The Impact of Quantitative Easing on Bank and Nonbank Lending During the Pandemic Mortgage Boom*

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Abstract

How did the Federal Reserve's Quantitative Easing (QE) program affect lending during the pandemic mortgage boom? Similar to previous rounds of QE, banks with greater exposure to Fed asset purchases increased activity, however, unlike earlier programs, banks expanded commercial loans more than real estate loans. Despite limited growth in the volume of real estate loans on bank balance sheets, mortgage application data shows that banks reduced rejection rates, particularly for home purchases. Furthermore, credit line information shows an increase in bank warehouse funding to nonbank mortgage lenders, suggesting a novel nonbank lending channel. Nonbanks obtained larger increases in warehouse funding from banks with greater exposure to Fed asset purchases, and nonbanks with greater indirect exposure to QE via their funding relationships in turn lowered rejection rates, particularly for refinance applications.

Keywords: Quantitative easing, Bank lending, Nonbank Financial Intermediaries, Covid-19, Mortgages.

JEL Classification code: E30, E44, E58, G21

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1 Introduction

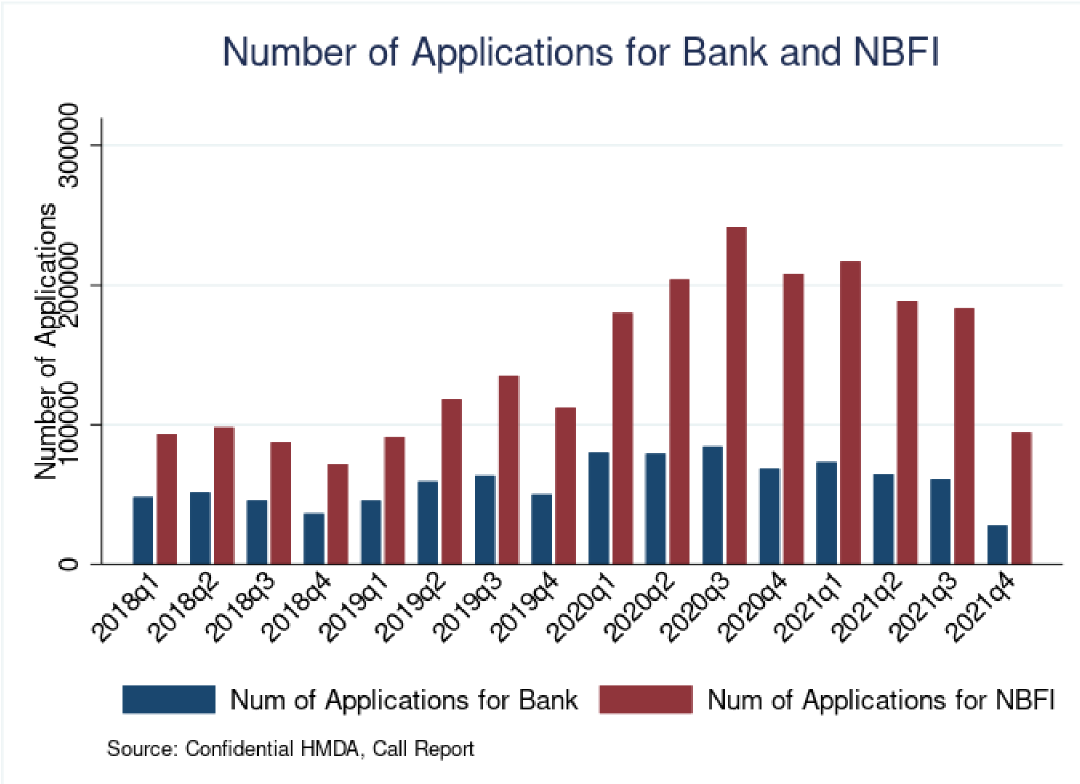
The period around the COVID-19 pandemic coincided with a dramatic boom in mortgage lending and house prices. New mortgage origination surpassed $4 trillion annually for the first time ever in 2020 and 2021, mortgage balances on consumer credit reports increased over 10% from 2020Q1 to 2021Q4, and house prices surged by more than 30% from January 2020 to December 2021.[1] While a variety of policies aimed at mitigating the impact of the pandemic may have influenced this boom, a particularly important one for easing financial conditions was the Federal Reserve's Quantitative Easing (QE) program, involving the large-scale purchase of Treasury and agency mortgage-backed securities in an attempt to support the flow of credit to households and businesses.

Growing evidence suggests that QE can support overall credit and liquidity conditions in financial markets through various channels. A specific line of research has focused on the impact of QE on bank lending. Prior studies have documented that earlier rounds of QE, following the 2008 Global Financial Crisis (GFC), resulted in a significant increase in bank mortgage lending (Rodnyansky and Darmouni 2017), while also inducing a "crowding out" effect for commercial and industrial (C&I) loans (Chakraborty et al. 2020). However, focusing only on mortgages originated by banks may overlook a crucial source of household credit, as nonbank financial institutions (NBFIs) have become an increasingly important source of credit origination in the US, especially for mortgages (Buchak et al. 2018; Jiang et al. 2020).

After a sharp pullback following the 2008 GFC, NBFIs became the dominant source of new mortgages in the US in the second half of the 2010s. Figure 1 shows that NBFIs have received more mortgage loan applications than banks since at least 2018. Indeed, the banking sector originated only about one-third of new mortgages from 2018 to 2021. Since, unlike banks, NBFIs do not have direct exposure to central bank large-scale asset purchases, the potential impact of QE on NBFI lending is unclear. On the one hand, overall improved credit conditions and liquidity may positively impact NBFI credit supply, while on the other, NBFIs largely depend on bank lending for funding (Jiang 2023). Thus, to the extent that QE negatively impacts bank C&I lending, it could also adversely impact NBFI funding from the commercial banking sector.

[1] New mortgage origination information is from Newton and Vickery (2022) who sourced the data from the Mortgage Bankers Association via Haver Analytics. Mortgage balance data is from the Federal Reserve Bank of New York's Quarterly Report on Household Debt and Credit. House price data is from the S&P CoreLogic Case-Shiller U.S. National Home Price Index.

Figure 1: Number of Applications for Bank and NBFI



Note: This figure presents the number of mortgage loan applications for bank and nonbank financial intermediaries by quarter from 2018 until 2021.

In this paper, we examine how the Fed's 2020-2022 QE program contributed to the pandemic-era mortgage boom through its effect on bank and nonbank lending. In doing so, we investigate a number of specific questions: Did direct exposure to QE increase mortgage lending from the traditional banking sector? Can the transmission of QE be traced from the banking sector to NBFI lenders? Did indirect exposure to QE affect NBFI mortgage lending?

We use the Call Reports, containing the universe of data on US commercial banks, as well as the Federal Reserve's confidential Home Mortgage Disclosure Act (HMDA) dataset, containing the universe of US mortgage applications, to examine the impact of the pandemic-era QE program on lending and mortgage outcomes. The Call Reports contain quarterly loan data for all US banks. Following prior studies in the QE and bank lending literature (Rodnyansky and Darmouni 2017; Luck and Zimmermann 2020; Chakraborty et al. 2020), these data also allows us to construct a bank's mortgage backed security-to-asset ratio (MBS ratio) prior to the onset of the 2020 QE program as a proxy for exposure to QE. The confidential HMDA dataset gives us detailed information on almost all US mortgage applications, including outcome, applicant characteristics, loan characteristics, lender characteristics, and property characteristics. Combining the two datasets allows us to examine how exposure to QE affects overall lending at the bank-level, as well as application-level outcomes such as rejection rates.

Since the majority of new mortgages during this time period are originated by NBFIs, we are also interested in accounting for the potential influence of QE on NBFI lending. We do this by exploiting information from the Mortgage Call Reports, which provide data on individual credit lines extended to NBFIs by banks. Data on warehouse lines of credit between banks and NBFIs allow us to make a direct link between bank QE exposure and NBFI funding. In particular, we can examine whether NBFIs receive an increase in funding from banks with greater exposure to QE after the onset of the program. We can also construct a novel measure of NBFI exposure to QE through their bank funding relationships, which allows us to test whether QE impacts NBFI lending.

Similar to studies on prior rounds of QE (Rodnyansky and Darmouni 2017), we find that banks with greater exposure to Fed asset purchases increased their lending. While total lending increased for banks with greater QE exposure, the increase during the pandemic was more strongly driven by an expansion in C&I loans than in real estate loans. This result notably contrasts with the evidence from QE1-QE3. While the previous literature generally agrees that QE1 and QE3 had positive effects on real estate lending, there is a debate whether a similar positive impact occurred for C&I lending, as Luck and Zimmermann (2020) find that QE3 increased C&I lending whereas Chakraborty et al. (2020) report that QE3 crowded out C&I lending to large firms.

While the bank-level results suggest only a weak increase in real estate lending, there are potential measurement issues with analyzing the change in end-of-quarter loan volumes on bank balance sheets, as mortgages that are originated and sold for secularization within a quarter will not be captured. To provide a more granular perspective, we exploit application-level data and find stronger evidence of an increase in bank mortgage lending. Specifically, banks with higher MBS ratios prior to the onset of the pandemic reduced rejection rates for both home purchases and refinances, with the decline being larger and more robust for home purchases.

