Banks' Credit Line Supply to Nonbanks and Financial Stability*

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Abstract

The interaction between banks and non-banks is growing and evolving. In this paper, we investigate whether they substitute or complement each other in the mortgage market. We find that in less liquid and more fragile segments of the market, they acted as complements. Less liquid banks extended more credit lines and took less direct mortgage market exposure in response to the liquidity injection associated with the 2020 quantitative easing (QE). Their balance sheet adjustments allowed them to enter quantitative tightening (QT) with reduced vulnerabilities to interest rate and bank run risks. These results demonstrate that, at least in this market segment during this episode, banks and non-banks complemented each other, thereby mitigating financial stability risks.

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> "*Nonbanks collectively originate and service the majority of U.S. residential mortgages. In 2022, they originated approximately two-thirds of mortgages and serviced the majority of mortgage balances. This is a substantial increase from 2008, when they originated 39 percent and serviced 4 percent.*"
>
> Janet Yellen, May 10, 2024.

1 Introduction

According to the Financial Stability Board, the share of global financial assets held by non-bank financial intermediaries has been increasing from about 42% in 2003 to almost 50% today. As Janet Yellen's quote above indicates, these dynamics are particularly pronounced in the US mortgage market. Several papers that we summarize in detail below argue that the rise in non-bank shares is evidence of a substitution between banks and non-banks, with a more favorable regulatory treatment of non-banks being one important driver. There is, however, also recent evidence that banks and non-banks complement each other. In particular, Acharya, Cetorelli, and Tuckman (2024a) show that banks to large extents finance non-banks, and vice versa, such that their abnormal returns are also tightly correlated. This complementarity view implies that banks potentially reduce their direct downstream lending to firms and households, but simultaneously raise their indirect exposure as they provide liquidity to non-banks that then, in turn, increase their loan supply in the downstream market.

In this paper, we examine the substitutability vs. complementarity of banks and non-banks in the mortgage market. We find that in less liquid segments of the market, they act as complements. In particular, we find that less liquid banks extended more credit lines to non-bank mortgage companies (NMCs) and took less direct mortgage market exposure via on-balance sheet mortgages or investments into mortgage-backed securities (MBS) in response to the liquidity injection associated with the 2020 quantitative easing (QE). The

rise in indirect real estate exposure, instead of direct exposures, allowed them to enter the quantitative tightening (QT) episode with reduced vulnerabilities to interest rate and bank run risks. These results demonstrate that, at least in this market segment and during this episode, banks and non-banks complemented each other, thereby mitigating financial stability risks.

This paper leverages two granular data sets—the FDIC Call Reports containing detailed *bank* balance sheet and income data, as well as Mortgage Call Reports for *NMCs*. The latter encompass quarterly information on balance sheets, income statements, and credit line facilities for every NMC holding a state license under the Nationwide Multistate Licensing System. The data are shared with the Federal Reserve under the Secure and Fair Enforcement for Mortgage Licensing Act of 2008 Importantly, the NMC-level data contain information on the banks that a NMC borrows from, enabling us to construct a bank-NMC-level panel data set that spans 1,179 unique credit line relationships between 405 NMCs and 105 banks.

In order to examine whether the aggregate liquidity shock affected banks' indirect vs. direct real estate exposure, we first use the FDIC Call Report data only. Based on these data, we estimate a series of bank-level difference-in-differences estimations around the vast liquidity injection associated with the 2020 QE intervention, using a bank's MBS share, on-balance sheet mortgage share and the share of a bank's credit lines to NMCs as outcomes. Following Kashyap and Stein (2000), we measure exposure to this aggregate liquidity injection by a bank's pre-shock liquidity ratio, i.e., its ratio of cash and reserves over total assets. In these regressions, we find that more exposed banks raise their indirect real estate exposure via credit lines to NMCs. In contrast, they tend to reduce their direct exposure via MBS holdings and on-balance sheet mortgages. As these regressions are at the bank level, they do not allow us to control for demand effects and might hence be subject to endogeneity concerns. To improve on identification and

to gauge that the increase in credit lines to NMCs is supply-driven, in the main part of the paper, we hence move on to specifications at the bank-NMC level.

The granularity of the data, here, enables us to control for credit line demand by means of NMC-time fixed effects in the spirit of Khwaja and Mian (2008). We hence examine whether, around the aggregate liquidity injection, the credit line volumes of a NMC that borrows from at least two banks increase more from a more relative to a less exposed bank. The corresponding results are in line with those at the bank level. Specifically, we find that banks with smaller pre-shock liquidity ratios expand their credit line supply to NMCs more. These results are robust to (i) using alternative bank exposure measures to the aggregate liquidity shock, (ii) changing the difference-in-differences window considered around the liquidity injection, and (iii) controlling for bank specialization effects similar to Blickle, Parlatore, and Saunders (2023) or Paravisini, Rappoport, and Schnabl (2023).

We further show that the additional credit line supply is mainly channeled to smaller NMCs, as well as those with a higher mortgage quality. Most of the increase does not come from a NMC's main bank, implying that relationship banking does not seem to be an important driver of bank-NMC lending. Zooming into the banks that predominantly drive our results, we find that these are the small and regional ones, not the large ones. We also identify a stronger effect for better capitalized banks, which the literature has shown to be banks with a lower risk-taking sensitivity (Holmstrom and Tirole, 1997).

All of these results are based on within-NMC regressions that focus on existing credit lines and hence the intensive margin of lending. As a consequence, they entirely ignore new and terminated credit line relationships, i.e., the extensive margin of credit line adjustments. To take into account the latter as well, in an additional estimation framework, we first collapse our data at the NMC level and then examine whether NMCs that have a higher pre-shock lending share of more exposed banks overall experience an increase in credit line volumes. In fact, we find that this is the case, which is evidence that the

extensive margin does not entirely offset our within-NMC results. In other words, a NMC that borrows from more exposed banks *overall* sees a higher supply of credit lines after the Fed's liquidity injection.

Previous results gauge that banks with a lower initial liquidity ratio raise their credit line supply to NMCs after the Fed's liquidity injection, while they reduce their on-balance sheet real estate loans and MBS holdings, which tend to have a long maturity and are hence likely more affected by the quantitative tightening episode starting after 2022:Q1. This, in turn, raises the question of whether these more exposed banks enter the tightening period with lower interest rate and bank run risks. To this end, we estimate a series of dynamic difference-in-differences regressions for the sample period of 2021:Q1-2023:Q3. Indeed, we find that the more exposed banks, i.e., those that mainly increase their indirect real estate exposure via credit lines to NMCs, have a lower MBS share, lower asset maturity, lower unrealized losses, and a lower share of uninsured deposits, relative to less exposed banks, when the Fed started its QT program. These results provide evidence that, at least in this special market segment and the time episode studied in our paper, banks and non-banks complemented each other, thereby mitigating financial stability risks for banks.

Related Literature This paper contributes to different strands of the literature. First, we speak to the growing literature on bank-nonbank linkages, most of which establishes that banks and non-banks act as substitutes to each other. Buchak, Matvos, Piskorski, and Seru (2018) shows that the shift in lending from banks to non-banks can mainly be explained by tighter regulatory constraints on banks, followed by technological advantages of non-banks. These results are confirmed by Irani, Iyer, Meisenzahl, and Peydró (2020), Begenau and Landvoigt (2021)), and Fuster, Plosser, Schnabl, and Vickery (2019), among others. Agarwal, Hu, Roman, and Zheng (2023) stress the role of non-banks in mortgage servicing that makes their lending more independent of mone-

tary policy changes. Consistent with this result, Elliott, Meisenzahl, and Peydró (2024) show that contractionary monetary policy increases non-banks', relative to banks', loan supply. This effect becomes even stronger for lending to riskier borrowers. Chen, Ren, and Zha (2018) use Chinese micro data to gauge that tighter monetary policy increases the lending share of nonbanks, similar to Drechsler, Savov, and Schnabl (2022), who base their analysis on the US mortgage market. While these papers argue that banks and non-banks are substitutes to each other, Acharya et al. (2024a) establish that non-banks are highly dependent on bank funding, and hence advocate a complementarity view: while banks reduce their downstream direct lending, they raise their indirect exposure via credit lines to non-banks. Similarly, Cucic and Gorea (2022) use household and firm data from Denmark to show that the increase in the market share of non-bank lenders is driven by long-term debt flows from banks to non-banks. Our paper speaks to this literature by showing that, in the US mortgage market and during the vast liquidity injection associated with the Fed's 2020 QE intervention, banks and non-banks indeed complemented each other, and that this reduced banks' financial vulnerability. Therefore, while our mortgage market results align with Sarto and Wang (2023), who attribute the growth of NMCs to expansionary monetary policy (lower interest rates), and with Fuster, Hizmo, Lambie-Hanson, Vickery, and Willen (2021), who relate NMCs' increase in market shares during COVID-19 to mortgage originators' capacity constraints, they differ from Darst, Kokas, Kontonikas, Peydró, and Vardoulakis (2025), who document that QE-induced uninsured deposit inflows led banks to reduce their credit line supply to *corporations*.

Second, our results speak to the growing literature on drivers for the US financial instability period in 2023. Jiang, Matvos, Piskorski, and Seru (2024) study the relationship between monetary tightening and bank stability, showing that banks with higher asset losses and a higher (uninsured) leverage are more fragile, consistent with the evidence presented in, among others, Drechsler, Savov, Schnabl, and Wang (2023). Other factors

that have been shown to make banks more vulnerable to instability risks in 2023 are a bank's social media exposure (Cookson, Fox, Gil-Bazo, Imbet, and Schiller, 2023) and degree of digitization (Koont, Santos, and Zingales, 2024). Our contribution, here, is to show that, when banks replace direct with indirect exposure to risky market segments (the real estate sector in our case), it can shield them from vulnerability risks. Potential reasons of why credit lines to NMCs bear only a small risk for banks are provided in Jiang, Matvos, Piskorski, and Seru (2023) and Begley and Srinivasan (2024), who argue that NMCs' bankruptcy rates are low due to their ability to downscale operations quickly and due to their capital ratios that are about twice as large as those of banks.

Third and finally, we contribute to the empirical literature on the transmission of unconventional monetary policy easing to (mortgage) credit conditions and the real economy. Rodnyansky and Darmouni (2017) and Chakraborty, Goldstein, and MacKinlay (2020) exploit variation in MBS holdings to analyze the effect of QE on bank lending. While the former finds strong effects of QE1 and QE3 on credit expansion, with MBS-dependent commercial banks increasing their mortgage market share, the latter document a "crowding out" effect on commercial lending for the most exposed banks. Luck and Zimmermann (2020) follow a similar strategy to show that banks increased lending to firms and home purchase mortgage origination during QE3, which led to an increase in employment. Di Maggio, Kermani, and Palmer (2019) provide evidence on the importance of banking-sector health and mortgage market segmentation in the transmission of QE interventions. While these papers argue that certain types of banks increase their mortgage market shares around QE, we show that large liquidity injections can also lead initially liquidity-scarce banks to substitute indirect real estate exposure via credit lines to NMCs for direct real estate exposure via MBS or on-balance sheet mortgages.

The rest of the paper is organized as follows. Section 2 describes the evolution of the mortgage market, bank balance sheets, and the market for warehouse financing during

the vast liquidity injection of 2020-2021. Section 3 presents the data. Section 4 looks at the substitution between direct and indirect real estate exposure using bank-level data. Section 5 zooms into banks' credit line supply to NMCs, employing granular bank-NMC-level data and a within-NMC identification strategy, whereas Section 6 provides the corresponding cross-sectional results at the NMC level. Afterwards, in Section 7, we study to what extent banks raising their indirect real estate exposure via credit lines were less vulnerable to the financial instability risks that arose after the start of quantitative tightening in 2022. Section 8 concludes.

2 Institutional Background

2.1 The Mortgage Market in 2020-2021

The sudden and deep economic downturn at the onset of COVID-19 led to a spike in unemployment and triggered concerns about an increase in mortgage defaults. At the same time, financial markets were volatile and mortgage originators faced up to $5 billion of higher margin calls on to-be-announced hedges.[1] The Federal Government and the Federal Reserve quickly responded, restoring market functioning by injecting large amounts of liquidity.

