Quantitative Easing, Nonbank Lending, and the Pandemic Mortgage Boom*

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Abstract

We investigate the role of the Federal Reserve's Quantitative Easing (QE) program in the 2020-2021 mortgage boom and identify a novel nonbank lending channel. Similar to previous rounds of QE, banks with greater exposure to Fed asset purchases increased lending. However, unlike earlier QE programs, banks expanded commercial and industrial (C&I) loans more than real estate loans. A notable subset of bank C&I lending that increased during the pandemic was warehouse funding to nonbank mortgage lenders. At the mortgage application-level, banks with greater direct exposure to QE and nonbanks with greater indirect exposure via their funding relationships both lowered rejection rates, especially for refinance applications. We provide evidence of a direct transmission mechanism from banks to nonbank lenders, as nonbanks obtained larger increases in credit line limits, usage, and utilization from banks that were more exposed to Fed asset purchases.

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

JEL Classification code: E30, E44, E58, G21

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1 Introduction

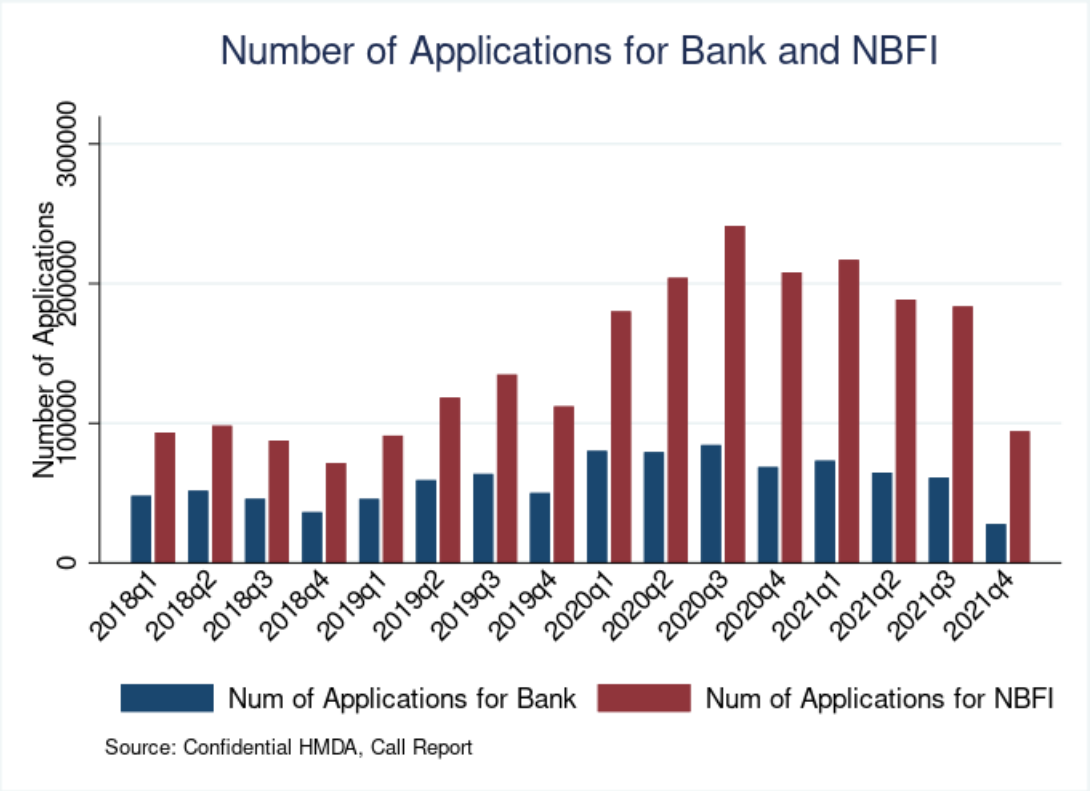
The period around the COVID-19 pandemic coincided with a dramatic boom in mortgage lending and house prices. New mortgage origination surpassed $4 trillion annually for the first time ever in 2020 and 2021, mortgage balances on consumer credit reports increased over 10% from 2020Q1 to 2021Q4, and house 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 (NBFI) 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 2018, with the NBFI share jumping noticeably during the pandemic. 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 impact of QE on NBFI credit supply 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. Since NBFIs are the primary originator of new mortgages during this period, and since the indirect influence of QE on NBFI credit supply could plausibly run in either direction, the overall effect of QE on the household mortgage market is unclear.

[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, with a particular focus on the indirect effects of QE on NBFI lending. In doing so, we investigate a number of specific questions: Did direct exposure to QE increase mortgage lending from the traditional banking sector? Did indirect exposure to QE affect NBFI mortgage lending? Can the transmission of QE be traced from the banking sector to NBFIs?

We use the Call Reports, containing the universe of data on US commercial banks, as well as the Federal Reserve's confidential 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), this 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 every US mortgage application, including outcome, applicant characteristics, loan 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 mortgage outcomes such as rejection rates.

