FHA market: as a result of its acquisition of Countrywide Financial in 2008, BOA was the MBS issuer for 35% of FHA mortgages in 2010 and was the largest FHA aggregator, accounting for 48% of FHA mortgage purchases by aggregating institutions (HMDA, 2009-2016). The variation in BOA's pre-exit market share across counties (from 0% to 60%, shown in Figure A.13(a)) also lends itself well to our empirical strategy.

While BOA's exit was more consequential for the FHA market than Chase's exit, the BOA event is not as clean for identification. BOA's pullback was related to its attempt to rightsize its balance sheet after the enormous losses it incurred from purchasing Countrywide, and so it pulled back from several mortgage businesses in addition to FHA loans, including mortgages eligible for sale to the GSEs. By dint of its Countrywide acquisition, BOA's portfolio was also concentrated in some of the counties most affected by the GFC housing boom and bust. Appendix Table A.16 illustrates the threat of imbalance, showing for example that counties with high BOA pre-exit market shares had larger swings in house prices during the GFC than counties with low pre-exit BOA market shares. To address these identification threats, as described in more detail in Appendix I and Table A.17, we utilize the propensity score matched treatment/control group strategy for the analysis of BOA's exit.

With those caveats, we examine the same outcomes from Sections 6 to 9 for the period 2009:q2 to 2013:q4 (six quarters before BOA's exit at year-end 2011 and 12 quarters thereafter). We find that BOA's exit caused an increase in the market share of nonbank issuers (Figure 9(a) and Table A.18), an easing of credit standards (Figure 9(b) and Table A.19), an increase in mortgage interest rates (Figure 9(c) and Table A.20), and an expansion in FHA originations for borrowers with low credit scores (Figure 9(d) and Table A.21). The similarity of these results to our Chase results supports our interpretation that our identification strategy is capturing the causal effects of a shift from bank to nonbank securitization.

Figure 9: Effects of BOA's exit (with propensity score matching)



(a) Nonbank issuer share

(b) Min Credit Score

(c) Mortgage Interest Rates

(d) FHA Quantity to Credit Scores ≤ 640

Note: Panels a, b, and c present estimates and 95% confidence intervals from equation (2) for the effects of a 100 pp decline in BOA's market share on the market share of nonbank issuers, the minimum credit score of the loan's originator type $\times$ issuer type $\times$ securitization channel, and interest rates, respectively. Panel d presents estimates and 95% confidence intervals from equation (3) for percent changes in total lending to borrowers with credit scores below 640. Standard errors clustered at the county level. Source: Authors' calculations based on the HMDA data (panel a) and the administrative FHA data (panels b, c, and d).

12 Conclusions and Policy Implications

We find that Chase's exit from FHA aggregation and MBS issuance led to a sharp increase in nonbanks' share of securitization, an easing of credit standards, a rise in interest rates, and an expansion in mortgage originations to lower-credit score borrowers. These findings do not appear to be temporary aspects of a transition to nonbank securitization, but rather are permanent features of an FHA mortgage program intermediated through nonbank MBS issuers. We establish these relationships using a causal identification strategy that preserves equilibrium effects in local markets, and we demonstrate that our findings are robust to a wide variety of confounding factors and other interpretations.

Our findings indicate that while many of the core functions of the mortgage market can be performed by both bank and nonbank firms, these types of firms are not perfect substitutes. Nonbanks' higher cost of funds and greater risk tolerance lead to a somewhat expanded pool of borrowers obtaining mortgages in the FHA market, albeit at a higher price. While other studies have found similar relationships for mortgage originators, we are the first to focus on aggregators and issuers, and we present evidence that this link in the intermediation chain is the more significant determinant of credit supply in FHA lending.

Our findings apply beyond the FHA market. Although aspects of the issuer role are specific to the Ginnie Mae market, aggregators are active in all types of mortgages funded through securitization and generally retain the servicing for the loans that they purchase. As in the FHA market, aggregators of other mortgages assume the liability of the originator, and as servicer may incur costs associated with defaulted loans. In total, nearly 30% of mortgage originations in early 2024 were originated by correspondent lenders and sold to aggregators (Inside Mortgage Finance, 2024), and nonbank aggregators have taken market share from bank aggregators in these other mortgage segments as well. Although mortgage credit availability is generally considered to have remained tight in the aftermath of the GFC (Urban Institute, 2024), our study suggests that credit might have been tighter still without the expansion of nonbank aggregators.

The rise of nonbank aggregators may raise other concerns, in addition to higher interest rates. Aggregators and issuers carry out key functions for the mortgage market, but nonbank firms carry out these functions without the benefit of government liquidity support or resolution tools. As highlighted in Financial Stability Oversight Council (2024), a mortgage market dominated by nonbank firms might be less resilient in the face of certain shocks. The same economic forces — including less regulation and less franchise value — that contribute to nonbanks' willingness to take on credit risk may also make these firms less stable long-term counterparties.

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A Supplemental Material for Section 3 "Data"

A.1 Matching FHA and HMDA data

We match the HMDA data to the FHA data using common fields: origination date, census tract, and loan amount rounded to the nearest thousand. For this match, we only use the first four-digit basic census tract code, ignoring the two-digit suffix. For example, for a census tract with the code of 6059.02, we only use 6059. When examining the quality of the census tract variable in the FHA data, the suffix does not appear to be well populated. Moreover, because HMDA reports loan amounts in thousands during our sample period, we cannot use the exact loan amount for the match. We match about 73% of observations in the FHA data using these three variables. We excluded a small number of loans that are identical in terms of these three variables.

To match additional loans, we use more lenient match criteria for unmatched loans after the first step. First, we match on county, instead of census tract, as well as origination date and loan amount. This additional step results in 5% more loans matched. Second, among unmatched loans after the match on county, we match on origination month, instead of origination date, as well as census tract and loan amount. This additional step results in 8% more loans matched. In the end, 86% of loans in the FHA data are matched to the HMDA originator record after this matching algorithm.

B Supplemental Material for Section 4 "Issuers and Credit Access: Descriptive Analysis"

B.1 Measuring Minimum Credit Score

This section explains how we measure the minimum credit score, which we use to gauge credit standards in Sections 4 and 7. Our approach closely follows Anenberg et al. (2019), which used a frontier estimation methodology to calculate the maximum loan amount given a particular set of underwriting characteristics.

We denote the credit score frontier by $\phi(x) = \sup\{-cs|x\}$, where x is a vector of county, quarter of origination, issuer type (bank or nonbank), originator type (bank or nonbank), and securitization channel (aggregation or integrated origination). This frontier reflects a lender's credit supply decision only to extend loans to borrowers with credit scores above a certain threshold.

Let (CS, X) be random variables from which the data $\{(cs_i, x_i)\}_{i=1}^n$ are drawn, where n refers to the number of observations. Let us define the expected minimum credit score function of order m as

$$\phi_m(x) = E[max\{-CS_1, -CS_2, ..., -CS_m\}|X_1, X_2, ..., X_m = x], \tag{4}$$

where $\{(CS_1, X_1), ..., (CS_m, X_m)\}$ are m independent and identically distributed (i.i.d.) pairs of random variables generated by the distribution of CS given $X = x$. Intuitively, $\phi_m(x)$ is the expected lowest credit score that would be observed out of m draws with borrowers of characteristics of x.

To construct the empirical analog to $\phi_m(x)$, we need to calculate the empirical CDF for $max\{-CS_1, -CS_2, ..., -CS_m\}$, denoted by $P(max\{-CS_1, -CS_2, ..., -CS_m\}|X_1, X_2, ..., X_m = x)$. Note that

$$P(max\{-CS_1, -CS_2, ..., -CS_m\} \leq -cs|X_1, X_2, ..., X_m = x) = P(-CS \leq -cs|X = x)^m. \tag{5}$$

Note that $P(-CS \leq -cs|X = x)$ can be calculated using the m draws as follows:

$$P(-CS \leq -cs|X = x) = \frac{\sum_{i=1}^m 1[-cs_i \leq -cs]}{m}. \tag{6}$$

This estimator approaches the underlying credit standard policy $\phi(x)$ as the number of draw (m) and the number of observations (n) grow large (Anenberg et al., 2019). In practice, we set $m = 1000$ when X.

C Supplemental Material for Section 5 "Identification and Estimation"

C.1 Propensity Score Matching

Throughout the text, we examine estimates based on treatment-propensity matched control groups for robustness to address concerns that bank exit shocks might be correlated with other county-specific factors that also determine nonbank entry and credit supply. To estimate a treatment-propensity score, we run a loan-frequency weighted regression of exposure to Chase's exit on matching variables:

$$S_c = Z_c \delta + \omega_c$$

where S_c is Chase's share as an aggregator of FHA loans in county c over 2012:Q1–2013:Q2. Match characteristics Z_c, shown in Appendix Table A.1, include county-level characteristics about the housing market or the macro economy from Table 2 as well as Chase's pre-exit share as an integrated originator. Matching on Chase's integrated originator share helps isolate the effects of Chase's exit as an issuer from its exit as an originator. We do not match on variables in Table 2 that are outcomes to be studied.