Bank mortgage lending appears to increase modestly with greater QE exposure, however the mortgage market may have also been indirectly influenced by the increase in bank C&I lending. NBFI mortgage lenders are financed to a significant degree by bank lines of credit. Therefore, the expansion of bank C&I lending may have included an increase in warehouse funding to NBFIs, which may in turn have affected NBFI lending behavior. Examination of credit line data provides evidence that the effects of QE were indeed transmitted to NBFIs through bank-NBFI warehouse funding relationships. Specifically, a within-NBFI specification shows that for NBFIs with multiple financing relationships, credit line usage and utilization increased more for lines issued by banks with greater QE exposure. NBFIs with greater indirect exposure to QE through their funding relationships then lowered rejection rates for refinances, but not for home purchases.

Overall, the results suggest that greater exposure to QE induced banks to increase lending for home purchase mortgages and NBFIs to increase lending for mortgage refinancing. The latter result is notable, as refinancing was an essential component of the mortgage market in this period, with sub-3% mortgage rates sparking a surge in demand. Indeed, as Newton and Vickery (2022) note, "refinancing more than doubled from 2019 to 2020, from $1.0 trillion to $2.6 trillion, accounting for the majority of the total rise in mortgage lending." The additional funding NBFIs received from banks with greater QE exposure appears to have supported NBFI lending in the face of this heightened demand.

Our paper relates to several strands of the literature. First, our work connects to the literature on the impact of QE on banks and bank lending. Rodnyansky and Darmouni (2017), Chakraborty et al. (2020), and Luck and Zimmermann (2020) find that banks with higher exposure to QE through MBS holdings on their balance sheet increased their mortgage lending following the pre-pandemic rounds of QE. However, Chakraborty et al. (2020) also provide evidence of a crowding-out effect of QE on corporate loans. Kapoor and Peia (2021) find that QE increased credit supply, mainly during the first and third rounds of QE. Di Maggio et al. (2020) show that mortgage refinancing increases following QE. Kandrac and Schlusche (2021) find that QE led to a rise in loan growth and bank risk-taking and Kurtzman et al. (2022) show that QE lowered lending standards and increased risk-taking. Diamond et al. (2024) emphasize the impact of the increase in bank reserves following QE. While an increase in reserves can reduce bank liquidity risk, which could support an increase in lending (Schaffer and Segev 2023), Diamond et al. (2024) argue that bank balance sheet expansion may induce regulatory constraints, such as the leverage ratio, which increases the costs of meeting capital requirements and can lead to a reduction in lending. We add to this collection of studies in two main ways. First, while most of the existing cross-sectional evidence has focused on earlier, pre-pandemic rounds of QE, this paper examines the impact of the pandemic-era QE program. Second, to the best of our knowledge, this paper is the first to study the transmission of QE to nonbank mortgage originators through wholesale funding relationships.

In a recent paper, Drechsler et al. (2024) show that the COVID-19 period QE program played a key role in the expansion of aggregate mortgage credit supply during the pandemic mortgage boom. They argue that the Fed and the banking system are the two major sources of credit supply in the US mortgage market and that monetary policy played a central role from 2020-2024 through QE, which drives the Fed's supply of mortgage credit, and through the deposits channel of monetary policy, which drives banks' supply of mortgage credit (Drechsler et al. 2017; Drechsler et al. 2021). In this view, investors who are the final buyers of MBS are the ultimate source of mortgage credit, rather than the institutions that originate mortgages.[2] Fuster et al. (2021) also highlight the importance of QE during this period, showing that jumbo and superconforming mortgages, which generally are not included in Fed asset purchases, display negative dynamics relative to conforming mortgages, which suggests that the pandemic QE program helped boost overall credit supply for conforming mortgages. Our work complements these studies by demonstrating how exposure to QE shaped cross-sectional differences in lending behavior across both bank and nonbank originators.

This paper also relates to the literature analyzing the increasing role of nonbanks as the primary source of mortgage origination in the US. A number of papers have focused on the causes and consequences of this shift in mortgage origination. Buchak et al. (2018) argue that regulatory arbitrage and technological advantages are the main reasons for the growth in NBFI mortgage lending. Buchak et al. (2024) show that NBFIs substitute for traditional banks among easily sold loans, such as conforming mortgages. Additionally, Fuster et al. (2019) show that because of technological advantage, NBFIs have fewer operating constraints and might be more suited to deal with large credit demand booms. NBFI FinTech lenders, which operate in the mortgage market, have also been found to mainly focus on mortgage refinances (Berg et al. 2022).

Fuster et al. (2021) argue that technology-based nonbank lenders were also better suited to deal with COVID-19 pandemic-related constraints, which helped these lenders increase market share during the period. Similar results are found by Allen et al. (2023) who show that, following natural disaster shocks, nonbank FinTech lenders increase the supply of reconstruction mortgages more than traditional banks. While the above studies have mainly highlighted the competitive impact of NBFIs versus banks in the consumer mortgage market, Jiang (2023) points out that banks' market power in the warehouse funding market, which constitutes a primary source of funding for NBFIs, reduces competition in the mortgage market. Similar to Jiang (2023), we also use the Mortgage Call Reports to explore the connection between banks and NBFIs via warehouse lines of credit. We are the first study, however, to analyze the impact of QE on the mortgage market through these connections.

Finally, our paper relates to the growing literature on the effect of the COVID-19

[2]For instance, NBFIs sell the vast majority of mortgages they originate to Fannie Mae and Freddie Mac who then package them into MBS.

shock on bank and nonbank credit. Li et al. (2020) document the huge credit-line draw-downs that banks faced in the early stages of the pandemic. Greenwald et al. (2024) suggest that the large credit line draw-downs had a crowding out effect on other commercial lending. Beck and Keil (2022) show that banks more exposed to pandemic-related health restrictions had an increase in loss provisions and non-performing loans. Regarding NBFIs, pre-pandemic cross-country evidence suggests that nonbank lenders might be a source of fragility during times of macroeconomic stress (Fleckenstein et al. 2020; Aldasoro et al. 2023). However, during the COVID-19 pandemic, NBFIs expanded credit and increased market share, especially in segments where they had continued access to funding, such as the mortgage market (Berg et al. 2022).

On the other hand, Ben-David et al. (2021) document the drop in small business lending in March 2020 through a marketplace platform that intermediates loans between nonbank lenders and small businesses, highlighting the crucial role of NBFIs as a funding source. In the context of the US Paycheck Protection Program (PPP), Erel and Liebersohn (2020) find that NBFI FinTech lenders increased access to the PPP by filling the gap for traditional banks, especially for lower income and minority-owned businesses. From an alternative perspective, Griffin et al. (2023) suggest that the high market share of PPP loans by nonbanks may be partly due to misreporting. Bao and Huang (2021) find that in China, NBFIs expanded credit more strongly relative to banks after the start of the pandemic. We add to this literature by documenting the role of NBFI-bank inter-linkages in transmitting the effects of central bank asset purchases to nonbank lending in the US mortgage market.

This paper suggests that the funding connections between banks and NBFIs can exacerbate policies that impact bank lending behavior. Thus, from a policy perspective, failing to consider and monitor these connections could lead to an inaccurate view of current and future credit conditions, rendering it more difficult to formulate optimal policy responses. This is especially relevant in an environment where lightly regulated NBFIs are gaining market share relative to the more stringently monitored traditional banking system.

The paper proceeds as follows. Section 2 discusses institutional details and our identification strategy. Section 3 explains our data and estimation. Section 4 presents results on the impact of QE on bank lending outcomes. Section 5 examines the transmission of QE to NBFIs and examines how indirect exposure to QE influences NBFI lending outcomes. Section 6 discusses and concludes.

2 Background and Identification Strategy

Following the 2008 financial crisis, the Federal Reserve implemented three different rounds of QE, commonly referred to as QE1 (November 2008-March 2010), QE2 (November 2010-June 2011), and QE3 (September 2012-October 2014). QE1 primarily involved the purchase of MBS, although Treasury securities were also purchased in smaller quantities. QE2, on the other hand, solely involved the purchase of Treasuries, while QE3 involved roughly equal purchases of MBS and Treasuries. From September 2011 to December 2012 the Fed also engaged in "Operation Twist," which involved selling short-term Treasuries and purchasing longer-dated Treasuries.

After engaging in two years of quantitative tightening from October 2017 to October 2019, the Fed re-started asset purchases and balance sheet expansion during the onset of the COVID-19 pandemic in 2020. On March 15, 2020 the FOMC announced monthly purchases of at least $500 billion in Treasuries and $200 billion in MBS. These purchases became open-ended on March 23, with the FOMC stating it would make purchases "in the amounts needed to support smooth market functioning and effective transmission of monetary policy to broader financial conditions."[3] These initial purchases resulted in a rapid balance sheet expansion, with total Fed assets increasing by approximately 70% in just three months. In June 2020 monthly purchases were reduced to $80 billion of Treasuries and $40 billion in MBS. The Fed began tapering purchases in November 2021 with the QE program terminating in March 2022. The program ultimately resulted in $4.6 trillion of purchases, which more than doubled the Fed's balance sheet.