Since the majority of new mortgages during this time period are originated by NBFIs, we must go beyond the existing literature and construct a measure of NBFI exposure to QE. We do this by exploiting information from Mortgage Call Reports, which provide information on individual credit lines extended to NBFIs by banks. Accordingly, we construct NBFI exposure to QE as the weighted average of the MBS ratios of banks that provide funding to a NBFI. This, analogously, allows us to estimate how indirect NBFI exposure to QE influences mortgage application outcomes. The data on warehouse lines of credit between banks and NBFIs also allow us to make a direct link between bank QE exposure and NBFI liquidity. In particular, we can examine whether banks with greater direct exposure to QE provide additional funding to their NBFI counterparties after the onset of the program.

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. Examination of Mortgage Call Report data shows that increased warehouse funding to NBFIs was a key subset of the expansion in bank C&I lending.

Turning to the application-level data, we find that QE exposure accelerated mortgage market activity for both banks and NBFIs. Banks with greater MBS ratios prior to the onset of the pandemic reduced rejection rates for both home purchases and refinances, with the decline being more than twice as large for refinance applications. Similarly, NBFIs with greater indirect exposure to QE lowered rejection rates for both types of mortgages, but the decline is almost three times as large for refinances. This result suggests that exposure to QE through bank financing relationships provided NBFIs with the necessary liquidity to expand lending. Additional evidence on bank-NBFI warehouse funding relationships confirms this, as a within-NBFI specification shows that for NBFIs with multiple financing relationships, credit line limits, usage, and utilization increased more for lines issued by banks with greater QE exposure.

Our results show that QE influenced refinancing activity more strongly than new home purchases for both types of lenders. Refinancing was an essential component of

the mortgage market in this period, as sub-3% mortgage rates incentivized homeowners to refinance. 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."

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) provide evidence of a crowding-out effect of QE on corporate loans. Kapoor and Peia (2021) also 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) similarly 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 bank lending supply (Schaffer and Segev 2023), Diamond et al. (2024) argue that the expansion of bank balance sheets may also induce regulatory constraints, such as the leverage ratio, which increases the costs of meeting capital requirements and can lead to a reduction in lending. In a recent paper, Drechsler et al. (2024) show that the COVID-19 period QE program played a significant role in the expansion of mortgage credit during the 2020–21 mortgage boom. We add to these studies in two main ways. First, while most of the existing empirical evidence has focused on earlier, pre-pandemic rounds of QE, this paper examines the impact of the pandemic-era QE program on bank mortgage lending supply. Second, to the best of our knowledge, this paper is the first to study the impact of QE on the supply of wholesale bank funding to non-bank mortgage originators.

This paper also relates to the literature analyzing the increasing role of non-banks 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 non-bank 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, non-bank FinTech lenders increase the supply of reconstruction mortgages more than traditional banks. While the above studies have mainly highlighted the competition impact of NBFIs versus banks in the consumer mortgage market, Jiang (2023) points out that banks' market power in the warehouse credit line market, which constitutes NBFIs primary funding source, reduces competition in the mortgage market. Similar to Jiang (2023), we also use the Mortgage Call Reports (MCR) 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 shock on bank and non-bank 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 non-bank 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 non-bank 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 non-banks 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 central bank asset purchases to nonbank credit supply in the US mortgage market.

This paper suggests that the funding connections between banks and NBFIs can exacerbate policies that impact bank credit supply. 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 explains our data and Section 3 discusses our empirical methodology. Section 4 presents results on the impact of QE on mortgage outcomes. Section 5 examines the transmission of QE to NBFIs. Section 6 discusses and concludes.

2 Data

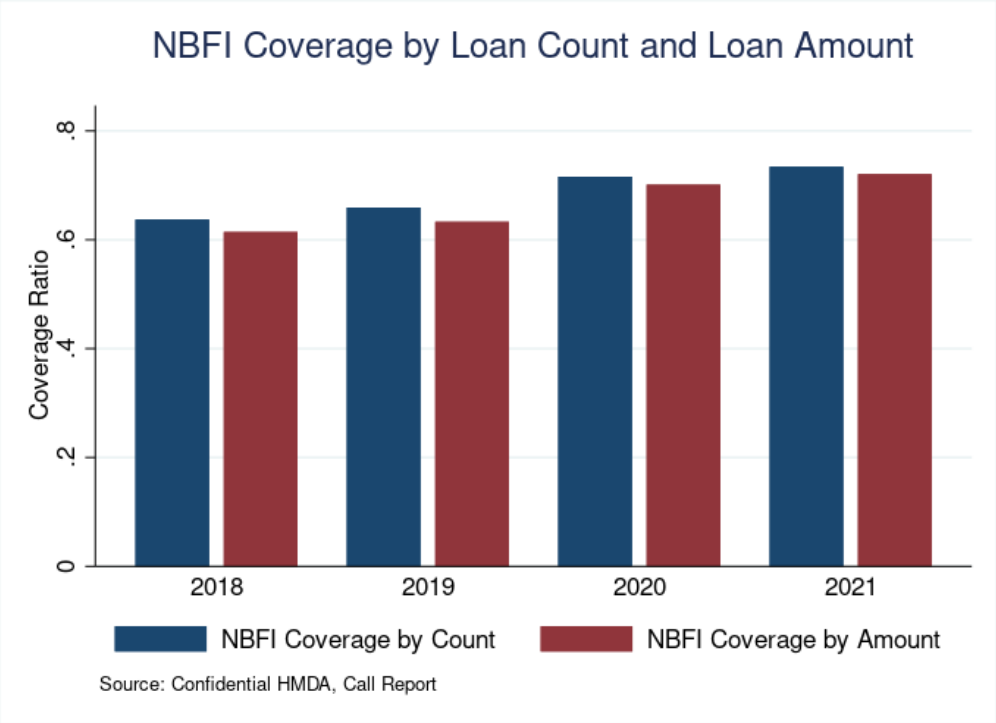
2.1 Data sources and sample construction