We compute treatment propensities $\hat{S}_c = Z_c \hat{\delta}$, and group counties into 20 equal-sized bins of the treatment-propensity score. Appendix Table A.1 shows that the propensity score accounts for about 9% of variation in Chase's pre-exit aggregator share. We then augment the DID regression specification (2) to have treatment-propensity-bin×quarter fixed effects. Giving each the treatment propensity score bin a separate time trend ensures the estimate is drawn off DIDs within matched groups of counties.

Table A.1: Regression Estimates for Chase's Exit Propensity Score

	(1)
log(Number of FHA Originations)	0.0036***
	(0.0010)
Tract-Level Median Family Income	0.0004***
	(0.0001)
Chase's Share as Integrated-Issuer	0.1292*
	(0.0716)
House Price Growth in 2012	-0.1983***
	(0.0540)
Unemployment Rate in 2012	-0.0015*
	(0.0008)
60+ Day Delinquency Rate in 2012	-0.4565***
	(0.1545)
Forclosure Rate in 2012	0.6499***
	(0.1712)
Constant	0.0603***
	(0.0124)
N. Obs.	2,727
Adj. R^2	0.09

Note: Estimates of the regression of Chase's pre-exit share on matching variables. Source: Authors' calculations based on the HMDA data.

C.2 Weighted averages in the two-way fixed effects regression

The two-way fixed effects DID regression estimator is a weighted average of exposure-level causal effects (Callaway et al., 2021). This weighted average may differ from the population average treatment effect on the treated (ATT). For the regression estimator to be interpreted as an ATT, the distribution of weights in the two-way fixed effects regression must align with the empirical distribution of treatment exposure.

To investigate whether our regression's α is approximating the ATT, following Lewis (2023), we decompose the estimator in terms of average causal responses of the treated $ACRT(s)$ using Theorem 3.4 in Callaway et al. (2021).

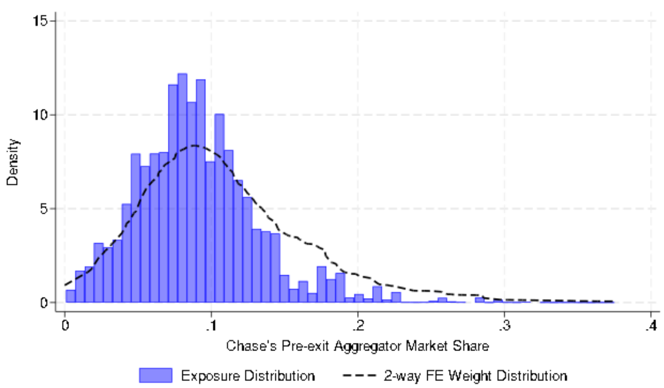
$$\alpha = \int_{s_L}^{s_U} w(s) ACRT(s) ds + w_0 ATT(s_L)/s_L$$

where the weights $w(s)$ and w_0 assigned by the regression are

$$w(s) = \frac{\big(\mathbb{E}(S|S \geq s) - \mathbb{E}(S)\big) \times \mathbb{P}(S \geq s)}{\mathbb{V}(S)} \quad \& \quad w_0 = \frac{\big(\mathbb{E}(S|S > 0) - \mathbb{E}(S)\big) \times \mathbb{P}(S > 0) \times s_L}{\mathbb{V}(S)}$$

The distribution of weights is similar to the empirical distribution of treatment exposure (Figure A.1). This finding suggests that the regression estimator (2) is a close approximation to the population ATT that we want to measure.

Figure A.1: Distributions of Treatment Exposure and Two-way FE Regression Weights

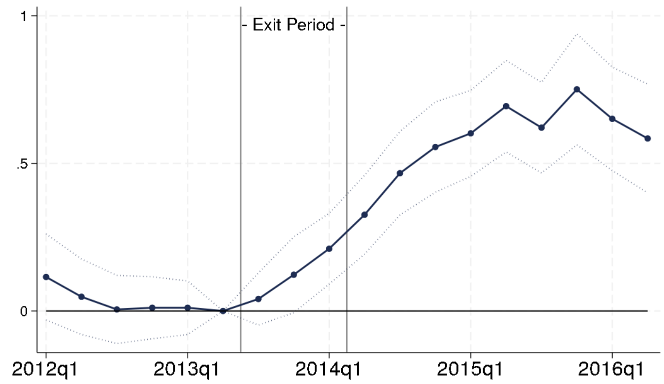


Note: Empirical density of Chase's pre-exit county level market share as an aggregator for treated counties, i.e. excluding zero exposure counties. And the estimated density of two-way fixed effects regression weights for positive exposure counties for the DID regression with continuous treatment exposure, from Callaway et al. (2021). Authors' calculations based on the HMDA data.

D Supplemental Material for Section 6 "Effects on Industrial Organization of the FHA Market"

D.1 Robustness: Propensity Score Matching

Figure A.2: Effects of Chase's Exit on Market Share of Nonbank Issuers (with propensity-score matching)



Note: Estimates and 95% confidence intervals from equation (2) for the effects of a 100 pp decline in Chase's market share on whether a loan is securitized by a nonbank Ginnie Mae issuer. In addition to county fixed effects and quarter fixed effects, these regressions also include the fixed effects for each of the 20 propensity score bin interacted with each quarter. Standard errors clustered at the county level. Source: Authors' calculations based on the HMDA data.

Table A.2: Effects of Bank Exit on Nonbank Ginnie Mae Issuer Market Shares, by Business Model (with propensity-score matching)

	(1) Nonbank issuer (aggregator or integrated originator)	(2) Nonbank aggregator	(3) Nonbank integrated originator
Exit Period ×			
Pre-exit County-level Share (S_c)	0.080	0.093**	-0.013
	(0.050)	(0.040)	(0.038)
Post Exit ×			
Pre-exit County-level Share (S_c)	0.559***	0.465***	0.094*
	(0.068)	(0.064)	(0.052)
Avg. Treatment Effects on Treated	0.051	0.042	0.009
County FE	Y	Y	Y
Quarter FE	Y	Y	Y
N. Obs.	2,858,105	2,858,105	2,858,105
Adj. R^2	0.88	0.78	0.74

Note: Estimates and standard errors from equation (2) for the effects of a 100 pp decline in Chase's market share. In addition to county fixed effects and quarter fixed effects, these regressions also include the fixed effects for each of the 20 propensity score bin interacted with each quarter. Standard errors clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Source: Authors' calculations based on HMDA data.

D.2 Robustness: Originator Fixed Effects

Table A.3: Effects of Bank Exit on Nonbank Ginnie Mae Issuer Market Shares, by Business Model (with originator FE)

	(1) Nonbank issuer (aggregator or integrated originator)	(2) Nonbank aggregator	(3) Nonbank integrated originator
Exit Period ×			
Pre-exit County-level Share (S_c)	0.060	0.021	0.039
	(0.055)	(0.037)	(0.036)
Post Exit ×			
Pre-exit County-level Share (S_c)	0.551***	0.394***	0.156***
	(0.073)	(0.064)	(0.046)
Avg. Treatment Effects on Treated	0.050	0.036	0.014
County FE	Y	Y	Y
Quarter FE	Y	Y	Y
Originator FE	Y	Y	Y
N. Obs.	2,018,066	2,018,066	2,018,066
Adj. R^2	0.54	0.39	0.71

Note: Estimates and standard errors from equation (2) for the effects of a 100 pp decline in Chase's market share. In addition to county fixed effects and quarter fixed effects, these regressions also include originator fixed effects. Standard errors clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Source: Authors' calculations based on HMDA data.

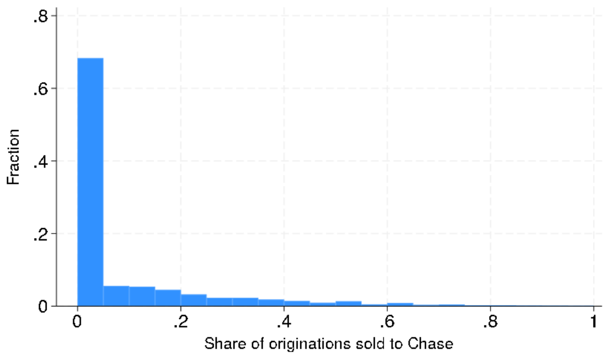
D.3 Retail Originator's Response Using Originator-Level Variation

As an alternative to the main regression specification using county-level variation, we examine how retail originators responded to Chase's exit using originator-level exposure to Chase as the identifying variation. Chase relied heavily on purchases from unaffiliated correspondent lenders to source FHA loans to deliver into Ginnie Mae MBS. About 85% of FHA loans that Chase securitized in 2012 were purchased from correspondent lenders. Thus, Chase's exit likely had substantial effects on the retail originators that typically sold large shares of their originations to Chase.