In terms of fiscal interventions, the Coronavirus Aid Relief and Economic Security (CARES) Act stabilized the mortgage market by imposing an eight-week foreclosure moratorium on residential mortgage loans guaranteed by the GSEs or Ginnie Mae. The CARES also introduced a twelve-month forbearance benefit for federally guaranteed mortgages and a cash assistance that helped many borrowers continue to make their payments. Cherry, Jiang, Matvos, Piskorski, and Seru (2021) shows that the CARES act resulted in a spike of debt forbearance, without a commensurate increase in delinquency

[1] Mortgage originators use margin calls on the to-be-announced hedges to protect against changes in the value of their mortgage originations that are not yet sold. For more detial on this episode, see https://news.bloomberglaw.com/banking-law/dirt-cheap-u-s-mortgages-thwarted-by-5-billion-in-margin-calls.

rates. The high wave of forbearance raised concerns that NMCs would not have the liquidity to advance funds to investors on behalf of borrowers in forbearance. In this regard, the FHFA and Ginnie Mae set up liquidity assistance measures to servicers in GSE and Ginnie Mae pools.

At the same time, the Federal Reserve reduced short-term interest rates to almost zero in March 2020 and turned to purchasing agency MBS and Treasury securities. The pace of purchases in the following months exceeded the total amounts of assets purchased during QE programs introduced after the Global Financial Crisis. Between March and May, the Fed purchased a total of about $ 2.1 trillion of Treasuries and MBS. As market conditions rapidly improved starting in June 2020, the Fed reduced the monthly purchases to $ 80 billion of Treasury securities and $ 40 billion of agency MBS per month until October 2021. The combination of lower interest rates and higher liquidity injections through QE, led to a mortgage boom and a surge in house prices of more than 20%. The mortgage boom was mainly driven to higher refinancing activity of high-income (Agarwal, Chomsisengphet, Kiefer, Kiefer, and Medina, 2024) and prime borrowers. Despite the historical proportions of the refinancing boom, Fuster et al. (2021) document an incomplete pass-through of lower interest rate spreads to mortgage borrowers due to capacity constraints and operational frictions of bank and non-bank intermediaries. The boom quickly reverted in 2022 after the Fed started to increase interest rates and subsequently house prices declined.

2.2 Bank Liquidity and the Market for Warehouse Credit Lines

In March 2020, non-financial firms experienced cash flow disruptions and drew down large amounts of credit lines (Acharya, Engle, Jager, and Steffen, 2024b), leaving the banking system struggling to provide liquidity. Chodorow-Reich, Darmouni, Luck, and Plosser (2022) and Greenwald, Krainer, and Pascal (2023) show that unused credit line capacity

was held by large firms that drew them down following the COVID-19 shock, putting pressure on bank balance sheets and crowding out lending to smaller firms.

Prompt and unprecedented fiscal and monetary policy interventions helped banks to satisfy their liquidity demands. In two quarters, bank deposits grew from $ 13 trillion to $ 15 trillion (Figure Fig. 1, Panel A). This huge deposit inflow is related to several factors, such as households' precautionary savings triggered by concerns about job market prospects (Levine, Lin, Tai, and Xie, 2021), firms' dash-for-cash (Acharya and Steffen, 2020; Li, Strahan, and Zhang, 2020), as well as fiscal stimulus and the Fed's QE program.

As shown in Acharya and Rajan (2024) and Acharya, Chauhan, Rajan, and Steffen (2023), the Fed implemented QE by purchasing securities from authorized primary dealers by crediting reserve balances on the accounts of banks associated with the dealer's counterpart. If the ultimate seller of these securities was a bank, securities were swapped with reserve balances, and banks' balance sheets did not grow. In most cases, however, the ultimate seller of the securities was not a bank. In this case, the Fed credited reserve balances to the accounts of the nonbank's correspondent bank, which then credited a deposit to the nonbank seller. This means that on the liability side, there was an expansion of demand deposits, especially uninsured deposits such as checking accounts that depositors can withdraw anytime (see Panel B of Fig. 1). At the same time, on the asset side, reserves mechanically increased, indicating that the monetary stimulus increased the aggregate liquidity in the banking sector (see Panel C of Fig. 1).[2] Banks responded to this large liquidity injection by accommodating liquidity demand from the corporate sector and originating off-balance sheet liabilities in the form of new credit lines. Both demand deposits and lines of credit are claims on bank's liquidity and require a stock of liquid assets (reserves and cash) to appropriately manage liquidity risk. Therefore, cash and reserve positions are central for the ability of banks to provide credit lines.

[2]Fig. A.1 shows a positive relationship between uninsured deposits over assets and liquidity (cash and reserves over assets) for the sample of banks with a warehouse credit line committed.

Indeed, early work of Kashyap and Stein (2000) shows that the effects of monetary policy changes on lending are stronger for initially liquidity-constrained banks—a result that has been confirmed by several papers later on.[3] In our empirical analysis, we hypothesize that banks that were less liquid before the shock experienced a larger relaxation of their liquidity constraints, allowing them to increase their lending more relative to less liquidity-constrained depository institutions. This should, in particular, also apply to banks' loan supply to NMCs. The demand for credit of those institutions is cyclical and negatively correlated with the level of interest rates. Lower interest rates should hence spur the mortgage market and the demand of credit of these institutions.

[Add Fig. 1 about here]

Unlike banks, NMCs cannot access insured deposit funding and are not required to maintain capital and liquidity buffers. They cannot obtain liquidity from the Federal Reserve or the Federal Home Loan Banks either and therefore their primary source of financing is warehouse lines of credit. Their funding structures expose them to liquidity shocks in the banking market.

Warehouse lines of credit are short-term in nature and are used to finance Mortgages Held for Sale (HFS). Each mortgage originated is temporarily pledged as collateral to warehouse lenders until it is sold in the secondary market (see Section B for further details). Warehouse credit lines can be quickly increased or canceled, and lenders can require additional guarantees on the collateral requirements. Mortgage Servicing Rights (MSR) can also be pledged as collateral; in this case, however, the lender might require margin calls, reprice, or cancel the credit line when interest rates fluctuate. The volume of warehouse credit lines in the system follows the dynamics of the mortgage market. Panel A of Fig. 2 shows the aggregate volumes of warehouse credit lines, while Panel C

[3]See, for example, Khwaja and Mian (2008) and Iyer, Peydró, da Rocha-Lopes, and Schoar (2013).

shows the aggregate origination volumes for NMCs and banks. As one can see, the total amount of warehouse credit committed almost doubled from $120 billion in 2019:Q3 to nearly $225 billions at the peak of the mortgage credit market boom in 2021:Q4. The amount used is on average 60% of the total amount committed and remained fairly stable over the period.

Despite the concerns about the ability of the banking system to supply contingent liquidity, credit flowed downhill to NMCs. The spike in forbearance granted to mortgage borrowers by the CARES act had a very limited effect on the market for warehouse financing. The concern rapidly eased after the FHFA announcement that GSEs would purchase mortgages already in forbearance.[4] However, despite this, Kim, Lee, Scharlemann, and Vickery (2024) and Pence (2022) document that NMCs facilitated fewer forbearances than banks.[5] To limit the risk of liquidity shortages of servicers, some lenders imposed stricter terms on warehouse credit lines (Pence, 2022).[6]

The sustained mortgage volumes in the second half of 2020 and 2021 increased the profits of NMCs and strengthened their balance sheets. The warehouse credit market expanded in tandem with the downstream mortgage originations of NMCs until the monetary policy tightening announcement in Q1 2022. In a rising interest rate environment, demand for mortgages decreased, and thus warehouse credit lines returned to a decreasing trajectory. The limited exposure of regional banks in this market prevented the emergence of liquidity tensions during the regional banking crisis.[7]

[4]See Economic commentary of the Federal Reserve bank of Cleveland at https://www.clevelandfed.org/publications/economic-commentary/ec-202115-no-nonbank-mortgage-servicer-liquidity-crisis.

[5]This behavior raised the concerns of the GFC documented in Aiello (2022) that financially constrained servicers pursued foreclosures and modifications at the expense of investors and borrowers.

[6]Data on interest rates, covenants, and collateral characteristics of each warehouse credit line are not available. Such information would have been of interest to draw inferences on how banks change margin calls on credit lines and impose stricter terms on NMCs following the COVID-19 shock. Pence (2022) report anecdotal evidence that some lenders required stricter covenants on warehouse credit lines during the COVID-19 period.

[7]None of the three failed regional banks—Silicon Valley Bank, Signature Bank, and First Republic—had credit line advances on NMCs.

[Add Fig. 2 about here]

3 Data

Our empirical analysis is based on data on warehouse lines of credit of NMCs from Mortgage Call Reports manually merged with bank balance sheet data from FDIC Call Reports. See Appendix Section B for further details.

Under the SAFE Mortgage Licensing Act, any NMC that holds a state license under the Nationwide Multistate Licensing System (NMLS) is required to compile a quarterly Mortgage Call Report (MCR) that includes information on the balance sheet, income statement, and credit line facilities. We obtain MCRs from the NMLS & Registry maintained by the Conference State of Banking Supervision (CSBS) and shared with the Federal Reserve under the Secure and Fair Enforcement for Mortgage Licensing Act of 2008. MCRs contain details about Financial Conditions (FC) and Residential Mortgage Loan Activities (RMLA). The FC details contain balance sheet and income statement information at the NMC level, while the RMLA details contain information on warehouse credit lines, mortgage originations, servicing and repurchases by state of each NMC. Both data are available at the quarterly frequency.

Crucial for our study is the information on credit line facilities, including the total amount of credit granted, the amount of credit used, and the name of the provider. We manually match names of credit line providers with unique commercial bank identifiers in the FDIC Call Reports.[8] Panel A of Table A.1 provides summary statistics regarding the NMCs. The average credit line committed is worth $123.1 million,[9], while the amount used is roughly 60% corresponding to $ 69.7 million. The average NMC has 3.7 credit

[8]The manual matching was done by searching the name of the funding provider through the FDIC Bank Find Suite.

[9]In some cases (5% of the observations), a lender has more than one warehouse credit line committed to a NMC. In that case, we aggregate the credit line volumes and treat them as a unique credit line. Note that we do not have information on the collateral pledged on these credit lines.

lines, with 15% of observations (the smaller ones in terms of assets) having only one credit line per NMC. Panel B of Fig. 2 provides information on the distribution of credit lines across NMCs. As one can see, most NMCs have a diversified funding structure with more than three lenders providing credit.

Panel A of Table A.1 further shows that the share of equity capital over total assets is 23% for the average NMC, while Mortgage Servicing Rights (MSR) are 25% of total book equity.[10] Mortgages Held For Sale (MHFS) are the main asset in NMCs' balance sheets, accounting on average for 72% of total assets.[11] These mortgages usually collateralize warehouse credit lines and are sold after origination in the secondary market. MHFS remain in NMCs for a shorter period of time, while MSRs remain on balance sheets for a longer time, have a limited secondary market and are subject to valuation changes due to interest rate fluctuations and credit risk.

In Panel B of Table A.1, we report summary statistics for our sample of warehouse banks. The average bank has $ 109 billions of total assets with a higher standard deviation, meaning that the sample contains all the largest banks in terms of total assets.[12] In Table A.3, we show that selected characteristics of more vs. less exposed banks (low vs. high liquidity ratios in 2019:Q2) are quite similar and in most cases not statistically different from each other. This is evidence that a potential non-random treatment assignment is unlikely to distort our analysis. The only statistically significant difference between both groups of banks is that the share of government securities of more exposed banks is lower, with the share of real estate loans in total assets being higher.

[10] MSRs are a significant source of revenue for NMCs. After a loan is sold and servicing is retained, the MSR should be capitalized as an asset and recorded in the balance sheet at fair value. Servicing is riskier than originating. For this reason, we scale this variable by total equity instead of total assets. In case of borrower default, the servicer is responsible for enforcing the mortgage contract and advancing missed payments until the foreclosure procedure starts.

[11] Only a very limited portion of NMCs hold mortgages on their balance sheet for investment purposes (not displayed). This confirms the findings in Buchak, Matvos, Piskorski, and Seru (2024) on the limited ability of shadow banks to perform intensive balance sheet mortgage originations, especially for mortgages that are not easy to sell.