To estimate the effects of the 2020-2022 QE program on the pandemic mortgage boom, we exploit cross-sectional variation in banks' exposure to central bank asset purchases. Following a number of previous studies in the QE and bank lending literature (Rodnyansky and Darmouni 2017; Luck and Zimmermann 2020; Kapoor and Peia 2021), our identification strategy is based on capturing an institution's exposure to QE through the size of their MBS holdings prior to the beginning of the Fed's asset purchases. Specifically, we measure a bank's exposure to the 2020-2022 QE program as its average MBS-to-total assets ratio (MBS ratio) in 2019. Banks with a higher MBS ratio had greater exposure to Fed asset purchases whereas banks with a lower MBS ratio had weaker exposure. Rodnyansky and Darmouni (2017) show that MBS ratios are reasonably sticky over time, suggesting that banks do not strategically alter their MBS holdings in anticipation of central bank asset purchases.

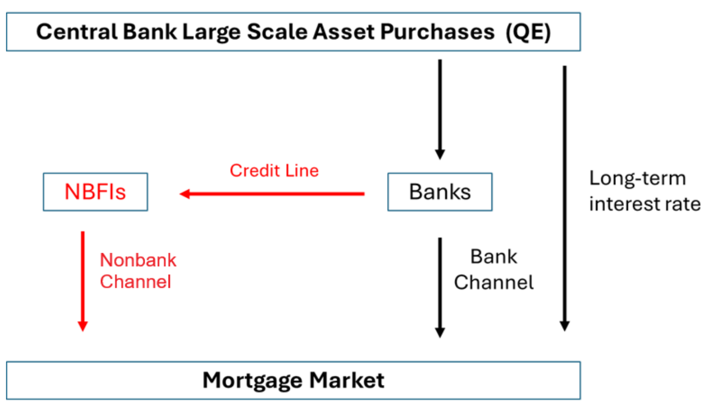
There are two primary reasons why the extent of a bank's MBS holdings captures exposure to QE. The first is through improved balance sheets and higher net worth. Central bank purchases push up MBS prices (Krishnamurthy and Vissing-Jorgensen

[3]https://www.federalreserve.gov/newsevents/pressreleases/monetary20200323a.htm

2011; Krishnamurthy and Vissing-Jorgensen 2013), thereby raising the value of bank asset holdings and increasing net worth. The second is through increasing liquidity. Banks with a higher share of MBS holdings prior to the onset of QE may be more active in the mortgage market. Central bank purchases can incentivize such banks to originate and securitize more new mortgages in order to sell the securities to the Fed (Chakraborty et al. 2020), resulting in a larger accumulation of bank reserves (Kandrac and Schlusche 2021).[4]

Although the 2020-2022 QE also involved large-scale purchases of long-term Treasuries, we focus on MBS holdings because they make up a more significant proportion of overall bank assets. The average bank MBS ratio in our sample is about 4%, whereas the average Treasury-to-total assets ratio is under 2%. Furthermore, previous work such as Rodnyansky and Darmouni (2017) and Luck and Zimmermann (2020) has found that QE2, which solely involved Treasury purchases, had no effect on bank lending.[5] Results in our Online Appendix confirm that banks with higher Treasury-to-asset ratios did not meaningfully increase lending during the pandemic-era QE, providing explicit support for our focus on MBS holdings.

Figure 2: Channels of QE Transmission to Mortgage Market



Note: This figure displays a conceptual diagram of the channels through which the Fed's QE program can impact the household mortgage market.

Figure 2 lays out the broad channels through which QE can influence the mortgage market. By pushing down long-term interest rates, QE can contribute to lower mortgage rates and encourage an increase in borrowing. On the supply side, a bank lending channel, which incorporates the more narrow net worth and liquidity channels dis-

[4]Rodnyansky and Darmouni (2017) provide evidence that increased bank lending following QE1 was due to improvements in net worth, whereas lending increases following QE3 were attributable to increased liquidity.

[5]Chakraborty et al. (2020), in contrast, find that banks with larger Treasury holdings increased C&I lending during QE2 to large firms in the syndicated loan market.

cussed above, has been studied for the previous rounds of asset purchases (QE1-QE3) but only to a limited degree for the 2020-2022 program.[6] In addition to providing the first detailed analysis of the bank lending channel for the pandemic-era QE, a key contribution of this study is the identification of an additional channel through which QE can affect mortgage market outcomes, namely, the nonbank lending channel, where NBFIs' indirect exposure to QE through their commercial bank warehouse funding relationships can influence nonbank lending behavior.

To identify NBFI exposure to QE, we exploit Mortgage Call Report data on warehouse lines of credit between NBFIs and commercial banks. This first allows us to determine whether NBFIs that receive financing from banks with greater exposure to QE obtain increases in funding. Specifically, we can estimate a within-NBFI specification that analyzes, for a single NBFI with credit lines from multiple banks, whether warehouse funding increases more from banks with higher MBS ratios after the onset of QE. In other words, this within-NBFI estimation allows to test whether QE transmits from the traditional banking system to the nonbank financial sector through warehouse funding relationships.

The credit line information also allows us to construct indirect MBS Ratios for NBFIs, to examine whether NBFIs with greater exposure to QE through their funding relationships increase their own mortgage lending. The indirect NBFI MBS Ratios are calculated as weighted averages of their funding banks' MBS Ratios, with weights being the share of total funding that an NBFI receives from an individual bank.[7] We are thus able to examine the nonbank lending channel by seeing whether NBFIs with higher indirect MBS ratios expanded mortgage lending to a greater degree after the onset of QE, relative to NBFIs with lower indirect MBS ratios.

3 Data and Estimation

3.1 Data Sources and Sample Construction

We utilize three main data sources. Bank-level information is from the Consolidated Reports of Condition and Income (Call Reports), which are filed on a quarterly basis by all banks in the United States. This data provides us with outcomes on total bank loans, C&I loans, and real estate loans. The key independent variable constructed from this data is the average mortgage-backed security-to-asset ratio (MBS ratio) over the

[6]Drechsler et al. (2024) and Fuster et al. (2021) provide evidence that the pandemic QE supported aggregate mortgage credit supply but do not attempt a cross-sectional, bank-level analysis.

[7]As an example, if NBFI A receives half of their credit line funding from Bank X, with a MBS Ratio of 3, and half of their credit line funding from Bank Y, with a MBS Ratio of 7, NBFI A's indirect MBS Ratio is 5.

four quarters of 2019, which captures a lender's exposure to the pandemic-era QE program. We also pull data on bank assets, loan-to-asset ratios, commercial and industrial loan-to-assets ratios, real estate loan-to-asset ratios, real estate mortgage loan-to-asset ratios, capital-to-asset ratios, return on assets, deposits-to-asset ratio, non-performing loan ratio, and bank holding company (BHC) affiliation. We exclude banks with missing variables in any sample quarter and winsorize balance sheet variables at the 1 and 99 percent levels.

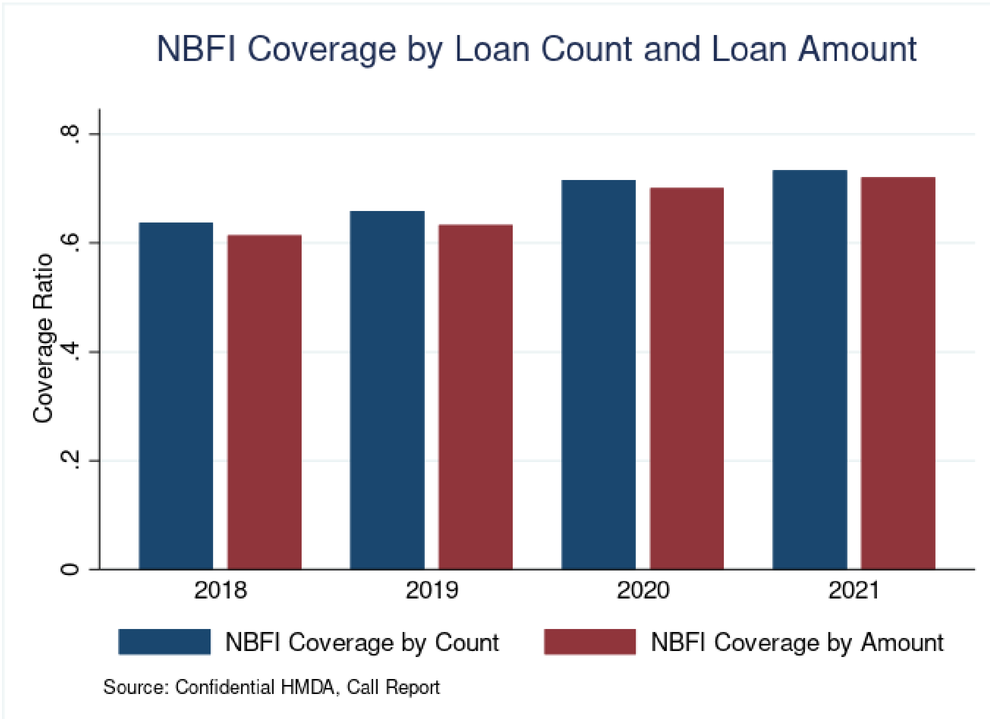
Mortgage application information comes from the confidential version of the HMDA data. HMDA requires financial institutions to disclose a rich set of information at the mortgage application level. Specifically, the data includes information on application outcomes (approval or rejection, interest rate in case originated, and processing time), application submission date and county, loan characteristics (e.g., loan type, loan amount, lien status), lender characteristics, and applicant characteristics (e.g., income level, race). Since application approval or rejection is the HMDA variable that most closely reflects an institution's lending behavior, the key outcome variable in our application-level estimation will be rejection rates. In contrast to the public version of the HDMA data, the confidential version includes two variables that are important for our analysis - first, the applicant's credit score, which significantly affects application outcomes, and second, a more precise application date (exact application date compared to year in the public version), which allows us to better identify the timing of any potential lending effects. Due to the large number of observations in the confidential HMDA data, we randomly select 20% to use in our application-level estimation. Furthermore, only applications for first-lien, 30 year, owner-occupied mortgages are included in the sample.