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 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 approved, 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). 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. Figure 1 details the number of mortgage loan applications from banks and NBFIs by quarter from 2018 until 2021.

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.[2] 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 2 shows that our NBFI sample from the Washington MCR data ends up covering the majority of nonbank mortgage applications in the national HMDA data.

Figure 2: 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 by loan count and loan amount from 2018 through 2021.

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 of QE - through traditional Call Reports, (ii) application-level mortgage outcomes from

[2]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.

the confidential HMDA database (covering both bank and nonbank lenders), and (iii) financing inter-linkages between banks and nonbanks through Mortgage Call Reports. Combined, the data allow us to perform a nuanced investigation of QE's role in the pandemic mortgage boom, particularly with respect to the differential behaviors of bank and nonbank lenders.

The period under consideration in this study is from 2019Q1 until 2021Q2, which includes four "pre-treatment" quarters, prior to the onset of the QE program, and six "post-treatment" quarters making up the majority of the program's duration.[3] We end our baseline sample period in 2021Q2 for two reasons: first, Fed asset purchases were most substantial early on in the program (March-June 2020) and tapering began in the second half of 2021. Second, interest rates started rising in expectation of a Fed policy pivot in the second half of 2021, bringing about a slowdown and eventual termination of the pandemic mortgage boom. Our "post-treatment" sample therefore consists of the key quarters in which the majority of the Fed's balance sheet expansion took place and in which mortgage originations grew most rapidly.[4]

2.2 Descriptive Statistics

Summary statistics at the credit line and bank levels for the primary variables used in our empirical analysis are presented in Table 1. Panel A shows credit line information for all credit lines in the MCR and is split by the type of credit line provider. Our full warehouse credit line sample includes 16,017 credit line relationships, of which banks provide 13,335. The average credit limit is $132 million with an average utilization of 52%. The 4th-6th columns provide statistics for credit lines provided by banks while the 7th-9th provide statistics for credit lines provided by other types of providers.[5] Panel B presents summary statistics at the credit line level only for the credit lines supplied by banks. The 4th-6th columns provide statistics for credit lines provided by banks with MBS ratios in 2019 below the sample median while the 7th-9th provide statistics for credit lines provided by banks with 2019 MBS ratios above the median. Although utilization rates are similar across both categories of credit providers, average size is larger for credit lines extended by high MBS ratio banks.

Panels C and D provide descriptive statistics at the bank-level from the Call Reports, also splitting by the level of MBS ratios in 2019. Panel C uses all banks in

[3]QE was announced and almost immediately implemented on March 15, 2020. For quarterly data estimations, we use a dummy equal to one for observations from 2020Q1. We also use a dummy equal to one from 2020Q2 as a robustness test. In the specifications using loan-level data where we have information on the exact application data, we use a dummy for any application after March 15 2020.

[4]The QE program officially terminated in March 2022. The results presented below are similar, with slightly attenuated estimates, when extending our sample through 2022Q1.

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

the Call Reports, while Panel D presents statistics only for banks that provide warehouse credit lines. Low MBS ratio credit line providers have an average MBS ratio of 2.2% whereas the high MBS ratio category average 13.5%. High MBS ratio banks also tend to be larger, with a lower share of loans-to-assets, a relatively higher share of commercial and industrial loans, and a relatively lower share of real estate loans.