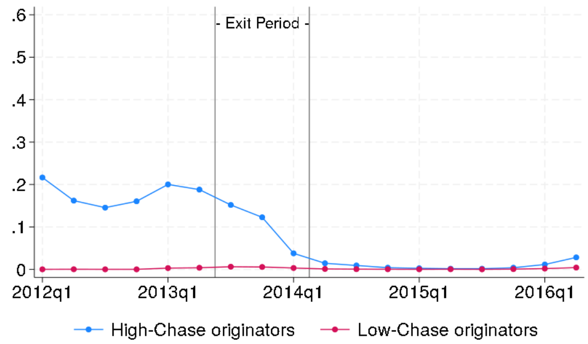
Originators that previously sold loans to Chase had two main options for how to respond to its exit. First, they could sell loans to another bank or nonbank aggregator. Second, they could securitize their own originations directly into Ginnie Mae MBS. Some originators might need to become Ginnie Mae issuers in order to take advantage of this option.

We examine originators' responses using variation across originators in the share of originations that they sold to Chase pre-exit, using the confidential HMDA data with matched loan origination and purchase records. As with the county-level variation used in our main results, the originator-level variation appears to be sufficient to estimate the effects of Chase's exit on the structure of the mortgage market. Figure A.3(a) shows that there is wide variation in pre-exit exposure to Chase across originators. Figure A.3(b) shows that the Chase share evolved largely in a parallel way for originators that sold large and small shares of their originations to Chase before its exit. After Chase's exit, the market shares declined gradually to near zero for both groups.

Figure A.3: Variation in Exposure to Chase's Exit



(a) Cross-Originator Variation



(b) Chase's originator-level share

Note: Panel (a) presents the distribution of Chase shares in 2012 as purchasers of FHA purchase originations across retail originators. Panel (b)displays unconditional averages of shares of loans sold to Chase at the originator level, respectively. high-Chase originators are originators with shares of their originations sold to Chase in 2012 above the median (0.2%). Source: Authors' calculations based on HMDA-Originator-Issuer data.

D.3.1 Decision to Whether and Who to Sell Loans

We first examine retail originators' decisions about whether and to whom to sell loans. We estimate loan-level equation (7):

$$y_{ijt} = \sum_{\tau=t^*-6}^{t^*+11} \beta_\tau H_j 1[\tau = t] + \delta_j + \delta_t + \epsilon_{ijt} \tag{7}$$

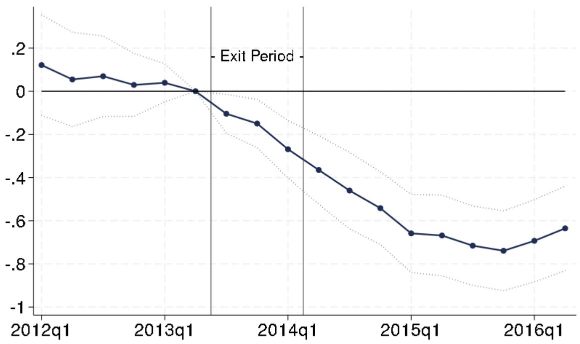
An originator j's treatment exposure is H_j, the share of loans originated by retail originator j that were sold to Chase in 2012. We calculate this exposure variable using the HMDA-Originator-Issuer data. The DID estimates are β_t. The regression includes fixed effects for originators (δ_j) and for quarters (δ_t). Because our goal is to study the effects of Chase's exit on unaffiliated originators, we exclude Chase as an originator from the sample in a regression examining the effects of Chase's on originators.[4]

[4]Prior to the exit, Chase had some market share in the origination market because some of the loans they securitized came from Chase's retail channel.

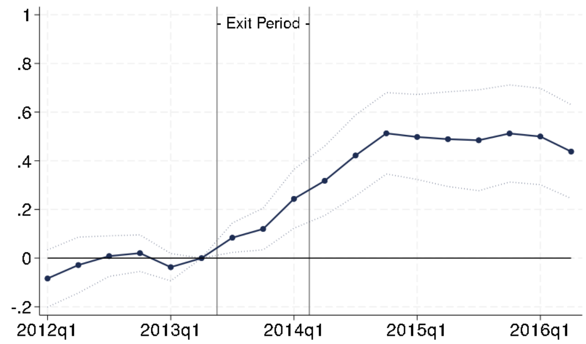
We begin showing the change in originator-aggregator relationships after Chase's exit by examining whether a loan is sold to a bank aggregator. Figure A.4(a) shows that about 70% of originations that previously were sold to Chase were not sold to another bank aggregator in 2015 and 2016. This decline is mainly driven by the exit of Chase. The fact that the estimate did not reach -100% implies that about 30% of loans that were previously sold to Chase were sold to another bank aggregator. This result is consistent with the increase in the county-level market share of nonbank issuers shown in Figure 5.

Figures A.4(b) and A.4(c) show which options retail originators took as an alternative to selling loans to bank aggregators. If not selling to bank aggregators, originators can either sell loans to nonbank aggregators or securitize their originations as issuers. The figure shows that both the share of loans sold to nonbank originators and the share of loans securitized by originators (as integrated originators) increased after the both exits, although the most common response was to switch to selling to a nonbank aggregator after Chase's exit. This result is consistent with the growth of county-level shares of both nonbank aggregators and nonbank integrated originators in Table 3.

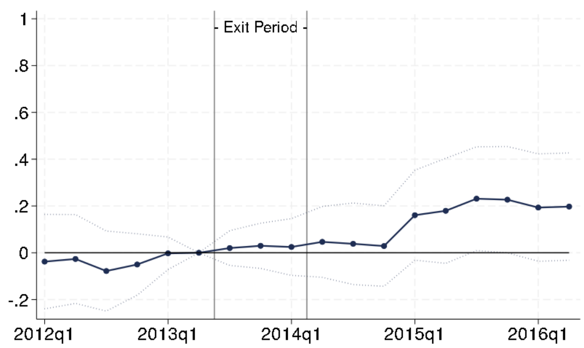
Figure A.4: Effects on Whether a Loan Is Sold to Bank Aggregators



(a) Bank aggregator



(b) Nonbank aggregator



(c) Share of loans securitized by originators

Note: Estimates and 95% confidence intervals from equation (7) for the effects of a 100 pp decline in exiting-bank market share on whether a loan is sold to a bank aggregator (panel a), whether a loan is sold to a nonbank aggregator (panel b), and whether a loan is securitized directly by the originator (panel c). Standard errors clustered at the originator level. Source: Authors' calculations based on the HMDA-Originator-Issuer data.

D.3.2 Decision to Become a Ginnie Mae Issuer

In this section, we show that originators with greater exposure to Chase were more likely to become Ginnie Mae issuers. This result suggests that the increased share of loans securitized by originators is in part because more originators became Ginnie Mae issuers.

Because we examine a originator-level decision, we use the originator-level regression of the following form, which is similar to Equation (7).

$$y_{jt} = \sum_{\tau=t^*-6}^{t^*+11} \beta_\tau H_j 1[\tau = t] + \delta_j + \delta_t + \epsilon_{jt} \tag{8}$$

Note that we do not have a subscript i for each loan in this regression.

Table A.4 shows that although Chase's exit did not have statistically significant effects for the average originator (column 1), larger originators that relied more on Chase were more likely to become Ginnie Mae issuers after Chase's exit (column 2).

Table A.4: Effects on whether a retail originator is a Ginnie Mae issuer

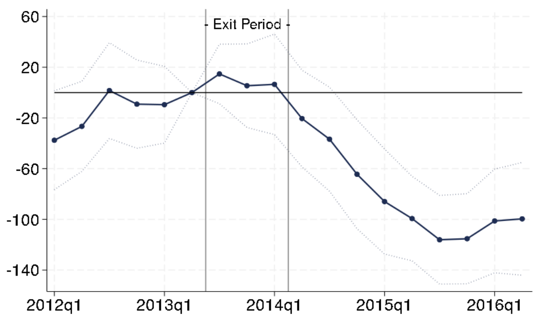
	(1)	(2)
$1[t^* \leq t \leq t^* + 5\ ] \times$ Pre-exit Originator-level Share (H_{jt})	-0.018	-0.005
	(0.027)	(0.023)
$1[t^* \leq t \leq t^* + 5\ ] \times$ Pre-exit Originator-level Share (H_{jt}) $\times$ Large originator		-0.017
		(0.063)
$1[t^* + 6 \leq t \leq t^* + 11\ ] \times$ Pre-exit Originator-level Share (H_{jt})	0.037	-0.053
	(0.051)	(0.039)
$1[t^* + 6 \leq t \leq t^* + 11\ ] \times$ Pre-exit Originator-level Share (H_{jt}) $\times$ Large originator		0.253**
		(0.115)
Lender FE	Y	Y
Quarter FE	Y	Y
N. Obs.	11,885	11,885
Adj. R^2	0.79	0.80

Note: Estimates and standard errors from equation (8) for the effects of a 100 pp decline in exiting-bank market share on whether a lender is a Ginnie Mae issuer in a particular quarter. An originator is defined as large if its origination volume is above the median in 2012. Standard errors clustered at the originator level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Source: Authors' calculations based on the HMDA-Originator-Issuer data.