Data on warehouse funding relationships between banks and NBFIs comes from Mortgage Call Reports (MCR). We collected MCR data through Freedom of Information Act (FOIA) requests to 51 state regulatory authorities (including the District of Columbia). The only state that granted our request was Washington. It is important to note, however, that despite receiving a response from only one state, this nevertheless provides us with access to *nationwide* data on all NBFIs that are authorized to originate mortgages in the state of Washington.[8] The only information that ends up being excluded from our sample, therefore, is for NBFIs that do not operate at all in the state of Washington. We link this MCR data to the confidential HMDA and Call Report databases based on lending institutions' names and physical addresses. Figure 3 shows that our NBFI sample from the Washington MCR data ends up covering the majority of nonbank mortgage applications in the national HMDA data over our period

[8]For example, if a NBFI originates mortgages in Washington and Oregon, the Washington MCR data covers the NBFI's activities in both states (not just in Washington). Similarly, if a NBFI originates mortgages in all 50 states, the Washington MCR data covers the NBFI's activities nationwide.

of analysis.

Figure 3: NBFI Coverage by Loan Count and Loan Amount



Note: This figure presents our sample coverage of nonbank financial intermediaries in the HMDA mortgage application data by loan count and by loan amount from 2018 through 2021.

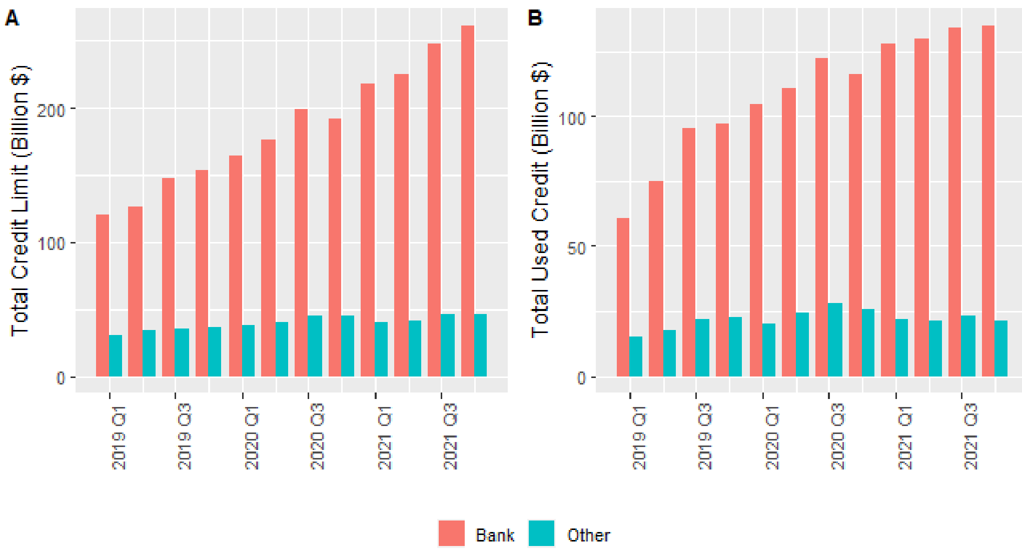
From the MCR data, we obtain end-of-the-quarter credit line limits and usage for every bank-NBFI relationship. Using the linked bank-level information, we construct an indirect MBS Ratio for each NBFI.[9] Figure 4 presents the total end-of-period credit line limits (Panel A) and total used credit (Panel B) from warehouse lines of credit extended to NBFIs by banks and other credit providers in our final linked MCR data.[10] The figure illustrates that banks are by far the dominant source of warehouse funding for NBFI mortgage lenders, consistently accounting for the majority of both credit line limits and credit used. Our empirical investigation focuses on the bank-provided warehouse credit lines (excluding nonbank providers), due to both their outsized role in financing NBFI mortgage lending and their link to QE policies.

To summarize, we link three main data sources: (i) bank-level information - particularly on lending outcomes and pre-pandemic MBS ratios, which capture the influence

[9]See Section 2 for details of how we calculate the QE exposure of each NBFI using the MBS Ratio of the NBFI credit line providers.

[10]Nonbank warehouse credit line providers include, for example, institutional investors, credit unions, private investors, financial service companies, etc.

Figure 4: Bank Provision of Warehouse Lines of Credit to NBFIs



Note: This figure presents the total end-of-the-period credit lines and credit used by mortgage NBFIs of warehouse lines of credit provided by banks and nonbanks.

of QE - through the Call Reports, (ii) application-level mortgage outcomes from the confidential HMDA database (covering both bank and nonbank lenders), and (iii) financing inter-linkages between banks and nonbanks through the MCR. Combined, the data allow us to perform a nuanced investigation of QE's role in affecting lending behavior during the pandemic mortgage boom. The period under consideration in this study is from 2019Q1 until 2021Q4, which includes five "pre-treatment" quarters, prior to the onset of the QE program, and seven "post-treatment" quarters making up the majority of the program's duration.[11] We end our baseline sample period in 2021Q4 when the tapering of the Fed asset purchase program began.

3.2 Descriptive Statistics

This subsection presents descriptive statistics of our main data sample from the various sources. Summary statistics at the credit line-level from the MCR and at the bank-level from the Call Reports for the primary variables used in our empirical analysis are presented in Table 1. Panel A presents summary statistics for credit lines supplied by banks. The 1st-3rd columns show statistics for all credit lines. The 4th-6th columns have statistics for credit lines provided by banks with MBS ratios below the 2019 sample median while the 7th-9th columns have statistics for credit lines provided by

[11]QE was announced and almost immediately implemented on March 15, 2020. We use a dummy equal to one for observations from 2020Q2.

banks with MBS ratios above the 2019 median.

There are slightly over 12,700 warehouse credit lines provided by banks in our sample, with about one third coming from low MBS ratio banks and two thirds coming from high MBS ratio banks. The average credit limit provided by all banks is roughly \$140 million, but is notably higher for high MBS ratio banks at nearly \$200 million relative to just under \$50 million for low MBS ratio banks. A similar pattern holds for credit usage, with an average for high MBS ratio banks slightly under \$120 million and an average just under \$30 million for low MBS ratio banks. Despite credit limits and credit usage being larger for high MBS ratio banks, utilization rates, i.e., the amount of credit used as a percentage of the overall credit limit, are similar across both categories of credit providers at 50-60%.

Panels B and C provide descriptive statistics for bank-level variables from the Call Reports, also splitting the sample into banks with low (below median) and high (above median) MBS ratios. Panel B uses all banks in the Call Reports, while Panel C presents statistics only for banks that provide warehouse credit lines. Bank variables are consolidated at the bank holding company (BHC) level. There are 4,375 BHCs in the full sample while 118 of these provide warehouse credit lines captured by the MCR.

In Panel B, low MBS ratio banks have an average MBS ratio of 0.4% whereas the high MBS ratio banks average 7.9%. High MBS ratio banks also tend to be larger, with a lower share of loans-to-assets, a relatively higher share of C&I loans, and a relatively lower share of real estate loans. In Panel C, banks that provide warehouse credit lines to NBFIs tend to be large, with average assets over \$100 billion compared to an average of \$4.6 billion for the full sample. Low MBS ratio credit line providers have an average MBS ratio of 2.6% whereas high MBS ratio providers have an average MBS ratio of 13.7%. Similar to the full sample in Panel B, high MBS ratio providers tend to be larger than low MBS ratio providers, with a higher share of C&I lending and lower share of real estate lending.