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

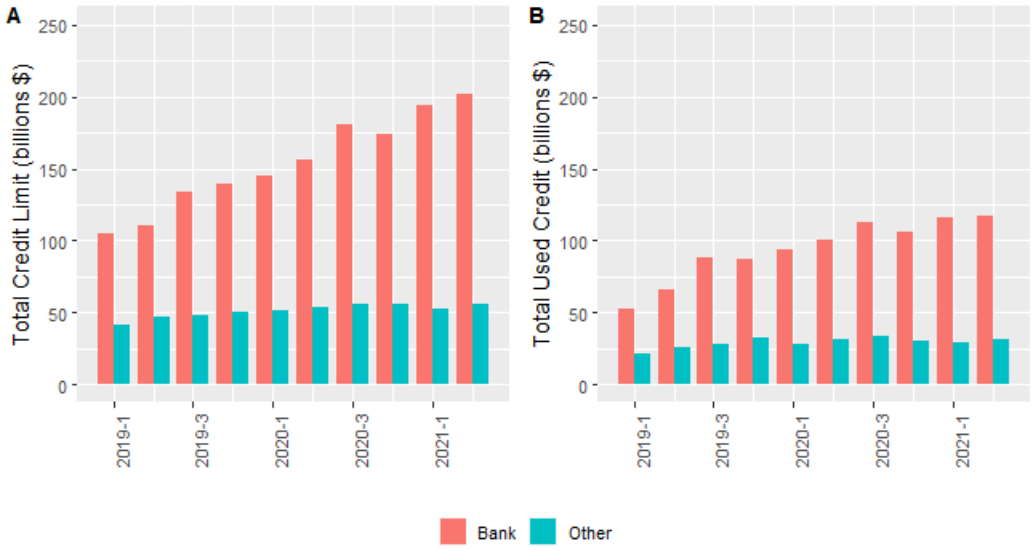
	All			Banks			Other		
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	Mean	Std. dev.	Median
Panel A: Warehouse credit lines by provider type									
Credit Limit (million $)	132.05	263.74	50	121.65	239.43	50	183.72	356.70	40
Remaining Credit (million $)	53.26	127.05	14.28	48.07	109.82	14.82	79.05	188.81	9.89
Utilization (%)	52.69	31.89	56.24	53.05	31.01	56.74	50.93	35.95	51.39
Obs.		16,017			13,335			2,682	
	All			Low MBS Ratio			High MBS Ratio		
	Mean	Std. dev.	Median	Mean	Std. dev.	Median	Mean	Std. dev.	Median
Panel B: Warehouse credit lines provided by banks									
Credit Limit (million $)	121.65	239.43	50	96.05	191.91	40	141.85	269.40	50
Remaining Credit (million $)	48.07	109.82	14.82	38.83	89.44	12.09	55.36	123.06	17.02
Utilization (%)	53.05	31.01	56.74	52.51	31.87	55.67	53.48	30.30	57.55
Obs.		13,335			5,881			7,454	
Panel C: Call reports, all banks									
log(assets)	12.66	1.51	12.49	12.14	1.17	12.11	13.17	1.63	12.92
Loans to Assets (%)	63.70	17.01	67.00	64.94	17.98	68.71	62.52	15.78	65.44
CI Loans to Assets (%)	9.52	7.99	7.85	9.24	8.42	7.49	9.78	7.48	8.22
RE Loans to Assets (%)	45.88	18.11	46.95	46.71	19.41	47.98	45.10	16.60	46.10
MBS to Assets (%)	4.11	6.65	1.23	0.31	1.05	0	7.94	7.66	5.83
CAP (%)	12.46	7.73	11.01	13.05	9.07	11.13	11.79	5.63	10.92
ROA (%)	0.32	1.74	0.26	0.36	2.41	0.26	0.27	0.50	0.26
Deposits to Assets (%)	82.91	10.26	85.13	82.62	11.83	85.37	83.29	8.08	84.92
Number of BHC		5,178			2,541			2,539	
Panel D: Call reports, banks providing warehouse credit lines									
log(assets)	15.64	2.26	15.42	14.60	2.00	14.28	16.68	2.02	16.47
Loans to Assets (%)	70.10	14.43	73.38	74.59	12.41	77.36	65.68	14.92	69.16
CI Loans to Assets (%)	14.36	9.20	13.07	13.72	10.54	10.45	14.99	7.61	14.92
RE Loans to Assets (%)	45.03	18.34	46.56	50.03	19.26	52.33	40.10	15.94	41.88
MBS to Assets (%)	7.89	8.37	6.01	2.20	2.56	1.35	13.50	8.33	11.62
CAP (%)	11.29	2.71	10.80	11.26	3.11	10.53	11.31	2.25	11.09
ROA (%)	0.30	0.32	0.30	0.33	0.31	0.30	0.27	0.33	0.30
Deposits to Assets (%)	80.85	6.89	81.69	80.08	8.11	81.53	81.60	5.32	81.86
Number of BHC		146			73			73	

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 - 2021Q2 sample period.

Figure 3 shows total end-of-period credit line limits and usage from the warehouse

lines of credit provided by banks and non-banks to NBFIs in our sample. The figure makes clear, first, that banks provide the majority of warehouse funding to NBFI mortgage lenders, and second, that there is a noticeable increase in credit lines supplied by banks during the pandemic.

Figure 3: 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 non-banks.