[12] See Table A.2 for a comparison with the entire sample of US banks.

Large banks with more than $ 250 billion of dollars provide on average 40% of the total volume of warehouse credit lines. The rest of the market is shared with small banks having assets below $ 50 billion (40%) and regional banks (20%).[13]

4 Liquidity Shocks and Changes in Banks' Real Estate Exposure

4.1 Research Design

We start the empirical analysis by exploring in a difference-in-differences setting how a large liquidity injection into the banking system affects banks' exposure to the real estate market. The aggregate liquidity shock we focus on is the QE intervention starting with the onset of COVID-19 in 2020:Q1, see Section 2 for further details. The regression specification is as follows.

$$Y_{b,t} = \beta_1(Liquidity_{b,pre} * Post_t) + X_{b,pre} + \alpha_b + \alpha_t + \epsilon_{b,t}, \tag{1}$$

where $Y_{b,t}$ is a bank's MBS holdings over total assets, on-balance sheet real estate loans over total assets, or the sum of all credit lines granted to NMCs over total assets. $Post_t$ is a dummy equal to one for the three quarters after the Fed's QE interventions (2020:Q2-2020:Q4), and zero for the 2019:Q2-2019:Q4. We achieve identification by following Kashyap and Stein (2000) and measuring banks' exposure to this aggregate shock by a bank's pre-shock liquidity ratio. Specifically, $Liquidity_{b,pre}$ is a bank's ratio of cash and reserves over total assets, fixed in 2019:Q4. The underlying idea is that an aggregate liquidity shock should allow initially liquidity-constrained banks to expand their activities. α_b and α_t are bank and time fixed effects that control for time-invariant heterogeneity across banks, such as their business model or general risk-taking tendency, and global shocks that affect all banks homogeneously. The standard errors are clustered at the

[13] In Fig. A.2, we plot the evolution of the market share of lenders by their size.

bank level.

4.2 Results

Table 1 reports the results. More liquidity-constrained banks react to the aggregate liquidity injection by granting more credit lines to NMCs. In contrast, their direct real estate market exposure, as proxied by MBS holdings or on-balance sheet real estate loans, shrinks.

Although these results only represent correlations at the bank level, mainly because the data do not allow us to control for credit line demand shifts, they nevertheless highlight the importance of credit lines to NMCs as a way for banks to scale up their real estate market exposure quickly when aggregate liquidity conditions brighten. In the rest of the paper, we expand on this relationship and gauge the causal relationship between liquidity shocks and banks' credit line supply to NMCs by leveraging our unique bank-NMC-level credit line data. Afterwards, we explore the financial stability implications of our results by asking whether indirect real estate exposures via credit lines, relative to direct exposures via MBS or real estate loans, enabled banks to better weather the financial instability period in 2023.

5 Banks' Credit Line Supply to NMCs: Within-NMC Analysis

In this section, we build on the previous evidence and examine the causal relationship between an aggregate liquidity shock and banks' credit line supply to NMCs. We first describe the econometric approach, then report the corresponding results.

5.1 Research Design

The main hypothesis is that more liquidity-constrained banks benefit more from an aggregate liquidity increase, allowing them to raise their supply of credit lines to NMCs.

Therefore, identification revolves around the ex-ante level of liquidity, with banks having a lower share of reserves and cash over assets being more exposed. The difference-in-differences analysis centers around the QE intervention of 2020:Q1 that significantly raised the supply of funding to the banking system.

Our matched NMC-bank-level data with NMCs borrowing from multiple banks allows us to account for unobserved heterogeneity in NMCs' credit demand by saturating the model with NMC fixed effects. Identification hinges on each NMC borrowing from at least two different banks before and after the shock. This strategy isolates within-NMC variation in the change in credit line supply from banks differently exposed to the shock. The regression specification is as follows:

$$\Delta log(Credit_{b,nmc}) = \beta_1 Liquidity_{b,pre} + X_{b,pre} + \alpha_{nmc} + \epsilon_{b,nmc}, \tag{2}$$

where $\Delta log(Credit_{b,nmc})$ is either: 1) the log-change in the logarithm of total committed credit; 2) or the ratio of used credit over total credit granted from bank b to NMC nmc from the pre- to the post-shock period. As in Khwaja and Mian (2008), the data are collapsed (time-averaged) into one single pre-shock period (2019:Q2-2019:Q4) and one post-shock period (2020:Q2-2020:Q4). The main independent variable of interest, $Liquidity_{b,pre}$, is a bank's pre-QE percentage of liquid assets (reserves plus cash) over total assets, measured in 2019:Q2. For ease of interpretation of the magnitudes, all variables are standardized, so that the coefficients measure the percentage change of the dependent variable for a one-standard-deviation change in the exposure variable $Liquidity_{b,pre}$. From the summary statistics in Table A.1 we can see that *Liquidity* has a mean of 0.122 and a standard deviation of 0.117, implying that it has substantial cross-bank variation. In Panel D of Fig. 1, we show the distribution of *Liquidity* in 2019:Q2 as a function of bank size for the sample of warehouse lenders included in the regression estimations.

$X_{b,pre}$ is a vector of bank characteristics also fixed in the pre-shock quarter 2019:Q2, including size (logarithm of total assets), the ROA (return on assets), and the capital ratio (book equity over total assets). α_{nmc} are NMC fixed effects that control for credit demand (Cingano, Manaresi, and Sette, 2016; Beck, Da-Rocha-Lopes, and Silva, 2020, among others). Finally, since the exposure to the shock is bank-specific, credit flows from the same bank might be correlated, and we hence cluster standard errors at the bank level.

5.2 Benchmark Results

Table 2 shows the results of the within-NMC estimation of Equation 2. In columns (1)-(3), the dependent variable is the log-change in credit granted, while in columns (4)-(6), the dependent variable is the ratio of credit used (the amount drawn) over credit granted. The sample includes 1,179 unique credit line relationships between 405 NMCs and 105 banks. All specifications focus on NMCs with multiple bank relationships and include the NMC fixed effects to ensure that our estimates capture supply effects and hence not the result of NMC-driven effects, such as loan demand. The estimates are progressively saturated with the set of bank control variables. Columns (3) and (6), respectively, condition the corresponding effects on the size of NMCs.

The negative and significant coefficient of the main variable of interest, *Liquidity*, suggests that banks more exposed to the funding shock, i.e., those with lower liquidity ratios before the shock, expand their credit line supply to NMCs more. The effect is also economically significant: a one-standard deviation decrease in *Liquidity* leads to a 6.5% higher expansion of credit granted. This result is consistent with our hypothesis, which predicts that banks with lower liquidity positions before the shock benefited more from the monetary policy interventions in 2020:Q1. In column (3) of Table 2, we interact the main variable of interest with the size of NMCs. $LargeNMC$ is a dummy variable

equal to one if a NMC's amount of total assets is above the median value in 2019:Q2, zero otherwise. *SmallNMC* is a dummy variable that equals one if a NMC's amount of total assets is below the median value in 2019:Q2, zero otherwise. The interaction terms suggest that both small and large NMCs are significantly affected by the liquidity shock. Yet, the economic magnitudes differ quite substantially, with small NMCs being more affected. The economic magnitudes indicate that a one-standard-deviation decrease in *Liquidity* is associated with a supply-driven increase in credit expansion for the average small NMC of 7.2%, compared with less than 6% for large NMCs. Therefore, smaller, potentially more opaque, NMCs seem to benefit even more from the credit line supply expansion following the QE liquidity injection.

In columns (4)-(6) of Table 2, we focus on the change in the amount of credit drawn over credit granted, i.e., the credit line utilization rate. We find that NMCs draw more on their credit lines from banks more exposed, i.e., those with lower *Liquidity*. This effect is again economically more significant for small NMCs.

[Add Table 2 about here]

5.3 Robustness Checks

The validity of our empirical strategy in Equation 2 rests upon two identifying assumptions. First, in the absence of the treatment, all banks would have had a similar trend in credit supply to NMCs (parallel trend assumption). Second, as in Khwaja and Mian (2008), we assume that NMCs change their loan demand proportionally across all banks that they are borrowing from.

Regarding the first assumption, although parallel trends cannot be tested due to the absence of a counterfactual, in Fig. 3 we use a version of Equation 2 to estimate a specification similar to Beck et al. (2020). In particular, we compute changes in the amount

of credit granted in each NMC-bank pair in a quarter relative to 2019:Q4 (the last quarter before the shock) and conduct separate regressions on bank exposure $Liquidity_{b,pre}$, controlling again, as in Equation 2, for bank control variables and NMC fixed effects. We plot the main coefficient of interest *Liquidity* for each regression in Fig. 3. Before the shock, the main coefficient of interest is never statistically significant, showing that the parallel pre-trend assumption likely holds. After the shock, it then turns negative and statistically significant. The result suggests that the credit line expansion was lower for less exposed, ex-ante liquidity-rich banks relative to liquidity-constrained, more exposed ones. Interestingly, credit supply decreased gradually over time, with the largest negative coefficients in 2020:Q3 and 2020:Q4.

[Add Fig. 3 about here]

In the Khwaja and Mian (2008) within-firm specification, the implicit assumption behind firm fixed effects to control for loan demand is that loan demand changes proportionally across all banks lending to a firm. In our setting, this assumption implies that a NMC borrowing from multiple banks take their lenders as perfectly substitutable. The recent literature on bank specialization argues that this is not necessarily the case. Instead, banks specialize in certain types of lending and credit demand shifts are likely bank-specific, with firms usually borrowing mainly from banks that are specialized in the same industry as the firm, see for instance Blickle et al. (2023) and Paravisini et al. (2023). In our case, NMCs are more likely to borrow from banks specialized in NMC lending and hence their loan demand changes are not uniform across banks. This would pose a second identification concern in our empirical setting.

In a next step, we control for potential specialization effects by saturating the previous regressions with dummy variables representing banks' specialization in NMC lending. As it is important to control for banks' specialization relative to other banks, we define

the specialization dummies as being equal to one when a bank belongs to the first, second, third, or fourth, respectively, quartile of the in-sample distribution in the ratio of credit granted to NMCs over total assets. This approach is similar to that proposed in Greenwald et al. (2023) to address the concern of specialization in credit lines and long-term loans.

Results of the estimation are shown in Table 3. In all specifications, we find that previous results are confirmed, despite a slight drop in statistical significance. This is evidence that our results are not distorted by bank specialization and hence robust to the fact that banks are not easily fungible for NMCs.

[Add Table 3 about here]

Our within-NMC estimates of Table 2 are robust to other important tests. First, we use two different bank exposure measures, i.e., the ratio of reserves over total assets and reserves over uninsured deposits. Both measures capture the exposure of a bank to the QE liquidity injection. As discussed in Section 2.2, the Fed bought securities from banks and nonbanks. In the first case, the increase in reserve is the result of a swap of elegible securities with reserves, while in the second case the balance sheet of the bank increases on both sides (uninsured deposits and reserves), without a direct swap of securities. Panel A of Table A.4 shows the estimates with reserves over assets, while Panel B displays the estimations with reserves over uninsured deposits. The results in both panels confirm the main estimates from Table 2. The economic magnitudes across specifications are also similar to those shown in the baseline estimations.

To further check the robustness of our results, we adjust the sample period. First, we use a shorter window of only two quarters before (2019:Q3-2019:Q4) and two quarters after (2020:Q2-2020:Q3) the QE intervention. Second, we only compare credit line volumes granted or used, respectively, in 2020:Q4 and 2019:Q4, excluding all other quar-

ters from the regression. Results are shown in Table A.5 and Table A.6. We find that the coefficient of interest is statistically significant and economically important in both cases. As compared to the coefficient in Table 2, the coefficient of *Liquidity* is similar in magnitude. All in all, our results are hence robust to these alternative choices of the event window.

5.4 NMC Heterogeneity

In Table 2, we gauge that smaller NMCs benefit disproportionately more from the increased post-liquidity injection credit line supply, implying that banks seem to raise their exposure even more to more opaque NMCs. In this sub-section, we examine whether our benchmark results also vary across other NMC dimensions. To this end, in Table 4, we introduce an interaction term between the bank exposure variable $Liquidity_{b,pre}$ and the following NMC-level characteristics measured before the shock in 2019:Q2: the ratio of MSRs over equity, equity over assets, cash over assets, the share of FHA mortgages, the share of GSE-securitized mortgages over the total amount of mortgages originated, the share of mortgages with a FICO score at or above the superprime level (a FICO score higher than 720), and a dummy variable that equals one when a specific bank is a NMC's main lender. While the first three characteristics represent standard balance sheet characteristics of NMCs, the following three capture the quality of mortgages originated in the downstream market. The last variable measures the importance of a bank-NMC relationship.