In Table 2, we report summery statistics for the HMDA application-level data, with Panel A showing statistics for home purchase applications and Panel B showing statistics for refinance applications. The average applicant credit score is 732.4 for home purchases and 739.6 for refinances, and average scores are lower for NBFI applications than for bank applications. The average income is \$118,191 for a home purchase applicant and \$125,332 for a refinance applicant, with NBFI applicants having lower average income than bank applicants. The average loan size is similar for both types of mortgages at just over \$310,000, although the average bank loan is roughly \$50,000 larger than the average NBFI loan. The table documents other important mortgage application characteristics such as loan-to-value and debt-to-income ratios that will be controlled for in our application-level estimation. The key outcome variable reflecting

Table 1: Descriptive Statistics at the Credit Line and Provider Levels

	All			Low MBS Ratio			High MBS Ratio		
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	Mean	Std. dev.	Median
Panel A: Mortgage Call Reports, warehouse credit lines provided by banks									
Credit Limit (mil)	143.03	250.04	60	48.48	71.99	28	196.96	295.33	100
Credit (mil)	86.50	177.26	29.56	28.50	58.05	12.35	119.59	210.73	47.07
Utilization (%)	0.55	0.29	0.58	0.52	0.30	0.53	0.57	0.28	0.60
Number of NBFI		355			178			177	
Obs.		12,718			4,619			8,099	
Panel B: Call Reports, all banks									
Total Assets (mil)	4,623	68,633	286	494	2,975	196	8,742	96,779	438
MBS to Assets (%)	4.16	6.33	1.35	0.42	1.35	0	7.89	7.10	5.92
Loans to Assets (%)	63.27	15.68	65.73	64.69	16.24	67.42	61.87	14.97	64.11
CI Loans to Assets (%)	9.59	7.71	7.90	9.43	8.13	7.61	9.76	7.26	8.18
RE Loans to Assets (%)	45.43	16.93	46.06	46.30	17.88	47.02	44.57	15.88	45.24
CAP (%)	11.53	3.53	10.81	11.80	4.10	10.87	11.25	2.83	10.76
ROA (%)	0.27	0.28	0.26	0.27	0.27	0.26	0.27	0.29	0.26
Deposits to Assets (%)	84.27	6.19	85.66	84.39	6.60	85.96	84.14	5.76	85.39
Number of BHC		4,375			2,188			2,187	
Obs.		52,025			25,979			26,046	
Panel C: Call Reports, banks providing warehouse credit lines									
Total Assets (mil)	107,505	393,574	5,613	39,285	208,013	1,995	175,726	507,375	17,180
MBS to Assets (%)	8.17	8.43	6.26	2.62	2.69	1.91	13.73	8.55	11.73
Loans to Assets (%)	69.34	15.43	72.98	74.70	12.91	77.91	63.97	15.87	67.73
CI Loans to Assets (%)	13.52	9.04	12.07	12.56	10.13	9.38	14.49	7.69	14.09
RE Loans to Assets (%)	44.92	18.51	46.37	51.13	19.23	53.25	38.72	15.44	40.84
CAP (%)	11.20	2.68	10.76	11.04	3.03	10.41	11.36	2.26	11.14
ROA (%)	0.31	0.28	0.30	0.34	0.29	0.31	0.28	0.26	0.30
Deposits to Assets (%)	81.06	7.02	82.09	80.37	8.36	82.04	81.74	5.27	82.27
Number of BHC		118			59			59	

Note: This table presents summary statistics for NBFI credit lines from the Mortgage Call Reports and for bank-level variables from the Call Reports for a 2019Q1 - 2021Q4 sample period.

lending behavior is the application rejection rate. The mean rejection rate is 6.9% for home purchase applications and 15.5% for refinancing applications. The sample is split almost evenly between home purchase applications and refinance applications. NBFI applications account for over 70% of both types of mortgages.

Table 2: Descriptive Statistics at the Mortgage Application Level

	Bank			NBFI			All		
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	Mean	Std. dev.	Median
Panel A: Home Purchase									
NBFI Indicator	0.000	0.000	0.000	1.000	0.000	1.000	0.715	0.451	1.000
Credit Score	746.380	52.754	759.000	726.851	67.425	737.000	732.408	64.203	744.000
Income ($)	152,988	296,026	94,000	104,583	173,922	83,000	118,191	216,461	85,000
Loan Amount ($)	352,368	297,264	260,000	295,685	173,089	259,801	311,711	217,083	260,000
Loan to Value Ratio (%)	84.295	14.495	87.516	88.239	12.919	95.000	87.117	13.504	93.056
Debt to Income Ratio (%)	35.819	11.148	36.410	38.333	10.766	39.193	37.618	10.935	38.407
Rejection Rate (%)	8.182	27.410	0.000	6.398	24.473	0.000	6.906	25.356	0.000
Age (year)	42.170	13.757	39.000	41.074	13.300	38.000	41.386	13.440	38.000
Interest Rate (%)	3.369	0.669	3.250	3.441	0.746	3.250	3.421	0.726	3.250
Processing Time (days)	51.296	42.363	40.000	51.750	48.456	37.000	51.621	46.804	38.000
QE Indicator	0.577	0.494	1.000	0.631	0.482	1.000	0.616	0.486	1.000
Observations	534,370			1,343,447			1,877,817		
Panel B: Refinancing									
NBFI Indicator	0.000	0.000	0.000	1.000	0.000	1.000	0.721	0.448	1.000
Credit Score	753.385	53.366	767.000	734.232	65.362	747.000	739.574	62.838	753.000
Income ($)	166,762	728,759	102,000	109,530	167,614	89,000	125,332	409,430	92,000
Loan Amount ($)	360,333	300,106	267,000	295,985	168,709	260,498	313,822	215,333	262,000
Loan to Value Ratio (%)	65.082	17.584	68.783	69.602	15.846	72.500	68.341	16.475	71.138
Debt to Income Ratio (%)	34.673	12.915	34.490	35.569	12.454	36.080	35.319	12.591	35.650
Rejection Rate (%)	15.217	35.919	0.000	15.588	36.274	0.000	15.485	36.176	0.000
Age (year)	50.463	14.117	49.000	49.501	13.883	48.000	49.770	13.956	48.000
Interest Rate (%)	3.326	0.651	3.250	3.285	4.115	3.125	3.296	3.509	3.250
Processing Time (days)	61.168	40.360	53.000	51.051	37.228	43.000	53.873	38.396	46.000
QE Indicator	0.624	0.484	1.000	0.700	0.458	1.000	0.679	0.467	1.000
Observations	539,344			1,394,188			1,933,532		

Note: This table presents summary statistics for mortgage application-level variables from the confidential HMDA data for 2019Q1 - 2021Q4 sample period.

3.3 Bank Level Estimation

We begin the empirical investigation by following the methodology of Rodnyansky and Darmouni (2017) and others who use bank-level Call Report data to study the impact of previous rounds of QE. The goal of this analysis is to determine how QE affected overall bank lending during the pandemic-era program. Specifically, we run the following specification:

$$y_{j,t} = \alpha_j + \delta_t + \beta QE_t * treat_j + \theta X_{j,t-1} + \epsilon_{j,t} \tag{1}$$

where $y_{j,t}$ is the log of lending, α_j is a bank fixed effect, δ_t is a time fixed effect, and QE is a dummy equaling one beginning in 2020Q2.

We study three lending outcome variables: total loans, real estate loans, and C&I loans. We also consider two variations of the treatment variable, $treat_j$, which captures a bank's exposure to Fed asset purchases. Our primary measure is simply a bank's average MBS-to-assets ratio in 2019, which allows us to include the full sample of banks in the estimation. For the sake of consistency with prior studies such as Rodnyansky and Darmouni (2017) and Kapoor and Peia (2021), we also use a dummy that equals one for banks in the top quartile of MBS ratio in 2019 and zero for banks in the bottom quartile (banks in the second and third quartiles are dropped from these specifications). While this alternative reduces the sample size, it offers a stronger delineation between banks that had high exposure to QE and banks with low exposure. $X_{j,t-1}$ are standard bank-level controls used in the literature, including the logarithm of total assets, deposits to assets ratio, equity to assets ratio (CAP), and return on assets (ROA). All bank-level controls are lagged by one period to mitigate simultaneity concerns. Standard errors are clustered at the bank-level.

3.4 Application Level Estimation

A limitation of the bank-level analysis using Call Report data is that loan variables are constructed based on quarter-to-quarter balance sheet changes, rather than directly capturing new originations. This is particularly troublesome when analyzing real estate lending, as many mortgages are originated and sold for securitization within a single quarter. To address this limitation, we examine the effect of QE on mortgage lending at the more granular application level. We do this by estimating the effect of QE exposure on mortgage application rejection rates. Specifically, we run the following specification:

$$y_{i,j,c,t} = \alpha_j + \omega_{c,t} + \beta QE_t * treat_j + \gamma Z_{i,j,c,t} + \epsilon_{i,j,c,t} \quad (2)$$

where $y_{i,j,c,t}$ is a dummy variable equaling 100 if application i, submitted to lender j, to finance a house in county c, in month t is rejected and 0 otherwise.

The measure of QE exposure, $treat_j$, is a bank's average MBS ratio during the four quarters of 2019. QE_t is an indicator variable taking on the value of 1 on and after 2020Q2. Z is a vector of mortgage application-level control variables which include the applicant credit score, applicant credit score squared, loan-to-value ratio, loan-to-value ratio squared, debt-to-income ratio, debt-to-income ratio squared, loan type, the logarithm of the applicant income, the logarithm of the loan amount, and applicant age. We also control for Automated Underwriting System (AUS) related variables. Specifically, we control for whether an application is AUS-approved, AUS-denied, or non-AUS. α_j is a lender fixed effect, which absorbs all time-invariant differences between lenders, and $\omega_{c,t}$ are county-month fixed effects (the county that the house is located in), which control for changing local conditions in the housing market (e.g., demand conditions and COVID-19 restrictions).