In Table 2, we report summery statistics for the 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 728.1 for home purchases and 743.5 for refinances, and average scores are lower for NBFI applications than for bank applications. The average income is $105,509 for a home purchase applicant and $114,291 for a refinance applicant, with NBFI applicants having lower average income than bank applicants. The average loan size is $287,671 for home purchases and $280,889 for refinancing, with bank loans having a larger average size than NBFI loans. The table documents other important mortgage application characteristics such as loan-to-value and debt-to-income ratios. The mean rejection rate is 12.0% for home purchase applications and 15.5% for refinancing applications. Roughly 40% of the sample is home purchase applications while 60% is refinancing 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.	Mean	Std. dev.	Mean	Std. dev.
Panel A: Home Purchase						
NBFI Indicator	0.00	0.00	1.00	0.00	0.71	0.45
Credit Score	745.6	54.5	722.3	64.8	728.1	63.2
Income ($)	122,021	92,822	99,593	69,033	105,509	76,674
Loan Amount ($)	317,678	291,113	276,056	188,412	287,671	222,689
Loan to Value Ratio (%)	81.6	15.7	86.1	14.7	84.8	15.1
Debt to Income Ratio (%)	35.5	11.6	38.4	11.8	37.7	11.8
Rejection Rate (%)	11.3	31.7	12.3	32.9	12.0	32.6
Age (year)	43.1	13.9	41.4	13.4	41.8	13.6
Interest Rate (%)	3.52	0.94	3.60	1.18	3.58	1.12
Processing Time (days)	49.0	37.5	50.5	47.6	50.1	45.0
QE Indicator	0.56	0.49	0.64	0.48	0.62	0.48
Observations	993,200		2,540,195		3,533,395	
Panel B: Refinancing						
NBFI Indicator	0.00	0.00	1.00	0.00	0.72	0.44
Credit Score	755.4	54.9	739.2	59.0	743.5	58.3
Income ($)	125,613	89,311	109,789	73,408	114,291	78,587
Loan Amount ($)	286,933	261,173	278,615	169,471	280,889	198,825
Loan to Value Ratio (%)	62.7	18.4	67.2	17.7	65.9	18.0
Debt to Income Ratio (%)	34.1	13.3	34.7	12.6	34.6	12.8
Rejection Rate (%)	17.1	37.6	14.9	35.6	15.5	36.2
Age (year)	50.9	13.4	49.6	13.5	50.0	13.5
Interest Rate (%)	3.31	0.85	3.16	0.75	3.20	0.78
Processing Time (days)	56.9	38.1	49.9	36.2	51.8	36.8
QE Indicator	0.62	0.48	0.72	0.44	0.69	0.45
Observations	1,474,606		3,889,716		5,364,322	

Note: This table presents summary statistics for mortgage application level variables from the confidential HMDA for a 2019Q1 - 2021Q2 sample period.

3 Empirical Methodology

3.1 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."[6] 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 trillion 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.

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. Bank purchases push up MBS prices (Krishnamurthy and Vissing-Jorgensen 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

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

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).[7]

We measure bank exposure to the 2020-2022 QE program as the average MBS-to-total assets ratio (MBS ratio) in 2019. Following Rodnyansky and Darmouni (2017) and Kapoor and Peia (2021), we assign banks in the top quartile of the 2019 MBS ratio to our treatment group and banks in the bottom quartile of 2019 MBS ratio to our control group. Banks in the treatment group therefore have the strongest exposure to Fed asset purchases whereas banks in the control group have the weakest.[8] 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.

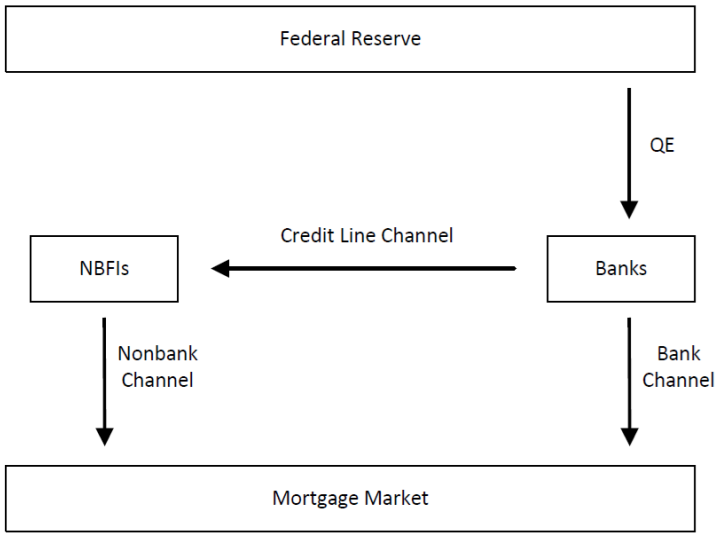
Although the 2020-2022 QE also involved significant purchases of long-term Treasuries, we focus on MBS holdings because they make up a more significant proportion of overall bank assets. The average bank MBS ratio in our sample is about 4%, whereas the average Treasury-to-total assets ratio is under 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.[9] Results in our Online Appendix confirm that lending from banks with higher Treasury-to-asset ratios did not meaningfully increase during the pandemic-era QE, providing explicit support for our focus on MBS holdings.