Columns (1)-(3) of Table 4 show that there are no differential effects along the three balance sheet features of NMCs considered, i.e., the share of MSRs over equity, cash shares and equity ratios do not play any role in explaining our benchmark effects. In columns (4)-(6), we add the variables approximating NMCs' mortgage quality. While the interactions are statistically insignificant throughout, the insignificant base effect of

$Liquidity_{b,pre}$ in columns (5) and (6) implies that more liquidity-constrained banks do not raise their credit line supply to NMCs with a lower mortgage quality (lower GSE shares or lower superprime shares). In other words, the additional credit line supply only benefits higher-quality NMCs.

Finally, in column (7) of Table 4, we show that the increase in credit supply to NMCs of more constrained banks is not driven by the main relationship banks. Instead, it seems that liquidity-constrained banks that do not have an important role for NMCs before the liquidity injection increase their credit line supply. This is evidence that relationship banking is not an important feature of bank-NMC lending behavior.

[Add Table 4 about here]

5.5 The Role of Bank Characteristics

In this sub-section, we investigate whether the increase in credit line supply of more liquidity-constrained banks depends on other bank characteristics, which is important for bank regulators that usually monitor such characteristics carefully.

In a first step, we take into account the role of bank size. During the COVID-19 period, credit line draw-downs were concentrated at large banks that typically serve large firms (Acharya and Steffen, 2020; Li et al., 2020). It is, therefore, possible that large banks were less able to accommodate higher liquidity needs of NMCs. Columns (1)-(2) of Table 5 show that indeed only small and regional banks, but not large ones, drive our benchmark effects. More constrained small and regional banks not only raise their credit line supply on average after the shock, but mainly so towards small NMCs (column (3)). When in columns (4)-(6), we use credit used instead of credit granted as outcome variable, we obtain a similar picture.

[Add Table 5 about here]

After showing that our benchmark effects are driven by smaller and regional banks, in Table 6, we test for a possible interaction of *Liquidity* with the following bank fundamentals: capital, ROA and the amount of eligible securities. Specifically, we define dummies that are equal to one for banks that have an above-median value of capital-to-asset ratios, returns on assets or ratios of eligible securities (MBS, government securities and treasuries) over assets.

While the latter two characteristics do not play any role for our results, as evidenced by economically small and statistically insignificant interaction coefficients, column (1) implies that our results are even stronger for banks with higher pre-shock capital ratios. As higher capital ratios lower a bank's agency problems, with better capitalized banks being more likely to internalize their default risks (Holmstrom and Tirole, 1997), these results underscore that banks with a lower risk-taking sensitivity drive our main results. We note, however, that even liquidity-constrained and poorly capitalized banks increase their credit line supply after the liquidity injection, as the base effect in column (1) is still statistically significant at the 5% level. Yet, the economic magnitude for such banks is smaller than for the better capitalized ones.

[Add Table 6 about here]

6 Banks' Credit Line Supply to NMCs: Cross-Sectional Analysis

6.1 Research Design

The within-NMC specifications based on Equation 2 allow us to examine whether banks with lower liquidity positions expand credit lines to NMCs disproportionately more. Yet, they focus on existing credit lines and hence the intensive margin of lending, ignoring

new and terminated credit line relationships, i.e., the extensive margin. We therefore continue estimating cross-sectional analyses at the NMC level that allow us to take into account both the intensive and extensive margin in the following setting:

$$\Delta log(Credit_{nmc}) = \beta_1 NMCExposure_{nmc} + \beta_2 X_{nmc,pre} + \alpha_{\hat{nmc}} + \epsilon_{nmc} \quad (3)$$

where $\Delta log(Credit_{nmc})$ is the log-change of total credit granted or the log-change of the ratio of total credit used over credit granted for NMC nmc from the pre- to the post-shock period. As in Equation 2, the data are collapsed (time-averaged) into a single pre-shock (2019:Q2-2019:Q4) and post-shock period (2020:Q2-2020:Q4). $Exposure_{nmc}$ is the weighted average of $Liquidity_{b,pre}$, computed across all banks with which a NMC has a lending relationship and using as weight the total credit volume. The NMC controls contained in $X_{nmc,pre}$ that we include in this analysis are: the logarithm of total assets, equity capital over assets and MSR over equity, all averaged before the shock.[14]. In Equation 3, NMC-specific shocks cannot be absorbed by means of fixed effects, and therefore the coefficient β would be biased if $NMCExposure_{nmc}$ was correlated with credit demand. Therefore, to control for credit demand, we saturate Equation 3 by the estimated NMC-fixed effects, $\alpha_{\hat{nmc}}$, from Equation 2. This approach is in line with previous work of Cingano et al., 2016, Beck et al., 2020 or Bonaccorsi di Patti and Sette, 2016.[15] As in Khwaja and Mian (2008), standard errors are clustered at the main bank level, i.e., the bank with the highest percentage of lending to a NMC before the shock.

[14]Since some NMCs, mainly smaller ones, only report data at a yearly frequency, we compute pre-QE averages, instead of fixing them in 2019:Q2. This allows us to expand the sample to small NMCs.

[15]In the case of endogenous bank-firm matching, we should observe a high correlation between the *Liquidity* variable and the $\alpha_{\hat{nmc}}$. We observe a small correlation coefficient equal to -0.0291.

6.2 Results

In this sub-section, we report the results corresponding to Equation 3 that investigates the broader impact of the liquidity shock on NMCs, taking into account both the intensive and extensive margin of credit line adjustments. The results of the estimation are shown in Table 7. We begin with the log change in the total amount of credit granted. Columns (1)-(2) show that, on average, NMCs borrowing from more exposed banks (those with lower initial liquidity) experience an overall increase in credit line volumes granted. As before, this effect is stronger for small NMCs (column (3)). All results, apart from the overproportional effect for small NMCs, are confirmed in columns (4)-(6), where we employ the fraction of credit used as outcome variable. Interestingly, when in columns (7)-(9), we compute the change in the logarithm of credit granted for new credit relationships only, i.e., we exclusively focus on the extensive margin, we find that NMCs borrowing from more exposed banks have *lower* credit line volumes. This is evidence that the results of columns (1) and (2) of Table 7 on the overall increase in credit for NMCs borrowing from more exposed banks are driven by the intensive margin of credit adjustments. The extensive margin is estimated imprecisely, but if anything has a countervailing effect.

[Add Table 7 about here]

6.3 Robustness Checks

The baseline results of Table 7 are robust to a battery of additional robustness checks. First, we consider an alternative time window that is based on two quarters before (2019:Q3-2019:Q4) and two quarters after the QE intervention (2020:Q2-2020:Q3). The results displayed in Table A.7 remain similar to those reported in Table 7.

As a further check, we consider alternative measures of bank exposure in Table A.8. Specifically, we use the level of reserves over assets and the level of reserves over uninsured

deposits as alternative bank exposure variables. In either case, and as in the case of the within-NMC estimations reported in Section 5, our conclusions remain the same.

7 Warehouse Lenders and Instability Risks After the Interest Rate Hike

We have shown in Section 4 that banks with a lower liquidity ratio raise their credit line supply to NMCs, while they reduce their on-balance sheet real estate loans and MBS holdings. In other words, they raise their indirect real estate exposure while lowering their direct one. It is the direct exposure, however, that has a long maturity and is hence likely more affected by the interest rate hike episode starting in 2022:Q2.[16] We thus hypothesize that the more exposed banks, by raising only their indirect real estate exposure via credit lines to NMCs, are more shielded than the directly exposed banks from the interest rate increases.

7.1 Research Design

To test this hypothesis, we estimate a dynamic difference-in-differences specification as follows:

$$Y_{b,t} = \sum_{t=-4}^{t=6} (\beta_t I_t * Liquidity_{pre}) + \gamma_b + \gamma_t + \epsilon_{b,t}. \tag{4}$$

The left-hand-side variable, $Y_{b,t}$, represents outcome variables that have been shown in the extant literature to affect banks' sensitivity to the hiking and financial instability episode of 2022-2023. In particular, they include asset-based maturity in years, gains on securities over assets, MBS over assets, and uninsured deposits over assets. $Liquidity_{b,pre}$ is the same bank exposure variable used in the previous specifications. I_t are the dynamic difference-

[16] For example, the average duration of MBS in 2022:Q1 was 14.3 years, while the average duration of bank securities in the same quarter was 9.2 years. Similarly, the average duration of RE loans in 2022:Q1 was 10 years, while the average duration of other loans was only 4.9 years.

in-differences time coefficients of interest. The (omitted) reference period corresponds to the announcement of Quantitative Tightening (QT) in 2022:Q1.[17] γ_b and γ_t are bank and quarter fixed effects, which ensure that we control for common shocks that affect bank's balance sheets during each quarter or bank-specific, time-invariant influences. Standard errors are clustered at the bank level.

7.2 Results

Figure 4 reports the corresponding dynamics. Panel A shows that banks with lower liquidity positions (more exposed banks) entered the beginning of the rate hike (after the second quarter of 2022) with a lower level of MBS over assets. As argued above, the interest rate risk of MBS is large. This is true also for other long-term, fixed-rate investments. Therefore, in Panel B, we turn to asset duration as an outcome variable. The plot confirms the lower asset maturity of more relative to less exposed banks, but only after the regional banking crisis, i.e., after 2023:Q2. Before that quarter, the point estimates are also positive but not statistically significant.

The estimated losses from an increase in interest rates can be computed by multiplying the duration of securities with the change in interest rates. Banks that ended the easing period with higher shares of MBS securities that entail a larger duration should hence have experienced higher unrealized losses during the sudden rise in interest rates. In fact, Panel C of Figure 4 shows that more exposed banks had lower losses on securities during QT. Taken together, the patterns depicted in Panel A, B and C offer evidence that banks with a higher expansion of credit lines to NMCs during the mortgage boom ended up with a lower interest rate risk exposure once the monetary policy stance reversed and QT began, relative to banks that raised their direct real estate exposure.

The banking fragility episode of 2023 was driven to large extents by outflows of unin-

[17] In January 2022, the Fed confirmed the plan to end its QE program in March 2022 and disclosed (without providing details) the roll-off schedule, which was later detailed in May 2022.

sured deposits from the banking system. In a final step, depicted in Panel D of Figure 4, we look at whether the dynamics of uninsured deposit ratios differ for more vs. less exposed banks. As one can see, banks with lower 2019 liquidity positions had lower uninsured deposit ratios in 2023, which is evidence that the initially liquidity-constrained banks, i.e., those that we have shown to mainly raise their indirect exposure to real estate via credit lines to NMCs, were more likely than other banks to weather the banking fragility storm in 2023.

8 Conclusions

In this paper, we study the substitutability vs. complementarity of banks and non-banks in the mortgage market. To this end, we exploit the substantial liquidity injection associated with the Federal Reserve 2020 QE program as a quasi-natural experiment, and investigate to what extent initially liquidity-scarce banks expand their indirect real estate exposure via credit lines to non-bank mortgage companies or their direct real estate exposure via MBS investments or on-balance sheet mortgages.

We find that banks more exposed to the liquidity injection, i.e., banks with lower ex-ante liquidity ratios, expand their credit lines to non-banks, but they do not raise their direct real estate exposure. We then leverage Mortgage Call Report data to construct a bank-NMC panel data set containing 1,179 unique credit line relationships between 405 NMCs and 105 banks. The advantage of using a bank-NMC panel is that we can improve on identification and control for credit line demand by means of NMC-time fixed effects a la Khwaja and Mian (2008). The corresponding results still point to a strong increase in credit lines for more exposed banks.

We finally show that these banks entered the quantitative tightening episode starting in 2022 with significantly lower interest rate and bank run risk than less exposed banks. These results demonstrate that, at least in this market segment during this episode, banks

and non-banks complemented each other, thereby mitigating financial stability risks.