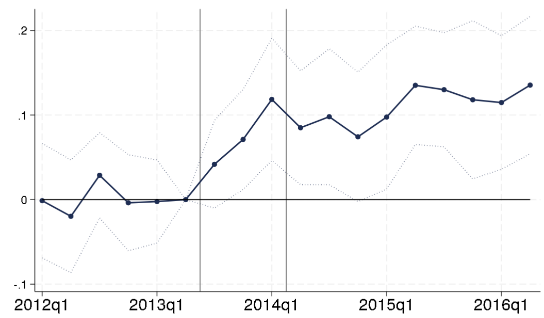
E Supplemental Material for Section 7 "Easing of Credit Standards"

E.1 Robustness: Propensity Score Matching

Figure A.5: Effects on Credit Standards (with propensity-score matching)



(a) Minimum Credit Score



(b) Credit Score ≤ 640

Note: Estimates and 95% confidence intervals from equation (2) for the effects of a 100 pp decline in exiting-bank market share on outcome variables for credit standards. Panel (a) presents the estimates for the minimum credit score for each combination of issuer type (bank or nonbank), originator type (bank or nonbank), origination channel type (correspondent origination or integrated origination), county, and quarter. Panel (b) presents the estimates for the minimum credit score for each county and quarter. Panels (c) and (d) present the effects on average credit scores and whether the borrower's credit score is below 660, respectively. Standard errors clustered at the county level. Source: Authors' calculations based on administrative FHA data.

Table A.5: Effects of Chase's Exit on Credit Risk Measures (with propensity score)

	(1) Min. CS	(2) 1[CS < 640]	(3) Average CS	(4) LTV	(5) DTI	(6) Ever 60+ DQ	(7) Ever 60+ DQ
Exit Period ×							
Pre-exit County-level Share (S_c)	12.385	0.071***	-2.893	0.110	1.038*	0.011	-0.000
	(13.706)	(0.020)	(2.683)	(0.276)	(0.553)	(0.015)	(0.014)
Post Exit ×							
Pre-exit County-level Share (S_c)	-90.380***	0.114***	-4.349	0.627*	0.816	0.058**	0.044*
	(16.457)	(0.031)	(3.237)	(0.321)	(0.594)	(0.025)	(0.023)
Avg. Treatment Effects on Treated	-8.171	0.010	-0.393	0.057	0.074	0.005	0.004
County FE	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y
Loan-level controls							Y
N. Obs.	1,202,341	2,681,376	2,681,376	2,681,376	2,681,376	2,681,376	2,681,376
Adj. R^2	0.31	0.02	0.03	0.02	0.04	0.01	0.06

Note: Estimates and standard errors from regression (2) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in Chase's market share. In addition to county fixed effects and quarter fixed effects, these regressions also include the fixed effects for each of the 20 propensity score bin interacted with each quarter. Loan-level controls in column 7 include log loan size, an indicator for first time homebuyers, and indicator variables defining 11 bins of credit scores, 7 bins of loan-to-value ratios, and 6 bins of debt-to-income ratios. Standard errors in parenthesis, clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Authors' calculations based on the HMDA-FHA matched sample (column 1) and FHA administrative data (columns 2-7).

E.2 Robustness: Originator Fixed Effects

Table A.6: Effects of Chase's Exit on Credit Risk Measures (controlling for originator fixed effects)

	(1) Min. CS	(2) 1[CS < 640]	(3) Average CS	(4) LTV	(5) DTI	(6) Ever 60+ DQ	(7) Ever 60+ DQ
Exit Period ×							
Pre-exit County-level Share (S_c)	13.323	0.086***	-8.820***	0.045	1.866***	0.006	-0.013
	(15.433)	(0.018)	(2.760)	(0.275)	(0.526)	(0.016)	(0.015)
Post Exit ×							
Pre-exit County-level Share (S_c)	-70.298***	0.080***	-8.496***	0.257	1.819***	0.073***	0.057***
	(17.074)	(0.025)	(3.064)	(0.337)	(0.594)	(0.024)	(0.022)
Avg. Treatment Effects on Treated	-6.356	0.007	-0.768	0.023	0.164	0.007	0.005
County FE	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y
Originator FE	Y	Y	Y	Y	Y	Y	Y
Loan-level controls							Y
N. Obs.	1,203,203	2,400,945	2,400,945	2,400,945	2,400,945	2,400,945	2,400,945
Adj. R^2	0.49	0.08	0.07	0.02	0.06	0.02	0.06

Note: Estimates and standard errors from regression (2) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in Chase's market share. In addition to county fixed effects and quarter fixed effects, these regressions also include originator fixed effects. Loan-level controls in column 7 include log loan size, an indicator for first time homebuyers, and indicator variables defining 11 bins of credit scores, 7 bins of loan-to-value ratios, and 6 bins of debt-to-income ratios. Standard errors in parenthesis, clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Authors' calculations based on the matched FHA-HMDA-Originator sample.

E.3 Controlling for Integrated Originators

Table A.7: Effects of Chase's Exit on Credit Risk Measures (controlling for integrated originators)

	(1) Min. CS	(2) 1[CS < 640]	(3) Average CS	(4) LTV	(5) DTI	(6) Ever 60+ DQ	(7) Ever 60+ DQ
Exit Period ×							
Pre-exit County-level Share (S_c)	3.279	0.112***	-11.077***	0.063	1.575***	0.015	-0.008
	(15.486)	(0.020)	(3.060)	(0.279)	(0.555)	(0.016)	(0.015)
Post Exit ×							
Pre-exit County-level Share (S_c)	-72.490***	0.131***	-13.030***	0.268	1.694***	0.091***	0.066***
	(16.690)	(0.028)	(3.606)	(0.344)	(0.622)	(0.025)	(0.023)
Integrated Issuer	-24.500***	0.098***	-7.158***	-0.246***	-0.471***	-0.005***	-0.016***
	(0.436)	(0.002)	(0.163)	(0.014)	(0.032)	(0.001)	(0.001)
Avg. Treatment Effects on Treated	-6.554	0.012	-1.178	0.024	0.153	0.008	0.006
County FE	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y
Loan-level controls							Y
N. Obs.	1,203,288	2,275,834	2,275,834	2,275,834	2,275,834	2,275,834	2,275,834
Adj. R^2	0.55	0.04	0.04	0.01	0.04	0.01	0.06

Note: Estimates and standard errors from regression (2) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in Chase's market share. In addition to county fixed effects and quarter fixed effects, these regressions also include a dummy variable that equals to one if an issuer is an integrated issuer. Loan-level controls in column 7 include log loan size, an indicator for first time homebuyers, and indicator variables defining 11 bins of credit scores, 7 bins of loan-to-value ratios, and 6 bins of debt-to-income ratios. Standard errors in parenthesis, clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Authors' calculations based on the matched FHA-HMDA-Originator-Aggregator sample.

E.4 Issuer Equilibrium Responses

Table A.8: Effects of Chase's Exit on Credit Risk Measures (issuer subsample)

	Bank Issuer Subsample				Nonbank Issuer Subsample			
	(1) Min. CS	(2) Min. CS	(3) 1[CS < 640]	(4) 1[CS < 640]	(5) Min. CS	(6) Min. CS	(7) 1[CS < 640]	(8) 1[CS < 640]
Exit Period ×								
Pre-exit County-level Share (S_c)	14.346	5.562	0.054**	0.075***	18.522	9.216	0.070	-0.013
	(14.754)	(14.460)	(0.024)	(0.022)	(43.275)	(42.737)	(0.055)	(0.045)
Post Exit ×								
Pre-exit County-level Share (S_c)	26.589	12.954	-0.005	0.023	-63.432	-80.595**	0.008	-0.080*
	(20.637)	(19.644)	(0.027)	(0.024)	(40.925)	(37.027)	(0.056)	(0.048)
Avg. Treatment Effects on Treated	2.404	1.171	-0.000	0.002	-5.735	-7.287	0.001	-0.007
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
Issuer FE		Y		Y		Y		Y
N. Obs.	508,602	508,593	886,693	886,682	463,894	463,889	699,378	699,372
Adj. R^2	0.26	0.37	0.01	0.05	0.19	0.33	0.02	0.11

Note: Estimates and standard errors from regression (2) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in Chase's market share on interest rates at loan origination. Columns 1–4 report results using the subsample of bank issuers, excluding loans securitized by Chase, and columns 5–8 report results using the subsample of nonbank issuers. In all regressions, we also restricted the subsamples to incumbent issuers who operated in a county before and after Chase's exit. Columns 2, 4, 6, and 8 include issuer fixed effects in additional to county fixed effects and quarter fixed effects. Standard errors in parenthesis, clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Authors' calculations based on the matched FHA-HMDA-Originator-Aggregator sample.