[7]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.

[8]In the Online Appendix we show our results are robust to alternative treatment classifications, including directly replacing the treatment dummy with a bank's 2019 MBS ratio.

[9]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.

Figure 4: 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 4 lays out the broad channels through which QE influences the mortgage market. The bank channel, which incorporates the more narrow net worth and liquidity channels discussed above, has been studied for the previous rounds of asset purchases (QE1-QE3) but not for the 2020-2022 program. In addition to being the first study to analyze the bank lending channel of QE for the pandemic-era program, a key contribution of this study is the identification of a new channel through which QE affects mortgage market outcomes, namely, the nonbank channel, where NBFI indirect exposure to QE through warehouse funding extended by commercial banks allows for an expansion of nonbank mortgage lending.

To identify NBFI indirect exposure to QE we exploit Mortgage Call Report data on warehouse lines of credit between NBFI's and commercial banks. NBFI's that receive funding from banks with greater exposure to QE may obtain easier terms of financing, allowing them to expand their own mortgage lending activity. The credit line information allows us to construct indirect MBS Ratios for NBFIs. 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.[10] We are thus able to estimate the extent of the nonbank channel by seeing whether NBFIs with higher indirect MBS ratios expanded mortgage lending to

[10]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 equals 5.

a greater degree after the onset of QE.

In reference to Figure 4's conceptual framework, we are also able to quantify the extent of the credit line channel by estimating whether there is a larger increase in NBFI warehouse funding from banks with higher MBS ratios after the onset of QE. Specifically, we can estimate a within-NBFI specification. For a single NBFI with credit lines from multiple banks, we can determine whether credit line limits and usage increase more from banks with higher MBS ratios after the onset of QE. This exploration of the credit line channel allows us to identify a direct mechanism through which QE transmits from the traditional banking system to the nonbank financial sector.

3.2 Lender 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 on bank lending. 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 2020Q1. We consider two variations of the treatment variable, $treat_j$, which captures a bank's exposure to Fed asset purchases. The first is simply a bank's MBS-to-assets ratio in 2019. The second is 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). $X_{j,t-1}$ are standard bank-level controls used in the literature, including the logarithm of total assets, deposits to assets ratio, equity to assets ratio, and return on assets. All bank-level controls are lagged by one period.

We next estimate Eq. (1) for NBFIs using Mortgage Call Report data. We aggregate credit lines in a given quarter for each NBFI in the sample, giving us a quarterly measure of NBFI total credit line limits and total credit used. $y_{j,t}$ for the NBFI specification is therefore: (i) the log of total credit lines available to the NBFI, (ii) the log of total credit used, and (iii) the credit line utilization ratio, which is the share of credit lines used.[11] Bank and time fixed effects are once again included, and QE is still a dummy equaling one beginning in 2020Q1. Exposure to QE for each NBFI, captured by $treat_j$, once again takes two forms. In the first variation, it becomes the weighted average of the $MBSRatio$s' of the banks from which the NBFI receives fund-

[11] We use zero in quarters where the NBFI had not used credit from the existing credit lines.

ing, weighted by the amount of credit provided. In the second variation, it is a dummy equaling one for NBFIs in the top quartile of weighted MBS ratio in 2019 and zero for NBFIs in the bottom quartile. We include analogous bank-level controls in $X_{j,t-1}$, also constructed as weighted averages. For the NBFI specification we also add the number of overall credit line providers and the number of credit lines from bank providers as additional controls.

3.3 Application Level Estimation

After establishing evidence at the provider-level (bank and NBFI), we next examine the effect of QE on mortgage outcomes at the application-level. We do this by estimating the effect of QE exposure on mortgage application rejection rates for banks and NBFIs. Specifically, we separately run the following specification for each type of lender:

$$y_{i,j,c,t} = \alpha_{j,t} + \omega_{c,t} + \beta QE_t * treat_j + \gamma Z_{i,t} + \epsilon_{i,j,c,t} \tag{2}$$

where $y_{i,j,c,t}$ is a dummy variable equaling one if application i, submitted to lender j, to finance a house in county c, in month t is rejected. $treat_j$ is the QE exposure for lender j. There are once again two variations: for banks, the first is the average MBS ratio during the four quarters of 2019, and for NBFIs, it is the weighted average of the $MBSRatio$s' of the banks from which the NBFI receives funding, weighted by the amount of credit. The second variation is a dummy equaling one if the bank/NBFI is in the top quartile of the MBS ratio distribution (for the respective type of lender) and zero if it is in the bottom quartile. QE_t is an indicator variable taking on the value of 1 after March 15, 2020 (after the start of the QE program). Z is a vector of mortgage application-level control variables which include the applicant credit score, applicant income, loan-to-value ratio, loan-to-value ratio squared, debt-to-income ratio, debt-to-income ratio squared, applicant age, and the logarithm of the loan amount. 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).