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Figure 1: Stylized Facts on Banks
This figure shows aggregate statistics of the banking sector. In Panel A, we plot the aggregate evolution of total bank deposits (line). The bars indicate the quarterly aggregate changes in billions of dollars (left axis). In Panel B, we plot the aggregate evolution of aggregate bank insured (red line) and uninsured deposits (blue line). Total deposits refer to the sum of non-interest-bearing (FFIEC Call report code rcon6631) and interest-bearing deposits (rcon6636). Insured deposits are deposit accounts of less than $ 250,000 (rconf049 + rconf050). Uninsured deposits are deposits accounts of more than $ 250,000 (rconf051 + rconf052). In Panel C, we show the distribution of reserves and cash (rconf0090 + rconf0080) (line) and the aggregate changes in reserves and cash in billion of $ (bars). Figures in Panels A-C are computed by using the entire sample of US commercial banks. In Panel D, we plot the histogram of reserves and cash over assets for the sample of banks that issued warehouse credit lines to NMCs. Banks are split by size in: small (those with total assets of less than $ 50 billions), regional (total assets from $ 50 to $ 250 billions), large (total assets equal or higher than $ 250 billions).

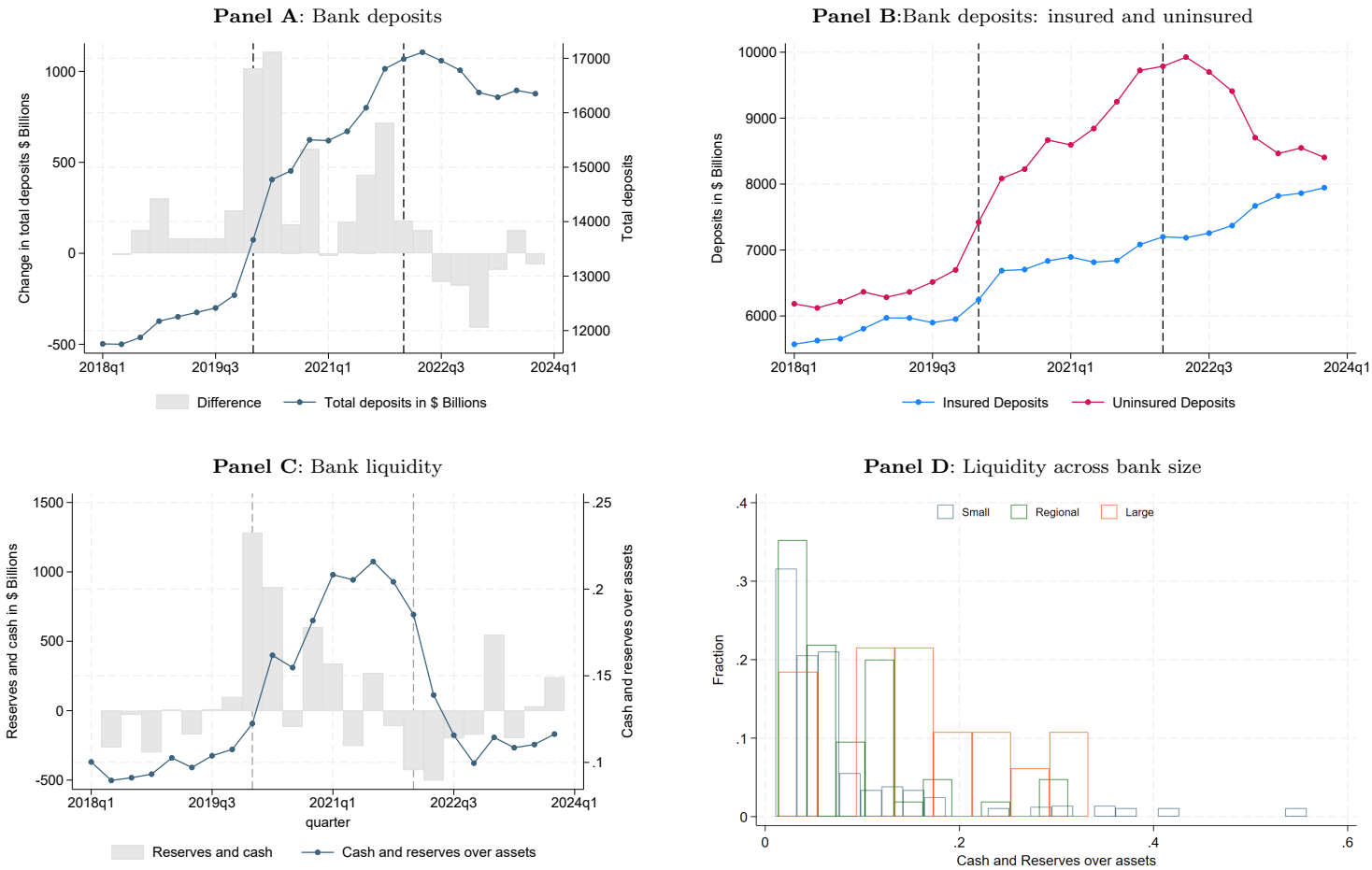


Figure 2: Stylized Facts on NMCs
This figures provides some stylized facts of NMCs. In Panel A, we plot the aggregate volume of credit granted (MCR call report LOC item: Credit Limit) and the aggregate volume of credit used (Credit Limit - Remaining Credit Available). In Panel B, we plot the histogram of the number of credit lines for each NMC in our sample using quarterly data over the 2018:Q1 to 2023:Q4 period. In Panel C, we plot the monthly volumes of mortgage originations of NMCs and Banks. Data are retrieved from cHMDA.

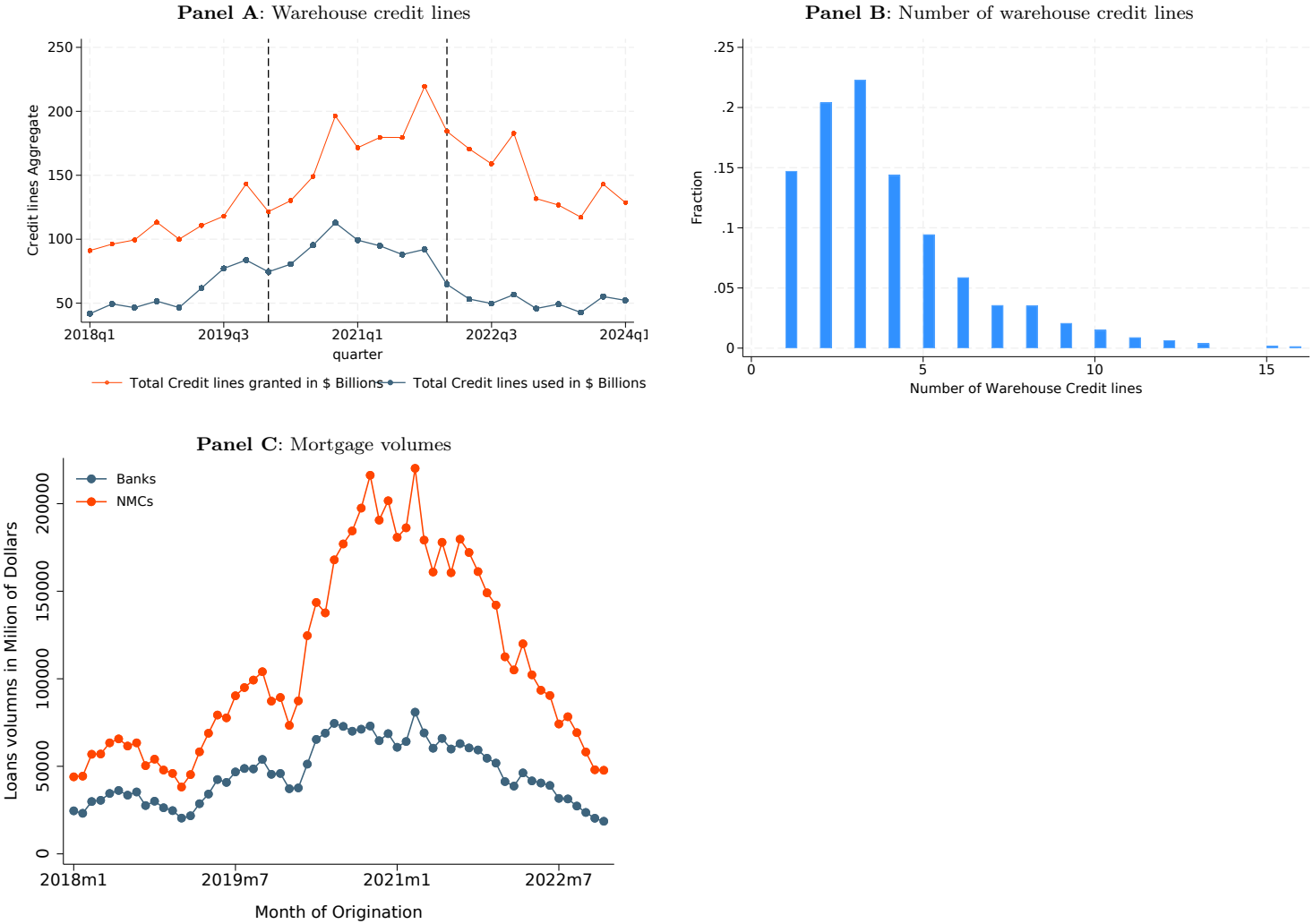


Figure 3: Liquidity and Bank Credit Supply to NMCs: Event Study Plot
This figure presents coefficient estimates of a modified version of Equation 2. Each coefficient estimate in each quarter corresponds to a different within-NMC regression, where the dependent variable is the change in the logarithm of total credit granted for each bank-NMC pair between the respective quarter and 2019:Q4 (the quarter before the shock). As in Equation 2, regressions include bank-specific controls fixed in 2019:Q2 and NMC fixed effects. To ease the interpretation of the results, the main variable of interest (*Liquidity*) is scaled by its standard deviation. The vertical bars denote 90% confidence intervals, based on standard errors clustered by bank

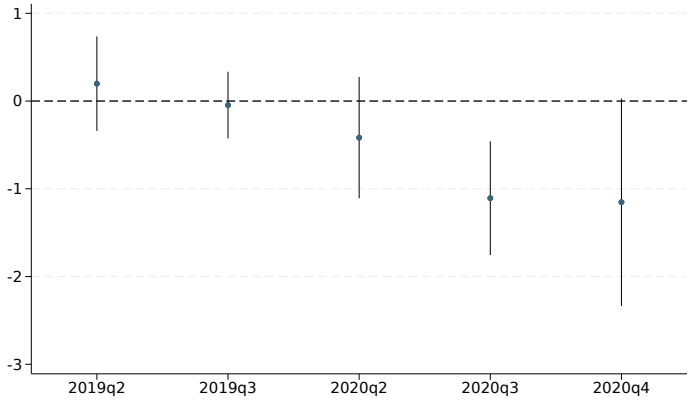


Figure 4: Are More Exposed Banks Less Exposed to Financial Instability Risks?
This figure plots the average marginal effects (AME) of *Liquidity* on selected bank-level outcomes over time based on the following specification:

$$Y_{b,t} = \sum_{t=-4}^{t=6} (\beta_t Liquidity_{pre} * \theta_t) + \gamma_b + \gamma_t + \epsilon_{b,t} \tag{5}$$

Where $Y_{b,t}$ is the outcome variable in the header of each panel for bank b at quarter t. $Liquidity_{b,pre}$ is the same bank exposure variable used in the previous specifications. θ_t are time dummies. The (omitted) reference period corresponds to the announcement of QT in 2022:Q1. The specification includes bank (γ_b) and quarter (γ_t) fixed effects. The vertical bars denote 90% confidence intervals, based on standard errors clustered by bank. The estimation sample includes only banks with NMC credit lines in the period 2019-2020.