F Supplemental Material for Section 8 “Increased Cost of Credit”

F.1 Measuring Short-term Funding Cost

This appendix provides details on the short-term funding cost outcome discussed in Section 8. To measure the MBS issuer’s short-term funding cost, we start with the matched HMDA-FHA sample to observe the identity of each issuer. For nonbanks, in the Mortgage Call Report (MCR) we observe each Ginnie Mae MBS issuer’s quarterly total warehouse credit expense and total dollar volume of issued loans. For banks, we do not directly observe their MBS business short-term funding cost, and instead take a proxy measure based on observed quarterly deposit interest expense from bank Call Reports and an assumption that the time to securitization is approximately one month. These sources together provide each issuer’s funding cost per dollar of lending. To convert these funding costs into the corresponding effect on mortgage interest rates, assuming that issuers pass the cost through fully to borrowers, we divide our funding cost measure by 4.4.[5]

F.2 Robustness: Propensity Score Matching

Figure A.6: Effects of Chase’s Exit on Interest Rates and Funding Costs (with propensity-score matching)

(a) Mortgage Interest Rate

(b) Funding Cost per Loan

Note: Estimates and 95% confidence intervals from equation (2) for the effects of a 100 pp decline in Chase’s market share on interest rates at loan origination (panel a) and issuer funding cost for each loan (panel b). Both regressions include loan-level controls for: log loan size, indicator variables for 11 bins of credit scores, indicator variables for 7 bins of loan-to-value ratios, indicator variables for 6 bins of debt-to-income ratios, and an indicator for first time homebuyers. Panel a is calculated from the FHA administrative data. Panel b is from the matched FHA-HMDA-Originator-Aggregator subsample with NMLS or bank call report data. Funding costs per loan are converted into their estimated effect on mortgage interest rates. Standard errors clustered at the county level.

[5] The normalization by 4.4 is based on a back-of-envelope calculation using the estimate from Huh and Kim (2021) in which a 100 bps change in MBS price is associated with 100/4.4 bps difference in mortgage rates in a sample period similar to ours. Our normalization is in line with the industry approximation that a 1 pp increase in mortgage points is equivalent to a 0.2 percentage point increase in mortgage interest rates (Bartlett et al., 2022).

Table A.9: Effects of Chase's Exit on Cost of Credit (with propensity-score matching)

	Mortgage Interest Rate				Funding Cost Per Loan
	(1) Full Sample	(2) CS < 640	(3) 640 ≤ CS < 680	(4) CS ≥ 680	(5)
Exit Period ×					
Pre-exit County-level Share (S_c)	0.083	0.115	0.152***	0.015	0.005
	(0.055)	(0.084)	(0.054)	(0.062)	(0.008)
Post Exit ×					
Pre-exit County-level Share (S_c)	0.143**	0.203**	0.170***	0.092	0.062***
	(0.062)	(0.091)	(0.065)	(0.069)	(0.008)
Avg. Treatment Effects on Treated	0.013	0.018	0.015	0.008	0.006
County FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y
Loan-level controls	Y	Y	Y	Y	Y
N. Obs.	2,681,376	369,352	1,049,752	1,262,176	1,975,139
Adj. R^2	0.50	0.36	0.48	0.50	0.07

Note: Estimates and standard errors from regression (2) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in Chase's market share on interest rates at loan origination (columns 1–4) and issuer funding cost for each loan (column 5). In addition to county fixed effects and quarter fixed effects, these regressions also include the fixed effects for each of the 20 propensity score bin interacted with each quarter. Columns 2, 3, and 4 present regression results using the subsample of borrowers with credit scores below 640, between 640 and 680, and at least 680, respectively. All regressions include loan-level controls for: log loan size, indicator variables for 11 bins of credit scores, indicator variables for 7 bins of loan-to-value ratios, indicator variables for 6 bins of debt-to-income ratios, and an indicator for first time homebuyers. Columns 1–4 are calculated from the FHA administrative data. Column 5 is from the matched FHA-HMDA-Originator-Aggregator sample with NMLS or bank call report data. Standard errors in parenthesis, clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

F.3 Robustness: Originator Fixed Effects

Table A.10: Effects of Chase's Exit on Mortgage interest rates (controlling for originator fixed effects)

	Mortgage Interest Rate				Funding Cost Per Loan
	(1) Full Sample	(2) CS < 640	(3) 640 ≤ CS < 680	(4) CS ≥ 680	(5)
Exit Period ×					
Pre-exit County-level Share (S_c)	0.059	0.145*	0.125**	-0.011	0.007
	(0.056)	(0.076)	(0.057)	(0.061)	(0.008)
Post Exit ×					
Pre-exit County-level Share (S_c)	0.168***	0.246***	0.211***	0.135**	0.061***
	(0.064)	(0.067)	(0.067)	(0.068)	(0.007)
Avg. Treatment Effects on Treated	0.015	0.022	0.019	0.012	0.006
County FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y
Originator FE	Y	Y	Y	Y	Y
Loan-level controls	Y	Y	Y	Y	Y
N. Obs.	2,400,945	330,054	938,454	1,132,059	1,977,526
Adj. R^2	0.46	0.49	0.44	0.41	0.38

Note: Estimates and standard errors from regression (2) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in Chase's market share on interest rates at loan origination (columns 1–4) and issuer funding cost for each loan (column 5). In addition to county fixed effects and quarter fixed effects, these regressions also include originator fixed effects. Columns 2, 3, and 4 present regression results using the subsample of borrowers with credit scores below 640, between 640 and 680, and at least 680, respectively. All regressions include loan-level controls for: log loan size, indicator variables for 11 bins of credit scores, indicator variables for 7 bins of loan-to-value ratios, indicator variables for 6 bins of debt-to-income ratios, and an indicator for first time homebuyers. Columns 1–4 are calculated from the matched FHA-HMDA-Originator-Aggregator sample. Column 5 is from the matched FHA-HMDA-Originator-Aggregator sample with NMLS or bank call report data. Standard errors in parenthesis, clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

F.4 Controlling for the Integrated Originator Channel

Table A.11: Effects of Chase's Exit on Cost of Credit (controlling for integrated issuers)

	Mortgage Interest Rate				Funding Cost Per Loan
	(1)	(2)	(3)	(4)	(5)
	Full Sample	CS < 640	640 $\leq$ CS < 680	CS $\geq$ 680	
Exit Period $\times$					
Pre-exit County-level Share (S_c)	0.066	0.181**	0.129**	-0.004	0.008
	(0.059)	(0.089)	(0.059)	(0.064)	(0.009)
Post Exit $\times$					
Pre-exit County-level Share (S_c)	0.196***	0.297***	0.228***	0.147**	0.069***
	(0.068)	(0.094)	(0.071)	(0.073)	(0.009)
Integrated Issuer	-0.062***	-0.098***	-0.068***	-0.049***	0.002**
	(0.005)	(0.006)	(0.005)	(0.005)	(0.001)
Avg. Treatment Effects on Treated	0.018	0.027	0.021	0.013	0.006
County FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y
Loan-level controls	Y	Y	Y	Y	Y
N. Obs.	2,275,834	313,065	889,778	1,072,839	1,892,790
Adj. R^2	0.38	0.28	0.36	0.34	0.06

Note: Estimates and standard errors from regression (2) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in Chase's market share on interest rates at loan origination (columns 1–4) and issuer funding cost for each loan (column 5). In addition to county fixed effects and quarter fixed effects, these regressions also include the dummy variable that equals to one if an issuer is an integrated issuer. Columns 2, 3, and 4 present regression results using the subsample of borrowers with credit scores below 640, between 640 and 680, and at least 680, respectively. All regressions include loan-level controls for: log loan size, indicator variables for 11 bins of credit scores, indicator variables for 7 bins of loan-to-value ratios, indicator variables for 6 bins of debt-to-income ratios, and an indicator for first time homebuyers. Columns 1–4 are calculated from the matched FHA-HMDA-Originator-Aggregator sample. Column 5 is from the matched FHA-HMDA-Originator-Aggregator sample with NMLS or bank call report data. Standard errors in parenthesis, clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

F.5 Issuer Equilibrium Response

Table A.12: Effects of Chase's Exit on Mortgage Interest Rates (subsamples for bank and nonbank issuers)

	Bank Issuer Subsample		Nonbank Issuer Subsample	
	(1)	(2)	(3)	(4)
Exit Period ×				
Pre-exit County-level Share (S_c)	0.095	0.075	0.113*	0.031
	(0.084)	(0.079)	(0.068)	(0.074)
Post Exit ×				
Pre-exit County-level Share (S_c)	0.223**	0.196*	0.172**	0.062
	(0.114)	(0.103)	(0.082)	(0.096)
Avg. Treatment Effects on Treated	0.020	0.018	0.016	0.006
County FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Loan-level controls	Y	Y	Y	Y
Issuer FE		Y		Y
N. Obs.	886,693	886,682	699,378	699,372
Adj. R^2	0.39	0.43	0.40	0.45

Note: Estimates and standard errors from regression (2) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in exiting-bank market share on interest rates at loan origination. Columns 1 and 2 report results using the subsample of bank issuers, excluding loans securitized by Chase, and columns 3 and 4 report results using the subsample of nonbank issuers. Columns 2 and 4 include issuer fixed effects in additional to county fixed effects and quarter fixed effects. In all regressions, we also restricted the subsamples to incumbent issuers who operated in a county before and after Chase's exit. All regressions include loan-level controls for: log loan size, indicator variables for 11 bins of credit scores, indicator variables for 7 bins of loan-to-value ratios, indicator variables for 6 bins of debt-to-income ratios, and an indicator for first time homebuyers. Standard errors in parenthesis, clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Authors' calculations based on the matched FHA-HMDA-Originator-Aggregator sample.