A second advantage of the application-level data is that it contains information on both banks and NBFIs. This allows us to not only obtain a more precise view of bank mortgage lending behavior, but also to investigate whether QE influences NBFI lending behavior. We therefore estimate Eq. (2) for a sample of NBFI mortgage applications, with the only difference between the bank and NBFI estimation being in the construction of $treat_j$. For NBFIs, $treat_j$ is the weighted average of $MBSRatio$s' of the banks from which an NBFI receives wholesale funding, weighted by the amount of credit. All other elements of Eq. (2) remain the same across the bank and NBFI application-level estimation. Standard errors are clustered at the lender-month level for both samples.

4 Bank Lending Channel

4.1 The Pandemic QE and Bank Lending

Results for estimating Eq.(1) using bank-level data from the Call Reports are presented in Table 3. Columns (1)-(2) pertain to total lending, columns (3)-(4) to RE lending and (5)-(6) to C&I loans. Consistent with studies on previous rounds of QE, we find that banks that are more exposed to QE increased lending more relative to banks with weaker exposure. Column (1) indicates that a one percentage point higher MBS ratio in 2019 resulted in an 11.4 basis point increase in total lending during the QE program. Column (2) similarly suggests that banks in the top quartile of the 2019 MBS ratio distribution increased lending by 2.3% relative to banks in the bottom quartile. The magnitude of these estimates are similar to those reported for QE1 and QE3 by Rodnyansky and Darmouni (2017).[12]

While the effect of the pandemic QE on total lending is consistent with the effects of QE1 and QE3, the effect on the loan components in columns (3)-(6) differ notably. Whereas Rodnyansky and Darmouni (2017), Luck and Zimmermann (2020), and Kapoor and Peia (2021) have documented that the previous rounds of QE had an overall stronger impact on real estate lending compared to commercial loans, we find the opposite result, with the effect on C&I lending being much larger in magnitude and stronger in statistical significance. Specifically, Column (3) and column (5) indicate a weakly significant positive effect on both real estate and C&I lending, however the magnitude of the effect is more than twice as large for C&I loans. There is an even more dramatic difference when comparing columns (4) and (6), as banks in the top of the MBS ratio distribution strongly increased C&I lending relative to banks in the bottom of the distribution, but show no differential effect in real estate lending .

What can explain this difference between the pandemic QE and QE1/QE3? One possibility is that banks sold new mortgages for securitization to a greater and/or quicker degree during the pandemic, so that new originations failed to be captured by end-of-quarter balance sheet changes. In this case, perhaps real estate lending was impacted more strongly than the results in Table 3 suggest. We turn to the HMDA application-level estimation in Section 4.2 to better analyze this point. Another possibility, however, is that banks with greater QE exposure may have shifted the composition of their mortgage-related lending toward relatively greater funding for nonbank mortgage lenders and relatively less for new in-house mortgage origination. In other words, perhaps QE's impact on bank mortgage credit shifted towards supporting NBFI financing rather than the financing of new bank mortgages. We investigate this possibility in Section 5.

[12]See columns (1)-(2) of Table 6, page 3873, of Rodnyansky and Darmouni (2017).

Table 3: The Impact of QE on Bank Lending

	log(Loans)		log(RE Loans)		log(C&I Loans)	
	(1)	(2)	(3)	(4)	(5)	(6)
MBS Ratio X QE	0.114***		0.087*		0.221*	
	(0.038)		(0.049)		(0.132)	
treat X QE		0.023***		0.008		0.061***
		(0.008)		(0.009)		(0.021)
Bank f.e.	Y	Y	Y	Y	Y	Y
Time f.e.	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	52,025	26,028	52,025	26,028	52,025	26,028
R^2	0.997	0.998	0.996	0.997	0.975	0.980
Adjusted R^2	0.997	0.997	0.996	0.997	0.972	0.978

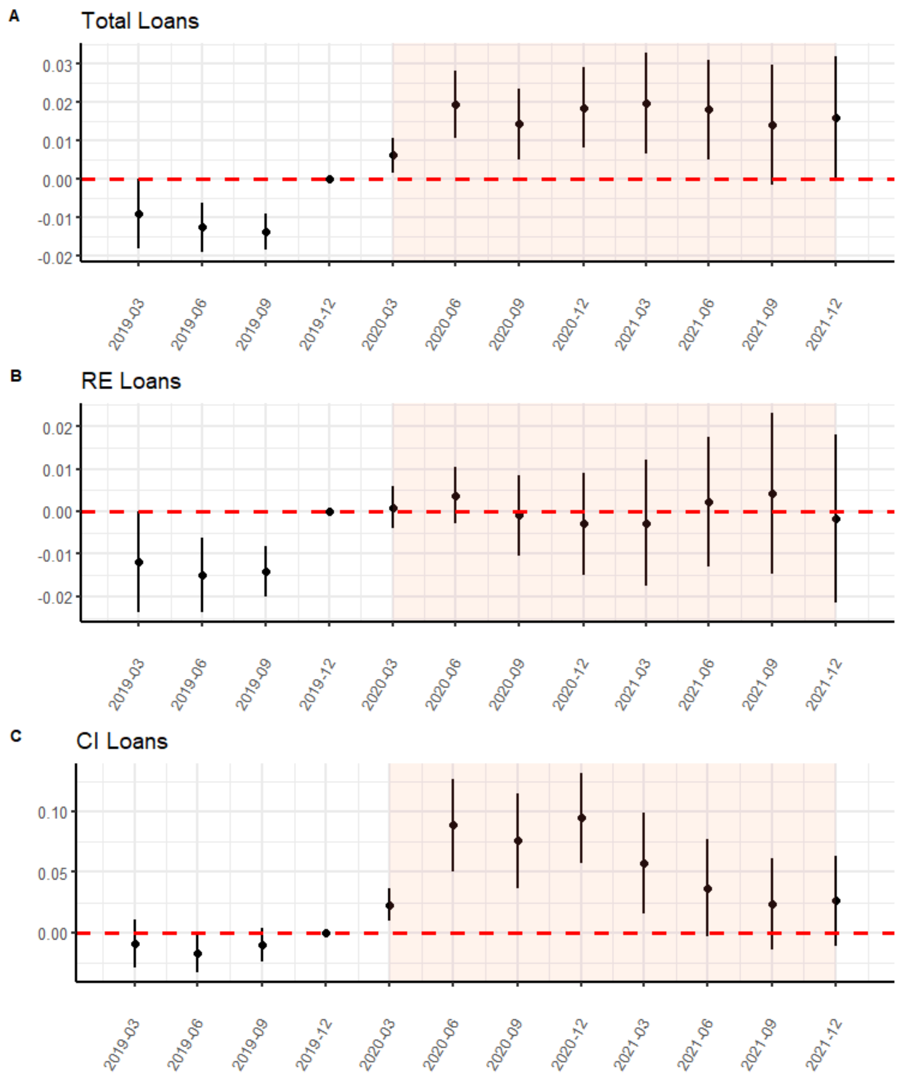
Notes: This table presents the results from estimating Eq. (1) using Bank-level variables from the Call Reports for the period of 2019Q1 - 2021Q4. QE is a dummy variable that takes the value of one for every quarter from 2020Q2. MBS Ratio is the bank average mbs-to-asset ratios averaged over the four quarters of 2019. treat is a dummy variable that equals one for banks in the top quartile of the 2019 MBS Ratio distribution, and that equals zero for banks in the bottom quartile. Standard errors, clustered at the bank level are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01

Figure 5 shows the dynamic effects from estimating Eq.(1) where the QE dummy is replaced by quarterly dummies, with 2019Q4 used as the benchmark period.[13] Panel (A) shows an immediate increase in total lending that stays elevated into 2021. Panel (B), on the other hand, shows a marginally significant positive effect on real estate loans in 2020Q2, with no impact in any other post-treatment quarter. Panel (C) shows a large jump in C&I loans which remains elevated and highly significant through the first quarter of 2021. The pre-treatment coefficients in Panels (A) and (C) do not suggest an upward trend in total lending or C&I lending for high MBS ratio banks beginning prior to 2020.

In the Online Appendix, we show that the results in Table 3 are robust to: (i) including an interaction between the QE dummy (QE_t) and the bank-level controls ($X_{j,t-1}$) to allow for possible heterogeneous responses as in Rodnyansky and Darmouni (2017) and Luck and Zimmermann (2020); (ii) starting the QE dummy from 2020Q1 rather than 2020Q2; and (iii) re-estimating the main specifications with bank Treasury-to-asset ratios replacing MBS ratios. Table A.1 confirms a significant increase in total lending and C&I lending but no effect on real estate lending for banks with the greatest QE exposure when interacting all control variables with the QE dummy. Table A.2 shows that the estimates are very similar when starting the QE dummy in 2020Q1 rather than 2020Q2. Lastly, Table A.3 shows little evidence of cross-sectional differences in lending during QE based on bank Treasury holdings, providing support for our focus on MBS holdings.

[13] For the dynamic specification we interact the quarter dummies with the *treat* dummy, which takes a value of one if a bank's average MBS ratio during 2019 was in the upper quartile of the distribution, or a value of zero if it was in the bottom quartile. Results are consistent, however, when replacing the *treat* dummy with the continuous MBS ratio in the dynamic specification.