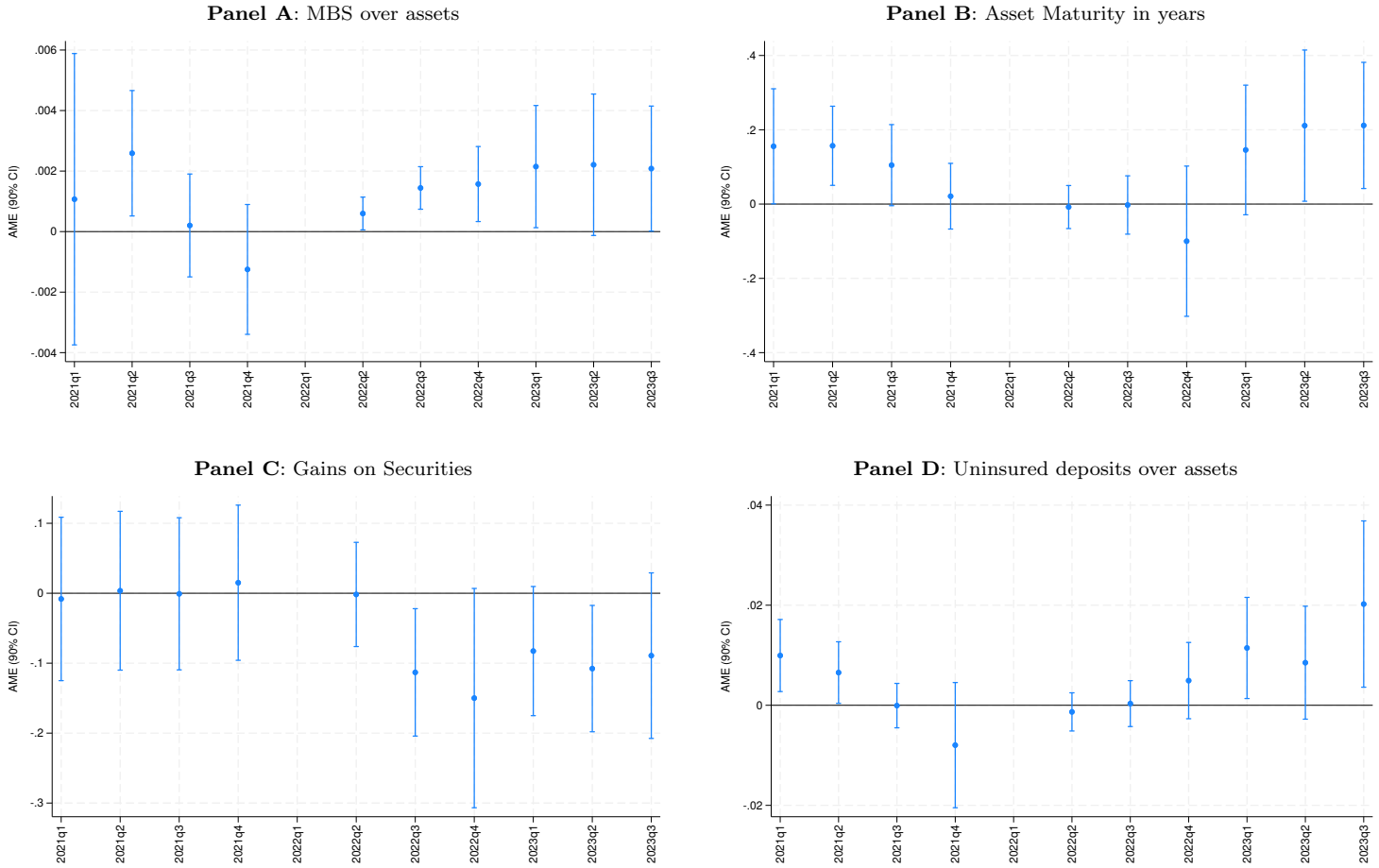


Table 1: Bank Liquidity and NMCs credit supply: preliminary test
This table shows preliminary correlation analysis across: *Liquidity* and: MBS over assets, Real Estate loans over assets; Credit lines granted to NMCs over assets; Credit lines to NMCs used over assets. Robust standard errors (in parenthesis) are clustered at the bank level. Statistical significance at the 10%, 5% and 1% level is denoted by *, **, and ***, respectively.

	MBS over assets	RE loans over assets	Credit lines granted	Credit lines used
	(1)	(2)	(3)	(4)
Liquidity * Post	0.00191**	0.00462*	-0.00650*	-0.00718*
	(0.000877)	(0.00261)	(0.00394)	(0.00370)
Bank controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
R^2	0.951	0.978	0.683	0.468
Observations	697	697	697	697
N. Banks	157	157	157	157

Table 2: Bank Liquidity and NMCs credit supply (Intensive Margin): baseline results
This table presents estimates of Equation 2, where the dependent variables are the change in the log of total granted (columns 1 and 2) or used (columns 3 and 4) credit lines between each NMC-bank pair. The quarterly data is collapsed into a single pre (2019Q2-2019Q4) and post (2020Q2-2020Q4) period. Bank exposure is the percentage of reserves and cash over assets. Bank controls are measured as of 2019Q2 and include: size, ROA and book equity over assets. All specifications include NMC fixed effects. Robust standard errors (in parenthesis) are clustered at the bank level. Statistical significance at the 10%, 5% and 1% level is denoted by *, **, and ***, respectively.

	$\Delta Log.Creditgranted$			$\Delta Log.Creditused$		
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity	-0.0612***	-0.0651***		-0.113***	-0.115***	
	(0.0167)	(0.0177)		(0.0349)	(0.0350)	
Liquidity*Large NMC			-0.0572***			-0.101**
			(0.0192)			(0.0398)
Liquidity*Small NMC			-0.0721***			-0.134**
			(0.0224)			(0.0599)
Bank control variables	No	Yes	Yes	No	Yes	Yes
NMCs FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.459	0.465	0.466	0.461	0.466	0.467
Observations	1,179	1,179	1,175	1,068	1,068	1,068
N. Banks	105	105	105	93	93	93
N. NMCs	405	405	403	361	361	361
Mean(y)	0.258	0.258	0.258	0.351	0.351	0.351

Table 3: Bank Liquidity and NMCs credit supply (Intensive Margin): lender specialization
This table presents estimates of Equation 2, where the dependent variables are the change in the log of total granted (columns 1 and 2) or used (columns 3 and 4) credit lines between each NMC-bank pair. The quarterly data is collapsed into a single pre (2019Q2-2019Q4) and post (2020Q2-2020Q4) period. Bank exposure is the percentage of reserves and cash over assets. Bank controls are measured as of 2019Q2 and include: size, ROA and book equity over assets. All specifications include NMC fixed effects interacted by bank quartiles of credit granded to NMCs over total assets to control for bank specialization. Robust standard errors (in parenthesis) are clustered at the bank level. Statistical significance at the 10%, 5% and 1% level is denoted by *, **, and ***, respectively.

	$\Delta Log.Creditgranted$			$\Delta Log.Creditused$		
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity	-0.0621***	-0.0548***		-0.124***	-0.101***	
	(0.0188)	(0.0183)		(0.0342)	(0.0330)	
Liquidity*Large NMC			-0.0431**			-0.0818**
			(0.0207)			(0.0370)
Liquidity*Small NMC			-0.0715***			-0.135**
			(0.0216)			(0.0557)
Bank control variables	No	Yes	Yes	No	Yes	Yes
NMCs FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.460	0.469	0.471	0.465	0.475	0.476
Observations	1,179	1,179	1,175	1,068	1,068	1,068
N. Banks	105	105	105	93	93	93
N. NMCs	405	405	403	361	361	361
Mean(y)	0.258	0.258	0.258	0.351	0.351	0.351

Table 4: Bank Liquidity and NMCs credit supply (Intensive Margin): NMC heterogeneity
This table presents estimates of Equation 2 augmented with NMC level interactions. The dependent variables are the change in the log of total granted credit lines between each NMC-bank pair. The quarterly data is collapsed into a single pre (2019Q2-2019Q4) and post (2020Q2-2020Q4) period. Bank exposure *Liquidity* is the percentage of reserves and cash over assets fixed at 2019Q2. Bank controls are measured as of 2019Q2 and include: size, ROA and book equity over assets. NMCs interactions are fixed at 2019Q2 and include: MSR over Equity, Equity over assets; Cash over assets; FHA exposure; GSE exposure; SuperPrime exposure; Main bank. All specifications include NMC fixed effects interacted by bank quartiles of credit granded to NMCs over total assets to control for bank specialization. The sample include NMCs with more than one credit line. Robust standard errors (in parenthesis) are clustered at the bank level. Statistical significance at the 10%, 5% and 1% level is denoted by *, **, and ***, respectively.

	Δ Log. Credit granted						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Liquidity	-0.0707***	-0.0751***	-0.0694***	-0.0719**	-0.0278	-0.0206	-0.106***
	(0.0204)	(0.0255)	(0.0175)	(0.0285)	(0.0831)	(0.0320)	(0.0171)
Liquidity * MSR over Equity	0.0265						
	(0.0333)						
Liquidity* Equity over Assets		0.0247					
		(0.0456)					
Liquidity * Cash Shadow			0.0183				
			(0.0198)				
Liquidity * FHA Exposure				0.0118			
				(0.0372)			
Liquidity * GSE Exposure					-0.0380		
					(0.0838)		
Liquidity * SuperPrime Exposure						-0.0472	
						(0.0393)	
Liquidity * Main Bank							0.0919***
							(0.0160)
Bank control variables							
NMCs FE							
R^2	0.417	0.413	0.418	0.413	0.432	0.432	0.481
Observations	864	876	877	899	941	941	1,190
N. Banks	86	86	86	82	82	82	106
N. NMCs	274	277	277	292	310	310	410
Mean(y)	0.265	0.262	0.259	0.279	0.278	0.278	0.258

Table 5: Bank Liquidity and NMCs credit supply (Intensive Margin): Lender size
This table presents estimates of Equation 2, where the dependent variables are the change in the log of total granted (columns 1 to 4) or used (columns 5 to 8) credit lines between each NMC-bank pair. In columns 1, 2, 5, 6 the sample includes warehouse credit lines to NMCs issued by large lenders (total assets equal or higher than $ 250 billion). In the other columns, the sample includes warehouse credit lines to NMCs issued by regional (total assets from $ 50 to $ 250 billions) and small banks (total assets lower than $ 50 billions). The quarterly data is collapsed into a single pre (2019Q2-2019Q4) and post (2020Q2-2020Q4) period. Bank exposure is the percentage of reserves and cash over assets. Bank controls are measured as of 2019Q2 and include: size, ROA and book equity over assets. All specifications include NMC fixed effects. Robust standard errors (in parenthesis) are clustered at the bank level. Statistical significance at the 10%, 5% and 1% level is denoted by *, **, and ***, respectively.

	Δ Log. Credit granted			Δ Log. Credit used		
Lender size:	Large	Small and Regional		Large	Small and Regional	
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity	-0.0426	-0.0739***		0.118	-0.132***	
	(0.0673)	(0.0176)		(0.0991)	(0.0296)	
Liquidity*Large NMC			-0.0617***			-0.119***
			(0.0197)			(0.0338)
Liquidity*Small NMC			-0.0885***			-0.138**
			(0.0241)			(0.0575)
Bank control variables	Yes	Yes	Yes	Yes	Yes	Yes
NMCs FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.532	0.501	0.503	0.580	0.486	0.487
Observations	109	970	966	112	866	866
N. Banks	10	89	89	10	78	78
N. NMCs	40	367	365	42	324	324
Mean(y)	0.237	0.270	0.270	0.173	0.379	0.379

Table 6: Intensive Margin (Intensive Margin): Bank Heterogeneity
This table presents estimates of Equation 2 augmented with bank level interactions. The dependent variables are the change in the log of total granted credit lines between each NMC-bank pair. The quarterly data is collapsed into a single pre (2019Q2-2019Q4) and post (2020Q2-2020Q4) period. Bank exposure *Liquidity* is the percentage of reserves and cash over assets fixed at 2019Q2 and interacted with bank characteristics as of 2019Q2. In column 1, the interaction is with a dummy variable equal to one if the book equity over assets is higher than the median value, zero otherwise. In column 2, *Liquidity* is interacted with the logarithm of size. In column 3 and 4, *Liquidity* is interacted with: a dummy variable equal to one if the bank ROA is higher than the median value, zero otherwise; and with a dummy that switches to one if the amount of elegible securities (MBS, treasuries and government securities) over assets is higher than the median value. The sample include NMCs with more than one credit line. Robust standard errors (in parenthesis) are clustered at the bank level. Statistical significance at the 10%, 5% and 1% level is denoted by *, **, and ***, respectively.