F.6 Discount Points

Table A.13: Effects of Chase's Exit on Discount Points

	(1) Discount Point	(2) Mortgage Rate	(3) Mortgage Rate
Exit Period ×			
Pre-exit County-level Share (S_c)	0.548*	0.216***	0.249***
	(0.326)	(0.070)	(0.070)
Post Exit ×			
Pre-exit County-level Share (S_c)	0.755*	0.331***	0.389***
	(0.410)	(0.098)	(0.101)
Discount Points			-0.040***
			(0.005)
Avg. Treatment Effects on Treated	0.068	0.030	0.035
County FE	Y	Y	Y
Quarter FE	Y	Y	Y
Loan-level controls	Y	Y	Y
N. Obs.	564,586	569,931	564,586
Adj. R^2	0.14	0.39	0.43

Note: Estimates and standard errors from regression (2) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in Chase's market share on discount points (column 1) and mortgage rates (columns 2 and 3). All regressions include loan-level controls for: log loan size, indicator variables for 11 bins of credit scores, indicator variables for 7 bins of loan-to-value ratios, indicator variables for 6 bins of debt-to-income ratios, and an indicator for first time homebuyers. Standard errors in parenthesis, clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Source: authors' calculation using Optimal Blue from 2013 to 2016.

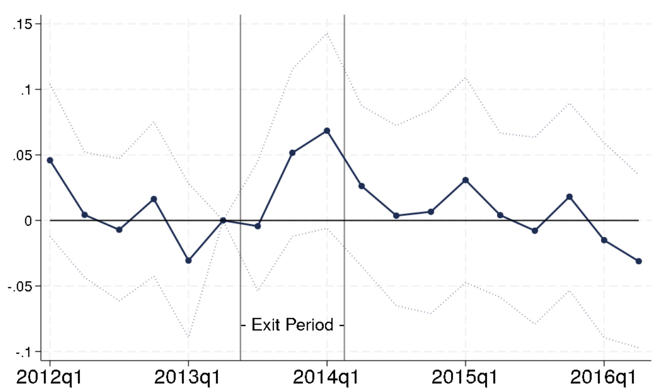
G Supplemental Material for Section 9 "Lending Quantity"

Table A.14: Effects of Chase's Exit on FHA + GSE Quantity

	Without Propensity Score				With Propensity Score			
	(1) Total Loans	(2) CS < 640	(3) 640 ≤ CS < 680	(4) CS ≥ 680	(5) Total Loans	(6) CS < 640	(7) 640 ≤ CS < 680	(8) CS ≥ 680
Exit Period ×								
Pre-exit County-level Share (S_c)	0.035	0.480***	0.056	-0.038	0.161	0.413***	0.212*	0.107
	(0.116)	(0.157)	(0.116)	(0.142)	(0.116)	(0.155)	(0.122)	(0.139)
Post Exit ×								
Pre-exit County-level Share (S_c)	-0.068	0.951***	-0.148	-0.194	0.097	0.738**	0.038	-0.010
	(0.194)	(0.318)	(0.201)	(0.202)	(0.188)	(0.305)	(0.201)	(0.193)
Avg. Treatment Effects on Treated	-0.006	0.086	-0.013	-0.018	0.009	0.067	0.003	-0.001
Zip3 FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N. Obs.	14,400	14,135	14,261	14,400	14,274	14,108	14,184	14,274
Adj. R^2	0.37	0.53	0.21	0.31	0.69	0.73	0.47	0.64

Note: Estimates and 95% confidence intervals from equation (3) for the effects of a 100 pp decline in Chase's market share on the percentage change in the combined number of originations of FHA loans and the subset of GSE loans that were below the FHA conforming loan limit and that had at least 95% loan-to-value. These regressions use the treatment exposure and geographic fixed effects at the 3-digit zip code level to accommodate the available GSE data. In addition to 3-digit zip code fixed effects and quarter fixed effects, columns 5–8 include the fixed effects for each of the 20 propensity score bin interacted with each quarter. Standard errors in parenthesis clustered at the 3-digit zip code level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Source: Authors' calculations based on the FHA administrative data, Freddie Mac Single-Family Loan-Level Dataset, and Fannie Mae Single-Family Loan Performance Data.

Figure A.7: Effects of Chase's Exit on FHA Application Acceptance

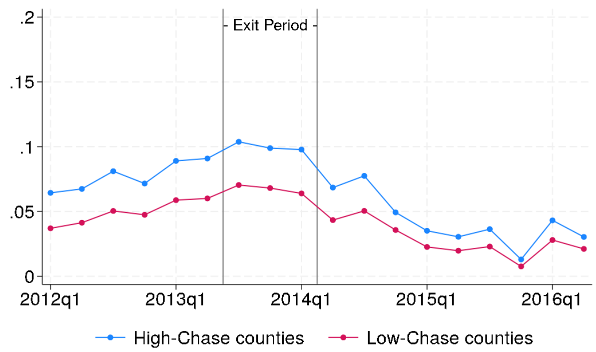


Note: Estimates and 95% confidence intervals from equation (2) for the effects of a 100 pp decline in Chase's market share on FHA application acceptance in the HMDA data. Standard errors clustered at the county level.

H Supplemental Material for Section 10 "Alternative Explanations"

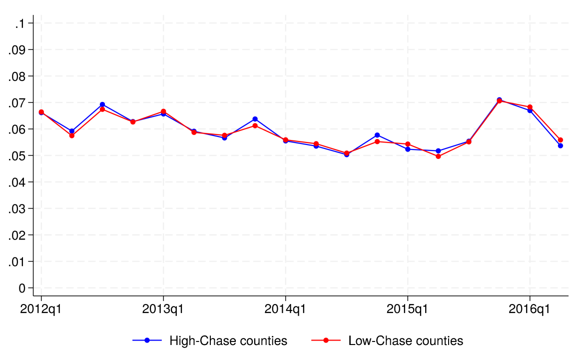
H.1 Chase's Market Share of Other Credit Markets

Figure A.8: Chase's County-level Market Shares of GSE Loan Securitization by FHA Exit Exposure

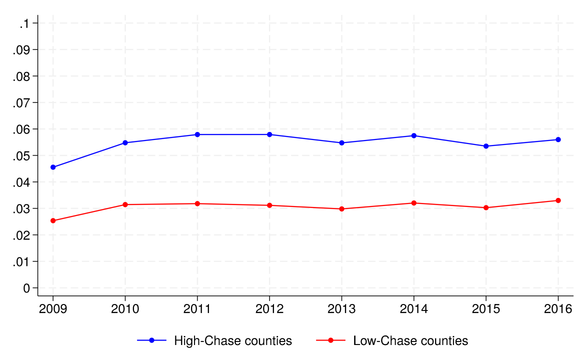


Note: This figure displays conditional averages of Chase's county-level market shares in GSE loan securitization over time around Chase's exit from FHA lending. High-Chase counties are counties where Chase pre-exit market shares were above the distribution median (8.2%). Source: Authors' calculations based on HMDA data.

Figure A.9: Chase's Auto and Small Business Lending County-level Market Shares by FHA Exit Exposure



(a) Chase's Auto Loan Market Share

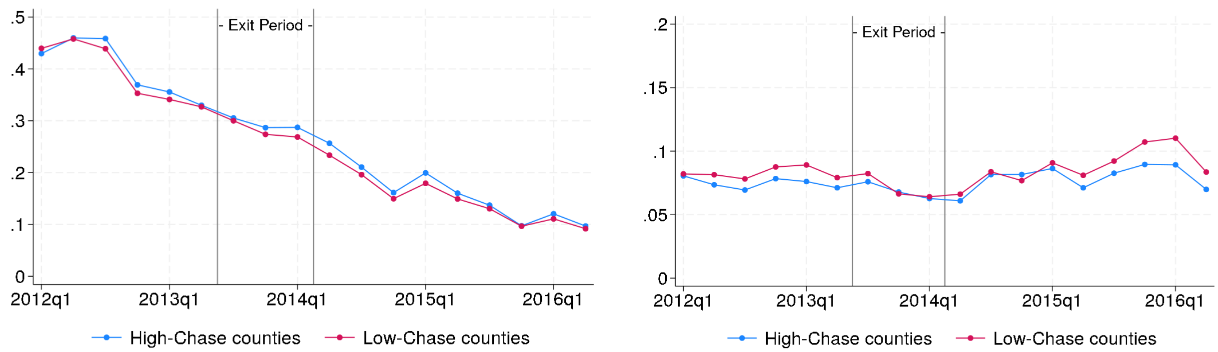


(b) Chase's Small Business Lending Market Share

Note: Panels (a) and (b) display conditional averages of Chase's county-level market shares in auto lending and small business lending, respectively, over time around Chase's exit from FHA lending. High-Chase counties are counties where Chase pre-exit market shares were above the distribution median (8.2%). Source: Authors' calculations based on Polk (auto) and Community Reinvestment Act (small business lending) data.