4 Results

4.1 Lender Level Results

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, respectively. Consistent with studies on previous rounds of QE, we find that banks that are more exposed to QE have increased lending more relative to other banks. However, while Rodnyansky and Darmouni (2017), Luck and Zimmermann (2020), and Kapoor and Peia (2021) have found that previous rounds of QE had an overall stronger impact on real estate lending compared to commercial loans, we find the opposite effect.

Table 3: The Impact of QE on Bank Lending

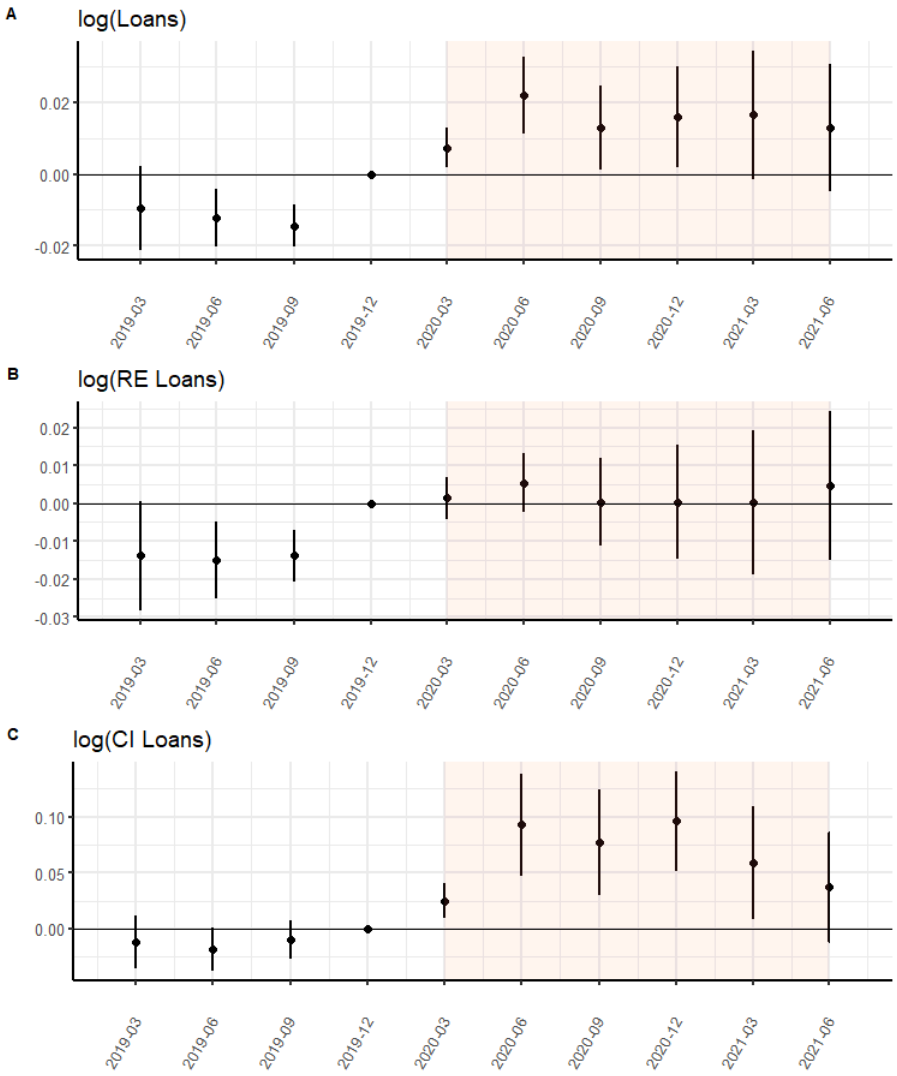
	log(Loans)		log(RE Loans)		log(C&I Loans)	
	(1)	(2)	(3)	(4)	(5)	(6)
MBS Ratio X QE	0.103***		0.091**		0.267**	
	(0.031)		(0.042)		(0.126)	
treat X QE		0.023***		0.013		0.074***
		(0.007)		(0.008)		(0.020)
Bank f.e.	Y	Y	Y	Y	Y	Y
Time f.e.	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	44,670	22,210	44,484	22,119	43,424	21,416
R^2	0.997	0.998	0.997	0.998	0.976	0.981
Adjusted R^2	0.997	0.998	0.997	0.997	0.973	0.979

Notes: This table presents the results from estimating Eq. (1 using Bank-level variables from the Call Reports for the period of 2019Q1 - 2021Q2. QE is a dummy variable that takes the value of one for every quarter from 2020Q1. 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) using Call Reports data and replacing the QE dummy with quarterly dummies, with 2019Q4 used as the benchmark period.[12] 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 banks with higher MBS ratios beginning prior to 2020.

[12]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 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.