	Δ Log. Credit granted			
	(1)	(2)	(3)	(4)
Liquidity	-0.0540**	-0.00162	-0.0630***	-0.0631***
	(0.0208)	(0.102)	(0.0144)	(0.0156)
Liquidity * Capital	-0.0379**			
	(0.0180)			
Liquidity* Size		-0.0613		
		(0.105)		
Liquidity * ROA			0.00305	
			(0.0187)	
Liquidity * Eligible securities				0.00734
				(0.0186)
Bank control variables				
NMCs FE				
R^2	0.465	0.461	0.461	0.461
Observations	1,190	1,190	1,190	1,190
N. Banks	106	106	106	106
N. NMCs	410	410	410	410
Mean(y)	0.258	0.258	0.258	0.258

Table 7: Bank liquidity and NMCs credit supply (Extensive margin): baseline results
This table presents estimates of Equation 3, where the dependent variables are: the change in the log of total granted (columns 1 and 2) or used (columns 3 and 4) credit lines at the NMC level; a dummy variable that switches to one if a NMC establish a new lending relationship. The quarterly data is collapsed into a single pre (2019Q2-2019Q4) and post (2020Q2-2020Q4) period. Bank exposure is the percentage of reserves and cash over assets weighted by the amount of credit granted before the shock. NMC controls include: MSR over assets, the logarithm of total assets; book equity vapital over assets all measured before the shock. Demand FE are a vector of dummies extracted from intensive margin estimations. Robust standard errors (in parenthesis) are clustered at the main lender level. Statistical significance at the 10%, 5% and 1% level is denoted by *, **, and ***, respectively.

	Δ Log. Credit granted			Δ Log. Credit used			New Relationship		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Liquidity	-0.0214**	-0.0260**		-0.154***	-0.0971***		0.0415**	0.0350*	
	(0.0108)	(0.0127)		(0.0292)	(0.0370)		(0.0161)	(0.0194)	
Liquidity*Large NMC			-0.0202			-0.123***			0.0386**
			(0.0136)			(0.0340)			(0.0182)
Liquidity*Small NMC			-0.0375***			-0.0152			-0.00227
			(0.0124)			(0.0279)			(0.0151)
NMCs controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Credit demand	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.490	0.497	0.500	0.180	0.205	0.202	0.019	0.036	0.038
Observations	408	397	397	393	384	384	410	399	399
Mean(y)	0.367	0.374	0.374	0.532	0.544	0.544	0.137	0.135	0.135

Appendix for: Banks' Credit Line Supply to Nonbanks and Financial Stability

A Additional Tables and Figures

Table A.1: Summary Statistics NMCs

	N. observations	Mean	Std. Dev	p25	p50	p75
Panel A: NMCs						
Credit line limit (in Millions of $)	9,779	123.1	351.0	32.10	139.00	571.00
Credit line used (in Millions of $)	9,779	69.7	98.8	15.0	45.00	100.00
N. credit lines	9,779	3.644	2.421	2	3	5
Total assets (in Billions of $)	9,779	1.21	6.90	0.15	0.45	1.00
Log. total assets	9,779	18.52	2.72	17.36	18.77	20.18
Equity capital over assets	9,577	0.23	0.19	0.12	0.16	0.25
MSR over Equity	9,577	0.25	0.39	0.00	0.05	0.37
Mortgages HFS over assets	7,340	0.72	0.19	0.65	0.78	0.84
Cash over assets	9,515	0.11	0.16	0.036	0.06	0.11
Origination income over assets	9,451	0.12	0.38	0.07	0.02	0.04
Panel B: Warehouse Banks						
Total Assets (in Billions of $)	822	109	373	3.5	10.5	39.8
Logarithm of total assets	822	16.414	1.862	15.080	16.173	17.500
Book equity over assets	820	0.115	0.027	0.097	0.112	0.130
Insured deposits over deposits	798	0.493	0.150	0.395	0.491	0.583
Uninsured deposits over deposits	798	0.522	0.151	0.426	0.524	0.629
Cash and reserves over assets	817	0.122	0.117	0.038	0.080	0.165
Cash over assets	815	0.072	0.065	0.027	0.049	0.095
Reserves over assets	817	0.050	0.054	0.010	0.031	0.068
MBS over assets	822	0.047	0.052	0.011	0.031	0.062
Gov. securities over assets	820	0.052	0.062	0.011	0.037	0.062
RE loans over assets	822	0.420	0.163	0.315	0.440	0.536
C&I loans over assets	816	0.142	0.081	0.080	0.135	0.196
Consumer Loans over assets	814	0.038	0.062	0.004	0.014	0.054
ROA	822	0.026	0.034	0.015	0.028	0.041

Table A.2: Summary statistics: Banking sample

	Count	Mean	SD	p25	p50	p75
Call Reports sample						
Total Assets (in Billions of $)	6,735	19.336	136.640	0.754	1.621	4.714
Logarithm of total assets	6,735	14.610	1.557	13.533	14.298	15.366
Book equity over assets	6,652	0.113	0.026	0.096	0.109	0.125
Insured deposits over deposits	6,613	0.567	0.156	0.471	0.576	0.678
Uninsured deposits over deposits	6,611	0.439	0.158	0.325	0.429	0.537
Cash and reserves over assets	6,683	0.128	0.112	0.044	0.094	0.174
Cash over assets	6,663	0.077	0.061	0.032	0.060	0.105
Reserves over assets	6,702	0.050	0.054	0.009	0.032	0.073
MBS over assets	6,698	0.044	0.047	0.009	0.030	0.063
Gov. securities over assets	6,675	0.068	0.070	0.020	0.047	0.093
RE loans over assets	6,672	0.480	0.175	0.389	0.502	0.600
C&I loans over assets	6,667	0.116	0.080	0.058	0.101	0.158
Consumer Loans over assets	6,653	0.033	0.063	0.003	0.011	0.031
ROA	6,735	0.030	0.044	0.015	0.026	0.040
Warehouse banks						
Panel B: Warehouse Banks						
Total Assets (in Billions of $)	822	109	373	3.541	10.563	39.815
Logarithm of total assets	822	16.414	1.862	15.080	16.173	17.500
Book equity over assets	820	0.115	0.027	0.097	0.112	0.130
Insured deposits over deposits	798	0.493	0.150	0.395	0.491	0.583
Uninsured deposits over deposits	798	0.522	0.151	0.426	0.524	0.629
Cash and reserves over assets	817	0.122	0.117	0.038	0.080	0.165
Cash over assets	815	0.072	0.065	0.027	0.049	0.095
Reserves over assets	817	0.050	0.054	0.010	0.031	0.068
MBS over assets	822	0.047	0.052	0.011	0.031	0.062
Gov. securities over assets	820	0.052	0.062	0.011	0.037	0.062
RE loans over assets	822	0.420	0.163	0.315	0.440	0.536
C&I loans over assets	816	0.142	0.081	0.080	0.135	0.196
Consumer Loans over assets	814	0.038	0.062	0.004	0.014	0.054
ROA	822	0.026	0.034	0.015	0.028	0.041

Table A.3: Selected Characteristics for Treated vs. Control Banks
This table reports summary statistics on banks with below-median *Liquidity* vs above-median *Liquidity* measured in 2019:Q2. The sample includes only banks with warehouse credit lines.

	Low Liquidity			High Liquidity			Mean-comparison test	
	Obs.	Mean	SD	Obs.	Mean	SD	Diff.	t-stat
Logarithm of total assets	62	15.886	1.541	59	16.392	2.170	-0.506	-1.486
Book equity over assets	62	0.120	0.022	59	0.117	0.029	0.003	0.726
Insured deposits over deposits	62	0.540	0.125	57	0.503	0.181	0.037	1.291
Uninsured deposits over deposits	62	0.476	0.120	57	0.511	0.185	-0.035	-1.236
MBS over assets	62	0.045	0.044	59	0.050	0.057	-0.006	-0.612
Gov. securities over assets	61	0.040	0.041	59	0.062	0.086	-0.022	-1.772*
RE loans over assets	62	0.492	0.130	59	0.409	0.198	0.084	2.761***
C&I loans over assets	62	0.140	0.070	59	0.117	0.089	0.023	1.586
Consumer Loans over assets	62	0.042	0.071	58	0.046	0.073	-0.005	-0.355
ROA	62	0.025	0.007	59	0.024	0.010	0.001	0.567

Table A.4: Bank Liquidity and NMCs credit supply (Intensive Margin): Robustness with alternative exposure variable

This table presents estimates of Equation 2, where the dependent variables are the change in the log of total granted (columns 1 and 2) or used (columns 3 and 4) credit lines between each NMC-bank pair. The quarterly data is collapsed into a single pre (2019Q2-2019Q4) and post (2020Q2-2020Q4) period. In Panel A bank exposure is the percentage of reserves over assets. In Panel B, bank exposure is the percentage of reserves over uninsured deposits. Bank controls are measured as of 2019Q2 and include: size, ROA and book equity over assets. All specifications include NMC fixed effects. Robust standard errors (in parenthesis) are clustered at the bank level. Statistical significance at the 10%, 5% and 1% level is denoted by *, **, and ***, respectively.

	$\Delta Log.Creditgranted$			$\Delta Log.Creditused$		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Reserves over Assets						
Reserves over Assets	-0.0645***	-0.0701***		-0.109***	-0.118***	
	(0.0168)	(0.0172)		(0.0364)	(0.0343)	
Reserves over Assets * Large NMC			-0.0597***			-0.0988***
			(0.0172)			(0.0363)
Reserves over Assets * Small NMC			-0.0644***			-0.117**
			(0.0201)			(0.0536)
Bank control variables	No	Yes	Yes	No	Yes	Yes
NMCs FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.461	0.467	0.468	0.460	0.467	0.467
Observations	1,179	1,179	1,175	1,068	1,068	1,068
N. Banks	105	105	105	93	93	93
N. NMCs	405	405	403	361	361	361
Mean(y)	0.258	0.258	0.258	0.351	0.351	0.351
Panel B: Reserves over uninsured deposits						
Reserves over Unins. Dep	-0.0634***	-0.0632***		-0.0970***	-0.0990***	
	(0.0183)	(0.0194)		(0.0368)	(0.0366)	
Reserves over Unins. Dep. * Large NMC			-0.0539***			-0.0828**
			(0.0180)			(0.0359)
Reserves over Unins. Dep. * Small NMC			-0.0745***			-0.132*
			(0.0255)			(0.0763)
Bank control variables	No	Yes	Yes	No	Yes	Yes
NMCs FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.463	0.467	0.469	0.463	0.469	0.470
Observations	1,156	1,156	1,152	1,045	1,045	1,045
N. Banks	104	104	104	92	92	92
N. NMCs	405	405	403	361	361	361
Mean(y)	0.260	0.260	0.261	0.356	0.356	0.356

Table A.5: Bank Liquidity and NMCs credit supply (Intensive Margin): Robustness with alternative window

This table presents estimates of Equation 2, where the dependent variables are the change in the log of total granted (columns 1 and 2) or used (columns 3 and 4) credit lines between each NMC-bank pair. The quarterly data is collapsed into a single pre (2019Q3-2019Q4) and post (2020Q3-2020Q4) period. Bank exposure is the percentage of reserves and cash over assets. Bank controls are measured as of 2019Q2 and include: size, ROA and book equity over assets. All specifications include NMC fixed effects. Robust standard errors (in parenthesis) are clustered at the bank level. Statistical significance at the 10%, 5% and 1% level is denoted by *, **, and ***, respectively.