Figure 5: The impact of QE on bank lending - Dynamic Impact



Note: This figure presents the dynamic effect of QE on the log of total bank loans (Panel A), the log of RE loans (Panel B), and the log of C&I loans (Panel C). The figure plots the regression coefficients from estimating Eq. (1) with dummy variables for each quarter instead of the QE dummy along with 90% confidence intervals. The coefficient for 2019 Q4 is normalized to zero. The shaded area represents the period from 2021 Q1.

4.2 Bank Mortgage Application Outcomes

While the results in Table 3 suggest that banks with greater QE exposure only modestly increased real estate lending, if at all, analyzing application-level data offers a more precise view of bank mortgage origination activity. The detailed application-level data from the confidential HMDA also allows us to better control for potentially confounding factors like borrower creditworthiness (via applicant credit score) and local demand conditions (through the inclusion of county-month fixed effects in the estimation). We focus on application rejection rates as the HMDA variable that best captures changes in bank lending behavior. We also split the sample into applications for home purchase mortgages and applications for refinancing an existing mortgage to differentiate the two major segments of the market.

We estimate Eq.(2) for mortgage applications submitted to banks with results presented in Table 4. The estimates in Table 4 show that, in general, banks with higher MBS ratios tend to have higher rejection rates. Specifically, the interpretation of the MBS ratio coefficient is that a one percentage point increase in a bank's MBS ratio is associated with a roughly 0.3 percent point increase in the bank's rejection rate for both home purchase and refinancing applications. The key variable of interest, however, is the interaction between the MBS ratio and the QE dummy variable, which is generally negative and significant, indicating that these differences narrowed during the QE period, as banks with greater exposure to QE experienced a significant decline in rejection rates.

In Panel A, the interaction coefficients suggest a highly significant 4 to 8 basis points decline in home purchase rejection rates for banks with greater exposure to QE. In Panel B, columns (1) and (2) suggest a significant 8 to 10 point decline in refinancing rejection rates. The interaction coefficient becomes insignificant in the preferred column (3) specification, however, which includes county-by-month fixed effects that effectively control for local demand conditions. Focusing on the preferred specification in both panels, it appears that QE exposure led banks to reduce rejection rates for home purchase applications but not for refinancing applications.

Overall, the results in Table 4 provide stronger evidence that banks with greater exposure to the pandemic QE increased mortgage lending, particularly for home purchase mortgages. This is consistent with evidence from QE1 and QE3, where Rodnyansky and Darmouni (2017), Luck and Zimmermann (2020), and Kapoor and Peia (2021) have documented a consistently positive relationship between bank QE exposure and real estate lending. The muted effect on bank-level real estate loans documented in Table 3 is therefore likely at least partly due to the limitations of analyzing end-of-quarter balance sheet changes.

Table 4: Bank Channel - Application Rejection Rates

	Rejection Rates		
	(1)	(2)	(3)
Panel A: Home Purchase			
QE	1.970***		
	(0.23)		
MBS Ratio	30.522***	31.033***	
	(2.05)	(2.12)	
MBS Ratio X QE	-8.111***	-8.469***	-4.109***
	(2.56)	(2.67)	(1.40)
Observations	517,597	497,094	497,075
Adjusted R^2	0.265	0.265	0.283
Panel B: Refinancing			
QE	3.187***		
	(0.50)		
MBS Ratio	29.248***	31.484***	
	(3.61)	(3.62)	
MBS Ratio X QE	-7.816*	-10.295**	-1.973
	(4.41)	(4.45)	(2.75)
Observations	519,866	501,243	501,214
Adjusted R^2	0.401	0.403	0.423
Control Variables	Y	Y	Y
County f.e.	Y	N	N
County-Month f.e.	N	Y	Y
Lender f.e.	N	N	Y

Notes: Application-level variables from 2019Q1 - 2021Q4. QE is a dummy variable that takes the value of one for every quarter after 2020Q1. MBS Ratio is the bank average mbs-to-asset ratios averaged over the four quarters of 2019. Standard errors, clustered at the lender-month level are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01

5 Nonbank Lending Channel

5.1 QE Transmission to NBFIs

Bank credit makes up a significant portion of NBFI financing (Jiang 2023). Given the increase in bank commercial lending documented in Table 3, a potential indirect channel through which QE can affect the mortgage market is by altering bank warehouse funding to NBFI lenders, and thereby influencing NBFI lending behavior. For such a nonbank lending channel of QE to be operative, it must be the case that (i) warehouse funding to NBFIs from banks with greater QE exposure must increase relative to funding from banks with weaker exposure, and (ii) NBFIs with greater indirect exposure to QE through their bank funding relationships must increase mortgage lending relative to NBFIs with weaker indirect exposure. This section empirically examines the first condition and Section 5.2 investigates the latter.

We use the credit line-level MCR data to examine how bank providers' exposure to QE impacted NBFI credit usage and credit line utilization during the pandemic. If QE induced banks to extend additional credit and improve credit line conditions, we would expect to see a larger increase in the use of credit lines provided by banks with higher MBS ratios. With a credit line-level estimation, we can exploit the variation in bank QE exposure to test if NBFIs shifted to credit line providers that were more exposed to QE. This within-NBFI estimation is akin to the specification used by Khwaja and Mian (2008), which examined firms borrowing from multiple banks to identify the causal impact of bank credit supply. This estimation strategy controls for the credit demand and economic conditions faced by each NBFI and ensures that bank credit line supply conditions drive the results. Specifically, we restrict our credit line database to only NBFIs that have at least two credit lines available from different banks and estimate the following specifications:

$$y_{i,j,t} = \alpha_{i,t} + \omega_{i,j} + \beta QE_t * MBSRatio_j + \gamma * X_{j,t-1} + \epsilon_{i,j,t} \tag{3}$$

where i is the NBFI with a credit line with bank j in quarter t. $y_{i,j,t}$ is one of two dependent variables: (i) the log of the credit being used by NBFI i in a given quarter; (ii) the credit line utilization defined as the ratio of the credit used and the total available credit line.[14] $MBSRatio_j$ is the average mortgage-backed securities-to-assets ratio during the four quarters of 2019, and QE_t is a dummy variable equal to one from the second quarter of 2020. $\alpha_{i,t}$ is the NBFI-quarter fixed effects that absorb all time-varying differences within each NBFI, including credit demand conditions. $\omega_{i,j}$

[14]Similar to Chakraborty et al. (2020), quarters without credit balances take on a zero value.

is NBFI-Bank fixed effects, which control for constant relationship conditions between each NBFI and bank credit line provider.

$X_{j,t-1}$ is a vector of additional bank-level controls. While we focus on bank exposure to QE through the MBS ratio, other bank characteristics may have also impacted banks' credit supply during the pandemic.[15] Thus, $X_{j,t-1}$ includes size (log of total assets), capital-to-assets ratio (CAP), return on assets (ROA), and deposits to total assets (DEP).

In this specification, our main coefficient of interest is β, which estimates the relationship between the specific credit line provider (bank) exposure to QE and credit line usage and utilization in the post-treatment period. Table 5 presents the results from estimating Eq. (3). The coefficients on the interaction between the MBS ratio and the QE dummy are positive and significant for both total credit usage and for credit utilization, suggesting that the credit provider's exposure to QE is positively associated with an increase in funding to NBFI borrowers.

Table 5: Credit line estimation level

	Dependent variable:	
	Log(Credit Usage)	Utilization
MBS Ratio x *QE*	0.756**	0.166*
	(0.368)	(0.092)
Control Variables	Y	Y
NBFI x Time F.E.	Y	Y
NBFI x Bank F.E.	Y	Y
Observations	13,652	13,652
R^2	0.824	0.679
Adjusted R^2	0.722	0.492

Notes: This table presents the results of estimating Eq.(3). Quarterly variables from 2019Q1 - 2021Q4. QE in a dummy variable that takes the value of one for every quarter after 2020Q1. MBS Ratio is the bank average MBS-to-asset ratio averaged over the four quarters of 2019. The bank-level controls lagged values of the capital-assets ratio (CAP), return on assets (ROA), deposits over total assets ratio (DEP), bank size (log of total assets). Standard errors, clustered at the credit provider level, are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

The interpretation of the coefficients is as follows. In the first column, the β coefficient estimate implies that for every percentage point increase in a funding bank's MBS ratio, NBFI credit usage during the QE period increased by 75.6 basis points. The coefficient in the second column indicates that for every percentage point increase in MBS ratio, the utilization rate of the credit line is, on average, over 16 basis points higher after the onset of QE.

The results in Table 5 indicate that the effects of QE were transmitted from the traditional banking sector to nonbank institutions through warehouse funding relationships. The next section revisits the HMDA mortgage application data to determine

[15]For example, see Berger and Demirgüç-Kunt (2021), Colak and Öztekin (2021), Beck and Keil (2022), and Neef et al. (2023) among others.

whether indirect exposure to QE through their funding relationships altered NBFI lending behavior.

5.2 NBFI Mortgage Application Outcomes

We examine the role of QE in impacting NBFI mortgage lending by estimating Eq.(2) for a sample of mortgage applications submitted to NBFI lenders. The key outcome variable from the HMDA data is once again application rejection rates, split into home purchase applications and refinancing applications. We measure each NBFI's indirect exposure to QE by using a weighted average of the MBS ratios of the banks from which the NBFI receives funding, weighted by the share of total funding provided by each bank. Other than the construction of the MBS ratio, the application-level estimation for this NBFI sample is equivalent to the application-level estimation conducted for the bank sample in Section 4.2.