H.2 FHA Market Share of Other Bank Issuers around Chase's Exit

Figure A.10: FHA Issuer Market Share of Wells Fargo and US Bank by Counties with High and Low Exposure to Chase's Exit



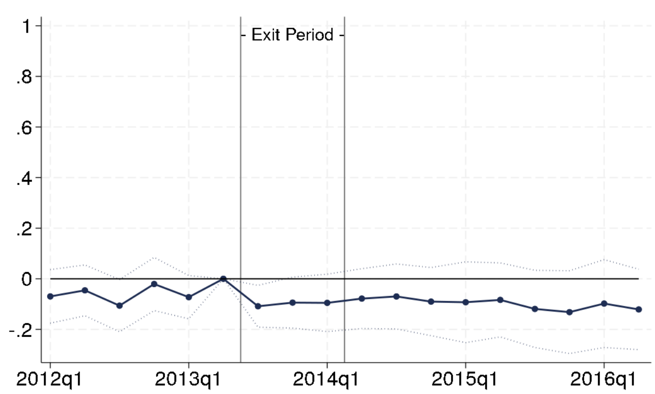
(a) Wells Fargo's Market Share

(b) US Bank's Market Share

Note: Panels (a) and (b) display conditional averages of Wells Fargo's and US Bank's pre-exit county issuer market shares over time, respectively. High-Chase counties are counties where Chase pre-exit market shareswere above the distribution median (8.2%). Source: Authors' calculations based on HMDA data.

H.3 Changes in Nonbank Originator Share around Chase's Exit

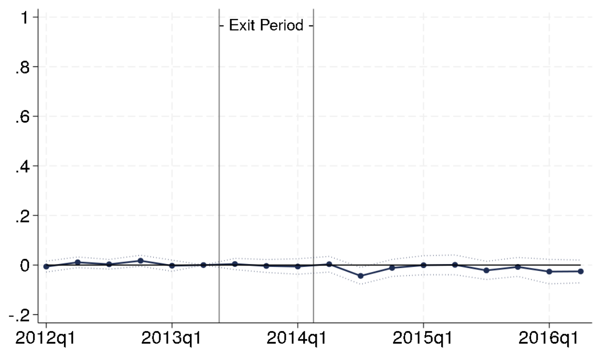
Figure A.11: Effects on Nonbank Originator Share



Note: Estimates and standard errors from equation (2) for the effects of a 100 pp decline in Chase's market share on nonbank originators' market shares. Standard errors clustered at the county level. Source: Authors' calculations based on HMDA data.

H.4 Fintech Market Share around Chase's Exit

Figure A.12: Effects on Market Share of Fintech Issuers



Note: Estimates and standard errors from equation (2) for the effects of a 100 pp decline in Chase's market share on market shares of fintech issuers. Standard errors clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Source: Authors' calculations based on HMDA data.

H.5 Market Concentration

Table A.15: Effects of Bank Exit on HHI

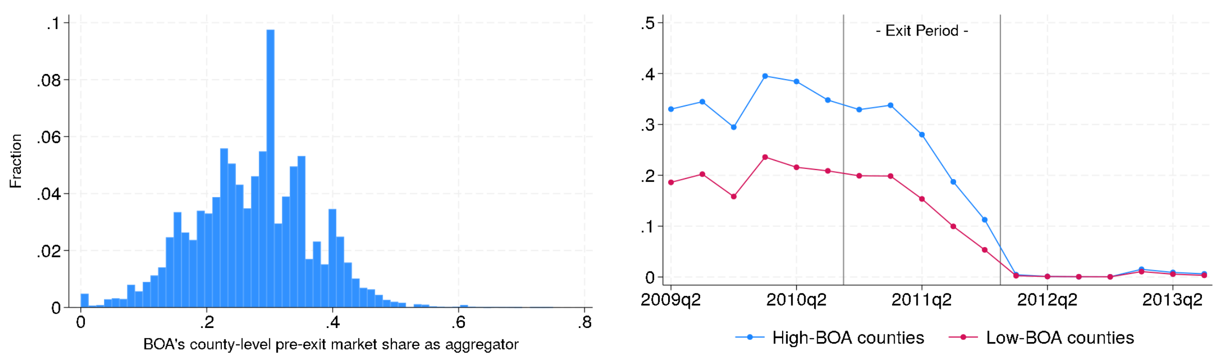
	Without Propensity Score		With Propensity Score	
	(1) Issuer HHI	(2) Originator HHI	(3) Issuer HHI	(4) Originator HHI
Exit Period ×				
Pre-exit County-level Share (S_c)	-141.298	-15.882	19.851	90.825
	(283.484)	(144.710)	(284.298)	(163.646)
Post Exit ×				
Pre-exit County-level Share (S_c)	-2.470	627.687***	-177.350	384.348
	(336.833)	(209.312)	(348.989)	(234.527)
Avg. Treatment Effects on Treated	-0.223	56.749	-16.034	34.749
County FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
N. Obs.	48,651	47,600	44,863	44,086
Adj. R^2	0.73	0.78	0.72	0.77

Note: Estimates and standard errors from equation (2) for the effects of a 100 pp decline in Chase's market share. The Herfindahl–Hirschman Index (HHI) is the sum of squared county-quarter market shares. Standard errors clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Source: Authors' calculations based on the HMDA data.

I Supplemental Material for Section 11 "Bank of America's Exit from FHA Lending"

Bank of America's (BOA) exit from the FHA market also lends itself to our identification strategy. There was significant geographic variation in the impact of the exit shock (Figure A.13(a)). The evolution of BOA market shares over time for counties with smaller and larger exposures also show similar trends (Figure A.13(b)). During the exit period, as BOA gradually withdrew, its local market share converged toward zero in high and low exposure counties alike. This variation suggests a DID estimator along the lines of our estimator for Chase's exit event, leveraging cross-county variation in exposure to BOA's exit as an FHA aggregator.

Figure A.13: Exposure to Chase's Exit from FHA Lending



(a) Cross-County Variation in Exposure to BOA Exit

(b) Timing of BOA's Exit, by Exposure Level

Note: Panel (a) plots histograms of county-level market shares of BOA as an aggregator over the period from 2009:q2 to 2010:q3 for FHA home-purchase loans. Panel (b) displays conditional averages of BOA's pre-exit county aggregator market shares over time. High-BOA counties are counties where BOA pre-exit market shares were above the distribution median. Source: Authors' calculations based on HMDA data.

Compared to the Chase analysis, exposure to BOA's exit exhibits more imbalance on county characteristics (Appendix Table A.16). BOA's pre-exit FHA footprint is correlated with house price growth, mortgage delinquencies, foreclosure, and unemployment trends during the GFC, for example. BOA was also a more significant integrated originator than Chase, and exited other mortgage product markets (e.g. GSE loans) around the same time. As some of these characteristics could determine nonbank issuer expansion and credit supply outcomes during the study period, the threat of imbalanced treatment/control groups around BOA's exit is somewhat more concerning.

To address these identification concerns, we utilize propensity score matched treatment/control groups

Table A.16: Summary Statistics for Treatment/Control Group Balance (BOA)

	(1) Below-Median BOA Exposure (raw)	(2) Above-Median BOA Exposure (raw)	(3) Below-Median BOA Exposure (propensity score)	(4) Above-Median BOA Exposure (propensity score)	(5) $\frac{m_a - m_b}{\sigma}$
Nonbank Issuer Share (%)	10.3	10.6	10.6	10.2	-0.08
Nonbank Originator Share (%)	51.2	61.8	55.2	57.7	0.18
1[Credit Score < 640] (%)	14.3	13.1	14.1	13.3	-0.18
Credit Score	694.9	696.0	695.2	695.8	0.09
LTV Ratio (%)	96.9	97.0	96.9	97.0	0.07
DTI Ratio (%)	40.2	41.0	40.5	40.7	0.15
Mortgage Interest Rate (%)	4.5	4.5	4.5	4.5	0.09
log(Number of FHA Originations)	7.5	8.2	7.8	7.9	0.04
Tract-Level Median Family Income (1000)	70.3	68.3	69.8	68.9	-0.06
BOA's Share as Integrated Originators (%)	7.7	7.5	7.7	7.5	-0.05
House Price Growth in 2006 (%)	7.1	9.1	8.0	8.2	0.04
House Price Growth in 2010 (%)	-3.9	-5.1	-4.3	-4.7	-0.08
Unemployment Rate in 2006 (%)	4.5	4.7	4.5	4.6	0.03
Unemployment Rate in 2010 (%)	9.0	10.4	9.7	9.7	-0.02
60+ Day Delinquency Rate in 2006 (%)	2.5	2.1	2.3	2.2	-0.04
60+ Day Delinquency Rate in 2010 (%)	8.2	9.0	8.7	8.5	-0.06
Forclosure Rate in 2006 (%)	0.6	0.5	0.5	0.5	-0.01
Forclosure Rate in 2010 (%)	3.5	3.2	3.4	3.3	-0.05
N. Obs.	2,010	1,204	1,724	973	