	Δ Log. Credit granted			Δ Log. Credit used		
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity	-0.0484***	-0.0462***		-0.0864**	-0.0839***	
	(0.0123)	(0.0134)		(0.0341)	(0.0314)	
Liquidity*Large NMC			-0.0368**			-0.0817**
			(0.0152)			(0.0319)
Liquidity*Small NMC			-0.0644***			-0.0690**
			(0.0201)			(0.0331)
Bank control variables	No	Yes	Yes	No	Yes	Yes
NMCs FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.441	0.448	0.450	0.456	0.466	0.466
Observations	897	897	895	843	843	843
N. Banks	81	81	81	75	75	75
N. NMCs	287	287	286	274	274	274
Mean(y)	0.200	0.200	0.200	0.290	0.290	0.290

Table A.6: Bank Liquidity and NMCs credit supply (Intensive Margin): Relative change 2020Q4-2019Q4
This table presents estimates of Equation 2, where the dependent variables are the change in the log of total granted (columns 1 and 2) or used (columns 3 and 4) credit lines between each NMC-bank pair. The quarterly data is collapsed into a single pre (2019Q4) and post (2020Q4) period. Bank exposure is the percentage of reserves and cash over assets. Bank controls are measured as of 2019Q2 and include: size, ROA and book equity over assets. All specifications include NMC fixed effects. Robust standard errors (in parenthesis) are clustered at the bank level. Statistical significance at the 10%, 5% and 1% level is denoted by *, **, and ***, respectively.

	Δ Log. Credit granted			Δ Log. Credit used		
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity	-0.0658***	-0.0607**		-0.118***	-0.118***	
	(0.0245)	(0.0261)		(0.0293)	(0.0311)	
Liquidity*Large NMC			-0.0358			-0.0951***
			(0.0293)			(0.0295)
Liquidity*Small NMC			-0.101***			-0.145***
			(0.0294)			(0.0450)
Bank control variables	No	Yes	Yes	No	Yes	Yes
NMCs FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.481	0.488	0.491	0.536	0.537	0.533
Observations	1,066	1,066	1,055	989	989	980
N. Banks	93	93	93	86	86	86
N. NMCs	381	381	376	352	352	348
Mean(y)	0.258	0.258	0.256	-0.395	-0.395	-0.394

Table A.7: Bank liquidity and NMCs credit supply (Extensive margin): Robustness with alternative event window.

This table presents estimates of Equation 3, where the dependent variables are: the change in the log of total granted (columns 1 and 2) or used (columns 3 and 4) credit lines at the NMC level; a dummy variable that switches to one if a NMC establish a new lending relationship. The quarterly data is collapsed into a single pre (2019Q3-2019Q4) and post (2020Q3-2020Q4) period. Bank exposure is the percentage of reserves and cash over assets weighted by the amount of credit granted before the shock. NMC controls include: MSR over assets, the logarithm of total assets; book equity vapital over assets all measured before the shock. Demand FE are a vector of dummies extracted from intensive margin estimations. Robust standard errors (in parenthesis) are clustered at the main lender level. Statistical significance at the 10%, 5% and 1% level is denoted by *, **, and ***, respectively.

	Δ Log. Credit granted			Δ Log. Credit used			New Relationship		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Liquidity	-0.0645***	-0.0674***		-0.111***	-0.0911***		0.0429**	0.0484**	
	(0.0155)	(0.0194)		(0.0282)	(0.0343)		(0.0168)	(0.0223)	
Liquidity*Large NMC			-0.0651***			-0.114***			0.0531**
			(0.0210)			(0.0356)			(0.0217)
Liquidity*Small NMC			-0.0741***			-0.0549			0.00478
			(0.0204)			(0.0437)			(0.0186)
NMCs controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Credit demand	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.389	0.387	0.394	0.212	0.210	0.201	0.016	0.038	0.040
Observations	289	279	279	279	270	270	302	281	281
Mean(y)	0.298	0.310	0.310	0.353	0.369	0.369	0.119	0.125	0.125

Table A.8: Bank liquidity and NMCs credit supply (Extensive margin): Robustness with alternative exposure variable.
This table presents estimates of Equation 3, where the dependent variables are: the change in the log of total granted (columns 1 and 2) or used (columns 3 and 4) credit lines at the NMC level; a dummy variable that switches to one if a NMC establish a new lending relationship. The quarterly data is collapsed into a single pre (2019Q2-2019Q4) and post (2020Q2-2020Q4) period. In Panel A bank exposure is the pecentage of reserves over assets. In Panle B, bank exposure is the percentage of reserves over uninsured deposits wighted by the total amount of credit granted before the shock. NMC controls include: MSR over assets, the logarithm of total assets; book equity vapital over assets all measured before the shock. Demand FE are a vector of dummies extracted from intensive margin estimations. Robust standard errors (in parenthesis) are clustered at the main lender level. Statistical significance at the 10%, 5% and 1% level is denoted by *, **, and ***, respectively.

	$\Delta Log.Creditgranted$			$\Delta Log.Creditused$			New Relationship		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Reserves over assets									
Liquidity	-0.0253**	-0.0315***		-0.152***	-0.0959***		0.0403**	0.0324*	
	(0.0104)	(0.0120)		(0.0285)	(0.0329)		(0.0157)	(0.0183)	
Liquidity*Large NMC			-0.0251**			-0.118***			0.0358**
			(0.0124)			(0.0308)			(0.0172)
Liquidity*Small NMC			-0.0391***			-0.00159			-0.00272
			(0.0127)			(0.0280)			(0.0150)
NMCs controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Credit demand	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.492	0.499	0.502	0.178	0.206	0.204	0.018	0.035	0.037
Observations	408	397	397	393	384	384	410	399	399
Mean(y)	0.367	0.374	0.374	0.532	0.544	0.544	0.137	0.135	0.135
Panel B: Reserves over uninsured deposits									
Liquidity	-0.0277***	-0.0379**		-0.145***	-0.0849**		0.0423**	0.0450*	
	(0.00970)	(0.0147)		(0.0256)	(0.0380)		(0.0167)	(0.0250)	
Liquidity*Large NMC			-0.0305**			-0.112***			0.0456*
			(0.0148)			(0.0351)			(0.0231)
Liquidity*Small NMC			-0.0454***			0.00199			-0.00324
			(0.0145)			(0.0297)			(0.0188)
NMCs controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Credit demand	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.493	0.500	0.503	0.174	0.200	0.197	0.020	0.039	0.041
Observations	408	397	397	393	384	384	410	399	399
Mean(y)	0.367	0.374	0.374	0.532	0.544	0.544	0.137	0.135	0.135

Figure A.1: Scatter Plot of Uninsured Deposits over Assets vs Bank Liquidity
This figure shows a scatter plot of uninsured deposits over total assets versus *Liquidity* (cash and reserves over total assets) for the sample of banks that issued a warehouse credit line.

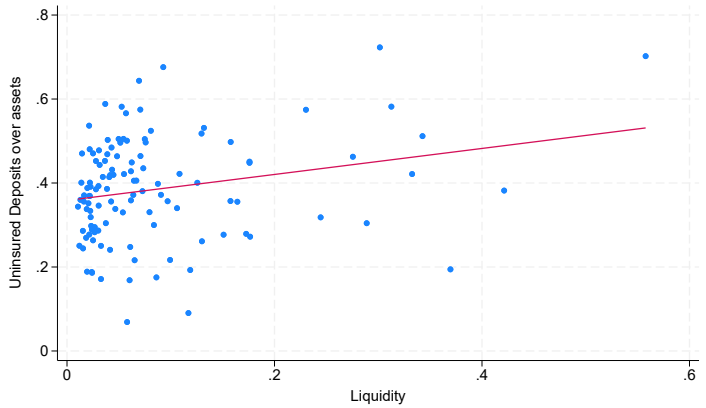
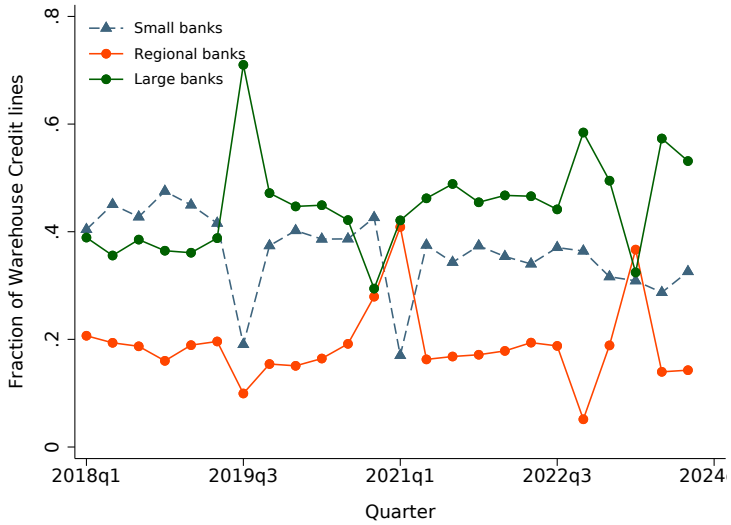


Figure A.2: Market Shares For Differentially-Sized Banks
This figure plots market shares of warehouse lenders splitted by size in: small (those with total assets of less than $ 50 billions), regional (total assets from $ 50 to $ 250 billions), large (total assets equal or higher than $ 250 billions).



B Additional information

B.1 Warehouse Funding

Warehouse funding refers to a short-term financing arrangement that allows NMCs to fund loans before they are sold to investors or agencies in the secondary market (e.g., Fannie Mae, Freddie Mac, or private investors). This type of funding ensures liquidity and smooth operations during the period between loan origination and loan sale or securitization. The main characteristics of Warehouse Line of credit (LOC) are the following:

- The provider is a bank or another financial institution;
- Each loan originated under the warehouse line of credit is temporarily pledged as collateral to the warehouse lender until the mortgage is sold. Once sold, the proceeds are used to repay the loan amount borrowed from the warehouse line, freeing up the funds for future originations.
- The warehouse loan is of short-term nature as it is designed to cover the period between loan origination and the loan's sale. It typically lasts for a few weeks to a few months.
- The interest rate is variable (Libor plus a credit spread).

Usage example: A mortgage lender issues a $300,000 home loan to a borrower. It draws the amount from its warehouse line to fund the mortgage. Once the loan is sold to Fannie Mae for $305,000 (including fees or servicing rights), the lender repays the warehouse loan with interest and keeps the difference as profit.

Why a LOC is important for NMCs:

- *Liquidity:* It provides mortgage lenders the funding to continuously originate without waiting for loans to be sold.
- *Operational Efficiency:* It allows NMCs to manage large loan volumes without tying up their own capital.

- *Facilitates Loan Origination:* Without warehouse funding, many lenders would struggle to originate loans at scale.

Warehouse funding plays a critical role in ensuring the smooth flow of capital to the mortgage industry, connecting the origination of loans with the secondary market.

B.2 Nationwide Multistate Licensing System

Nonbank-Mortgage Companies operate under the regulatory framework of the Nationwide Multistate Licensing System (NMLS). The NMLS is a platform that facilitates the regulation and licensing of financial services firms and professionals - most notably in the mortgage industry but also including non-mortgage financial services, such as consumer lending, debt collection, student loan servicing, check cashing services, and other money services businesses. When an NMC holds a state license via the NMLS, it means that:

- It has obtained a license from a specific state (or multiple states) to legally offer non-mortgage financial services.
- The NMLS serves as the central repository for maintaining information on the company, tracking licenses, and ensuring regulatory compliance across multiple states.
- Each state has unique licensing and regulatory requirements, such as minimum capital, consumer protection obligations, and annual audits, which the company must meet.
- Regulators use the NMLS to monitor the compliance of NMCs by reviewing reports, complaints, and renewals on a regular basis.

B.3 Dataset Construction

This section describes how we construct the bank-NMC and NMC-cHMDA datasets used for our analysis. We combine data from the following sources:

- FFIEC 031/041 (Call Report);
- Avery HMDA Lender Files (relationship file between HMDA ID and Bank RSSD IDs);
- Mortgage Call Reports
- confidential version of the HMDA mortgage level data

Warehouse credit line-level dataset. The first step was to assemble the sample of warehouse credit lines of NMCs with the FFIEC Call reports. Since the RMLA section of the MCR contains information on bank names without including RSSD IDs, we manually search bank RSSD IDs (RSSD 9001 code in FFIEC Call Reports) through the FDIC BankFind website. For warehouse credit providers that are not banks, we leave the field emply. This step results in X banks and XY NMCs.

cHMDA merge with MCR. To merge the NMC data with the cHMDA we proceed in two steps. The first step was to extract NMCs names and NMLS from the MCR dataset. Since the cHMDA does not contains NMLS IDs on banks and NMCs, we manually search for the legal entity identifier through the Avery HMDA Lender Files. We double check the results with the NMLS Consumer Access platform.