Table 6 presents the results for the NBFI sample of mortgage applications. The coefficient estimate on the weighted average MBS ratio in Panel A suggest that NBFIs with higher indirect QE exposure tended to have higher rejection rates prior to the pandemic. The coefficient of interest on the interaction between the QE dummy and the MBS ratio is statistically insignificant in all three columns of Panel A, which indicates that exposure to QE had no significant impact on NBFI home purchase rejection rates.

Turning to refinancing applications in Panel B, the interaction coefficient between the MBS Ratio and QE dummy becomes negative in all three columns. While it is statistically insignificant in the first two columns, it grows much larger in magnitude relative to the estimates in Panel A. More notably, it becomes significant while remaining at an economically meaningful magnitude in the preferred specification of column (3), which controls for local demand conditions through county-by-month fixed effects. Specifically, the estimate indicates that a one percentage point increase in an NBFI's weighted MBS ratio leads to a 12 basis point reduction in refinance application rejection rates. Focusing on the preferred specification in both panels, it appears that QE exposure led NBFIs to reduce rejection rates for refinancing applications but not for home purchase applications.

Overall, the evidence in Table 6 indicates that NBFIs with greater indirect exposure to QE through their bank warehouse funding relationships altered their lending behavior, most notably by reducing rejection rates for refinancing applications. This result supports the existence of a nonbank lending channel of QE during the pandemic mortgage boom. It also stands in contrast to the results in Section 4.2 which showed the opposite pattern for banks - namely, that banks with greater QE exposure reduced rejection rates for home purchase applications, but not refinancing applications. This pattern is consistent with prior studies that suggest NBFI lenders may have a

Table 6: Nonbank Channel - Application Rejection Rates

	Rejection Rates		
	(1)	(2)	(3)
Panel A: Home Purchase			
QE	0.380		
	(0.40)		
MBS Ratio	7.686***	7.652***	
	(2.40)	(2.26)	
MBS Ratio X QE	1.112	0.737	3.140
	(3.41)	(3.37)	(2.35)
Observations	859,410	840,276	840,275
Adjusted R^2	0.256	0.266	0.299
Panel B: Refinancing			
QE	1.565		
	(1.18)		
MBS Ratio	15.885	13.511	
	(10.00)	(9.59)	
MBS Ratio X QE	-15.855	-13.219	-12.024**
	(11.64)	(11.23)	(5.14)
Observations	1,012,942	993,595	993,594
Adjusted R^2	0.350	0.358	0.402
Control Variables 1	Y	Y	Y
County f.e.	Y	N	N
County-Month f.e.	N	Y	Y
Lender f.e.	N	N	Y

Notes: Application-level variables from 2019Q1 - 2021Q4. QE is a dummy variable that takes the value of one for every quarter after 2020Q1. MBS Ratio is the weighted average of all the MBS ratios of the banks from which the NBFI receives funding, where each bank's MBS Ratio is the average MBS-to-asset ratio averaged over the four quarters of 2019. Standard errors, clustered at the lender-month level are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

comparative advantage in mortgage refinancing (Buchak et al. 2018).

6 Conclusion

Previous studies have documented a bank lending channel of QE, where greater exposure to Fed asset purchases increases lending - particularly real estate lending (Rodnyansky and Darmouni 2017; Chakraborty et al. 2020; Luck and Zimmermann 2020). This paper offers two key contributions advancing this literature. The first is by investigating the dynamics of the most recent pandemic-era QE program. Banks with greater exposure to QE increased both C&I and real estate lending. In contrast to previous rounds of QE, the increase in loans held on bank balance sheets was more strongly concentrated in commercial loans. Evidence from mortgage application data, however, indicates that banks with greater QE exposure meaningfully reduced rejection rates for new home purchases. The second contribution involves tracing the effects of QE to nonbank mortgage lenders and presenting evidence of a novel nonbank lending channel. NBFIs received increases in warehouse funding from banks with greater QE exposure, and NBFIs with greater indirect exposure through their funding relationships lowered rejection rates for mortgage refinancing.

These results have important implications for both monetary policymakers and financial regulators. First, they show how the effects of QE can be transmitted from banks to other nonbank financial institutions. Understanding this transmission mechanism is of vital importance for optimally implementing large-scale asset purchase programs in the future. Second, they further clarify funding relationships between the banking sector and nonbank institutions. Mapping such relationships is an important component in better understanding network effects and designing policy to promote financial stability. A more precise understanding of financial interrelationships generally, and of the QE transmission mechanism specifically, will continue to be an important area for future work.

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A Online Appendix

A.1 Robustness tests

Here, we present a number of robustness tests for the estimation of Eq. (1) and the bank-level results.

A.1.1 Model specification - interacted controls

Table A.1 presents results when incorporating to the baseline specification additional interactions between the QE dummy and the bank-level controls, as in Rodnyansky and Darmouni (2017). The additional interaction captures the potential differential impact of other bank characteristics on lending during the QE period. While some significance is lost when using the continuous MBS ratio measure, the overall results are consistent, indicating that banks with greater exposure to QE during the COVID-19 pandemic increased total lending and C&I lending, but not real estate lending.

Table A.1: Additional Interactions

	log(Loans)		log(RE Loans)		log(C&I Loans)	
MBS Ratio X QE	0.066		0.075		0.160	
	(0.040)		(0.053)		(0.142)	
treat X QE		0.015**		0.005		0.062**
		(0.007)		(0.009)		(0.024)
Observations	52,025	26,028	52,025	26,028	52,025	26,028
R^2	0.997	0.998	0.996	0.997	0.975	0.980
Adjusted R^2	0.997	0.997	0.996	0.997	0.972	0.978
Bank f.e.	Y	Y	Y	Y	Y	Y
Time f.e.	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Interacted controls	Y	Y	Y	Y	Y	Y

Notes: This table presents the results from estimating Eq. (1) with additional interactions between the QE dummy and the bank controls. The time period is 2019Q1 - 2021Q4. QE is a dummy variable that takes the value of one for every quarter from 2020Q4. Standard errors, clustered at the lender level, are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

A.1.2 Timing

The pandemic QE program was announced at the end of 2020 Q1 (March 15th). Since QE was not operative for the majority of Q1, the QE dummy in our baseline estimation switches to 1 from 2020 Q2 on. Table A.2 presents results from alternatively setting the QE dummy to 1 from 2020 Q1 on, instead of Q2. The estimates are very similar to those in Table 3.

Table A.2: Alternative QE starting date

	log(Loans)		log(RE Loans)		log(C&I Loans)	
MBS Ratio X QE	0.126***		0.107**		0.237*	
	(0.037)		(0.051)		(0.125)	
treat X QE		0.025***		0.011		0.063***
		(0.007)		(0.009)		(0.020)
Observations	52,025	26,028	52,025	26,028	52,025	26,028
R^2	0.997	0.998	0.996	0.997	0.975	0.980
Adjusted R^2	0.997	0.997	0.996	0.997	0.972	0.978
Bank f.e.	Y	Y	Y	Y	Y	Y
Time f.e.	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Notes: This table presents the results from estimating Eq. (1) when starting the QE dummy from 2020 Q1. The time period is 2019Q1 - 2021Q4. QE is a dummy variable that takes the value of one for every quarter from 2020Q1. Standard errors, clustered at the lender level are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01

A.1.3 Alternative exposure

While the pandemic QE involved the purchase of both MBS and Treasuries, prior literature on the relationship between QE and bank lending has found that bank lending behavior is primarily shaped by MBS purchases, which raises the price and liquidity of banks' MBS holdings. Additionally, Treasuries tend to be a much smaller share of bank security holdings than MBS. Thus, the literature has argued that the impact of QE on banks' balance sheets works through a "narrow window", which implies a stronger impact on banks with more MBS holdings (Luck and Zimmermann 2020; Kurtzman et al. 2022). However, theoretically, QE could also impact bank lending by raising the price of other bank securities, improving banks' net worth and capital position.

In Table A.3 we use the 2019 average share of Treasuries-to-total assets as an alternative measure of bank exposure to QE (Rodnyansky and Darmouni 2017). Consistent with previous literature, we find very little effect of Treasury holdings on bank lending after the onset of QE.

Table A.3: Alternative Exposure

	log(Loans)		log(RE Loans)		log(C&I Loans)	
Treasury Ratio X QE	11.774		24.182		−26.965	
	(18.794)		(21.485)		(32.226)	
treat X QE		0.009**		0.007		−0.021
		(0.004)		(0.006)		(0.021)
Observations	52,025	25,942	52,025	25,942	52,025	25,942
R^2	0.997	0.998	0.996	0.997	0.975	0.976
Adjusted R^2	0.997	0.997	0.996	0.996	0.972	0.974
Bank f.e.	Y	Y	Y	Y	Y	Y
Time f.e.	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Notes: This table presents the results from estimating Eq. (1). The time period is 2019Q1 - 2021Q4. QE is a dummy variable that takes the value of one for every quarter from 2020Q2. Standard errors, clustered at the lender level are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01