Note: conditional means by above/below median county-level exit exposure during the pre-exit period (2009q2-2010q3). The measure $\frac{m_a - m_b}{\sigma}$ gives the significance of the difference in conditional means $m_a = \mathbb{E}(x|\text{above-median exposure})$ and $m_b = \mathbb{E}(x|\text{below-median exposure})$ relative to the standard deviation of the characteristic $\sigma = \sqrt{\mathbb{V}(x)}$. Authors' calculations based on the FHA and HMDA data.

for all of our analysis of BOA's exit event. The treatment propensity score regression includes match characteristics analogous to Chase's exercise, and additional match characteristics that correspond to distinct sources of imbalance for BOA (Appendix Table A.17). The estimated propensity score explains about 28% of the cross-county variation in BOA's pre-exit FHA aggregator market share. Mirroring Chase's analysis, we form 20 equal sized groups of counties based on quantiles of the treatment propensity score and include propensity score group × quarter fixed effects in the regressions.

We analyze the nonbank IO, credit standards, interest rate, and quantity outcomes from Sections 6–9 using BOA's exit variation in the propensity score matched DID design. We cannot analyze the funding cost outcome for BOA's exit because the nonbank credit line data do not exist until 2012. As shown in Appendix Tables A.18–A.21 and in Figure 9 in the main text, the results are broadly consistent with our findings for Chase's exit.

Table A.17: Regression Estimates for Propensity Score (BOA)

	(1)
log(Number of FHA Originations)	0.0084***
	(0.0023)
Tract-Level Median Family Income	-0.0002
	(0.0003)
BOA's Share as Integrated-Issuer	-0.4559***
	(0.0531)
House Price Growth in 2006	-0.0123
	(0.0899)
House Price Growth in 2010	0.0873
	(0.0924)
Unemployment Rate in 2006	-0.0245***
	(0.0040)
Unemployment Rate in 2010	0.0193***
	(0.0026)
60+ Day Delinquency Rate in 2006	0.0741
	(0.5684)
60+ Day Delinquency Rate in 2010	1.0193***
	(0.3075)
Forclosure Rate in 2006	-3.0698
	(2.1315)
Forclosure Rate in 2010	-2.4953***
	(0.3733)
Constant	0.1969***
	(0.0310)
N. Obs.	2,697
Adj. R^2	0.28

Note: Estimates of the regression of BOA's pre-exit share on county-level matching variables. Source: Authors' calculations based on the HMDA data and the FHA data.

Table A.18: Effects of BOA's Exit on Nonbank Ginnie Mae Issuer Market Shares, by Business Model

	(1) Nonbank issuer (aggregator or integrated originator)	(2) Nonbank aggregator	(3) Nonbank integrated originator
Exit Period ×			
Pre-exit County-level Share (S_{ct})	0.080***	-0.007	0.087***
	(0.021)	(0.016)	(0.017)
Post Exit ×			
Pre-exit County-level Share (S_{ct})	0.583***	0.261***	0.322***
	(0.054)	(0.028)	(0.036)
County FE	Y	Y	Y
Quarter FE	Y	Y	Y
N. Obs.	3,114,814	3,114,814	3,114,814
Adj. R^2	0.80	0.62	0.76

Note: Estimates and standard errors from equation (2) for the effects of a 100 pp decline in BOA's market share. Standard errors clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Source: Authors' calculations based on the HMDA data.

Table A.19: Effects of BOA's Exit on Credit Risk Measures (with propensity score matching)

	(1) Min. CS	(2) 1[CS < 640]	(3) Average CS	(4) LTV	(5) DTI	(6) Ever 60+ DQ	(7) Ever 60+ DQ
Exit Period ×							
Pre-exit County-level Share (S_c)	-26.029***	-0.011	-2.065	0.066	0.114	-0.008	-0.011
	(8.839)	(0.012)	(1.519)	(0.211)	(0.276)	(0.008)	(0.007)
Post Exit ×							
Pre-exit County-level Share (S_c)	-40.346***	0.037**	-11.125***	-0.204	-0.395	-0.006	-0.020**
	(9.952)	(0.014)	(2.297)	(0.169)	(0.375)	(0.010)	(0.009)
Avg. Treatment Effects on Treated	-11.142	0.010	-3.072	-0.056	-0.109	-0.002	-0.006
County FE	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y
Loan-level controls							Y
N. Obs.	1,434,504	3,052,337	3,052,337	3,052,337	3,052,337	3,052,337	3,052,337
Adj. R^2	0.42	0.02	0.02	0.02	0.04	0.01	0.08

Note: Estimates and standard errors from regression (2) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in BOA's market share. In addition to county fixed effects and quarter fixed effects, these regressions also include the fixed effects for each of the 20 propensity score bin interacted with each quarter. Loan-level controls in column 7 include log loan size, an indicator for first time homebuyers, and indicator variables defining 11 bins of credit scores, 7 bins of loan-to-value ratios, and 6 bins of debt-to-income ratios. Standard errors in parenthesis, clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Authors' calculations based on the HMDA-FHA matched sample (column 1) and FHA administrative data (columns 2-7).

Table A.20: Effects of BOA's Exit on Cost of Credit (with propensity score matching)

	Mortgage Interest Rate			
	(1) Full Sample	(2) CS < 640	(3) 640 ≤ CS < 680	(4) CS ≥ 680
Exit Period ×				
Pre-exit County-level Share (S_c)	0.092***	0.178***	0.082***	0.088***
	(0.018)	(0.042)	(0.021)	(0.017)
Post Exit ×				
Pre-exit County-level Share (S_c)	0.197***	0.408***	0.186***	0.194***
	(0.023)	(0.049)	(0.024)	(0.022)
Avg. Treatment Effects on Treated	0.054	0.113	0.051	0.054
County FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Loan-level controls	Y	Y	Y	Y
N. Obs.	3,052,337	402,488	959,391	1,690,346
Adj. R^2	0.85	0.75	0.85	0.87

Note: Estimates and standard errors from regression (2) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in BOA's market share on interest rates at loan origination. In addition to county fixed effects and quarter fixed effects, these regressions also include the fixed effects for each of the 20 propensity score bin interacted with each quarter. Columns 2, 3, and 4 present regression results using the subsample of borrowers with credit scores below 640, between 640 and 680, and at least 680, respectively. All regressions include loan-level controls for: log loan size, indicator variables for 11 bins of credit scores, indicator variables for 7 bins of loan-to-value ratios, indicator variables for 6 bins of debt-to-income ratios, and an indicator for first time homebuyers. Standard errors in parenthesis, clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Source: Authors' calculations based on the FHA administrative data.

Table A.21: Effects of BOA's Exit on Quantity (with propensity score matching)

	FHA				FHA + GSE			
	(1) Total Loans	(2) CS < 640	(3) 640 ≤ CS < 680	(4) CS ≥ 680	(5) Total Loans	(6) CS < 640	(7) 640 ≤ CS < 680	(8) CS ≥ 680
Exit Period ×								
Pre-exit County-level Share (S_c)	0.085	0.036	0.141**	0.032	0.091	0.040	0.137*	0.076
	(0.063)	(0.096)	(0.059)	(0.074)	(0.076)	(0.121)	(0.073)	(0.075)
Post Exit ×								
Pre-exit County-level Share (S_c)	0.117	0.329***	0.203***	-0.047	0.184	0.352**	0.200**	0.148
	(0.076)	(0.115)	(0.076)	(0.090)	(0.122)	(0.151)	(0.096)	(0.140)
Avg. Treatment Effects on Treated	0.032	0.091	0.056	-0.013	0.051	0.097	0.055	0.041
Zip3 FE					Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
N. Obs.	48,195	44,679	46,926	47,665	14,274	14,108	14,184	14,274
Adj. R^2	0.67	0.67	0.30	0.60	0.67	0.82	0.56	0.61

Note: Columns 1–3 present estimates and standard errors from regression (3) with a pooled pre-period and two post-period DID estimates for the effects of a 100 pp decline in BOA's market share on percent changes in the number of FHA loan originations (columns 1–3). Columns 4–6 present estimates and standard errors for the effects on percent changes in the combined number of originations of FHA loans and the subset of GSE loans that were below the FHA conforming loan limit and that had at least 95% loan-to-value. For columns 4–6, the treatment exposure and geographic fixed effects are at the 3-digit zip code level to accommodate the available GSE data. All re Standard errors in parenthesis clustered at the county level ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Columns 1–3 use the FHA administrative data. Columns 4–6 use the FHA administrative data, Freddie Mac Single-Family Loan-Level Dataset, and Fannie Mae Single-Family Loan Performance Data.