Table 4 presents the results when focusing on bank wholesale funding to NBFI mortgage lenders using the aggregated lender-level MCR data. Columns (1) and (2) show that NBFIs that receive funding from banks with higher average MBS ratios saw an incrase in credit line limits. Columns (3) and (4) show that these NBFIs also experienced an increase in credit line usage following the onset of QE. Columns (5) and (6) summarize the previous columns, showing that NBFIs that received funding from banks with higher MBS ratios increased their credit line utilization by 4.1-13.4%.

Table 4: The Impact of QE on Bank Wholesale Funding to NBFIs

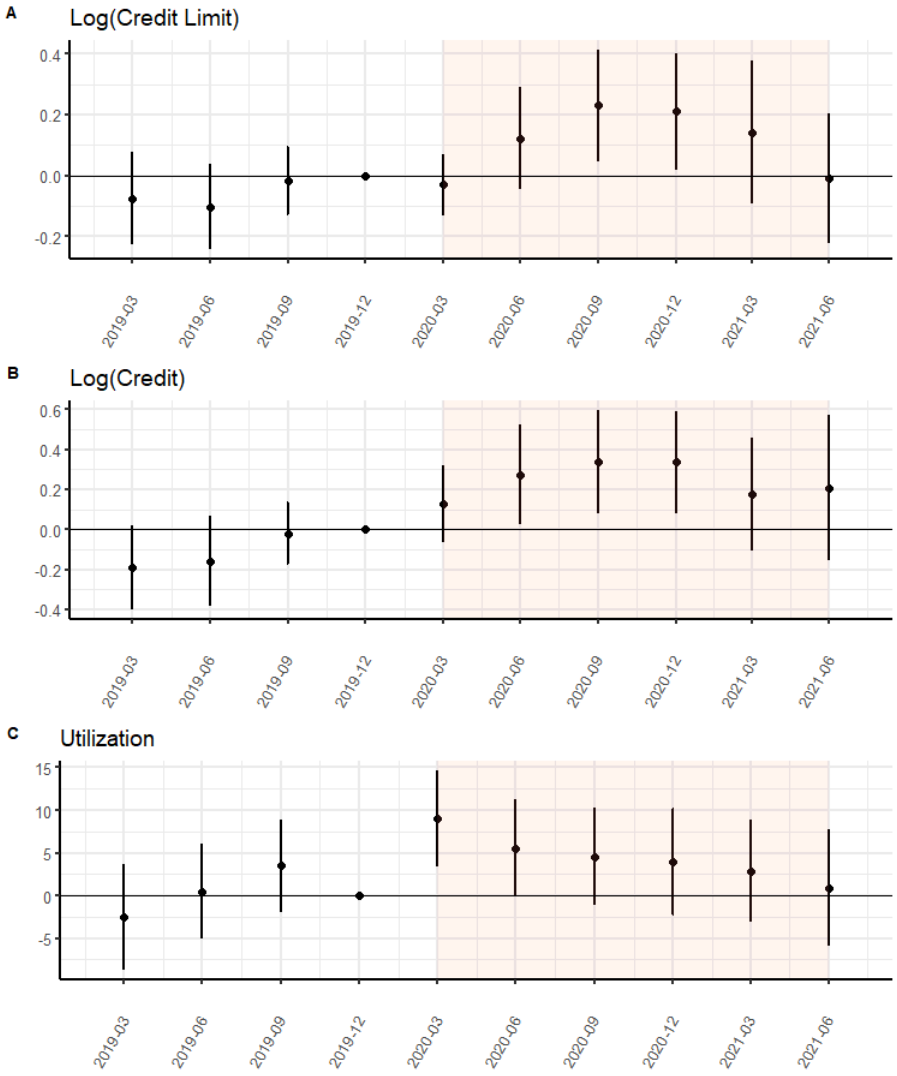
	$log(CreditLim)$		$log(Credit)$		$Utilization$	
	(1)	(2)	(3)	(4)	(5)	(6)
MBS Ratio X QE	0.512**		0.730**		13.372**	
	(0.258)		(0.321)		(6.693)	
treat X QE		0.224**		0.400***		4.125*
		(0.094)		(0.119)		(2.158)
NBFI f.e.	Y	Y	Y	Y	Y	Y
Time f.e.	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	4,445	2,169	4,445	2,169	4,445	2,169
R^2	0.929	0.935	0.893	0.891	0.614	0.650
Adjusted R^2	0.920	0.926	0.880	0.876	0.564	0.603

Notes: This table presents the results from estimating Eq. (1) using NBFI-level variables from Mortage Call Reports for the period of 2019Q1 - 2021Q2. QE is a dummy variable that takes the value of one for every quarter from 2020Q1. MBS Ratio is the weighted average of 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. treat is a dummy variable that equals one for NBFIs in the top quartile of the 2019 weighted MBS Ratio distribution, and that equals zero for NBFIs in the bottom quartile. Standard errors, clustered at the NBFI level, are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

Figure 6 shows the dynamic effects from estimating Eq.(1) using Mortgage Call Report data. The QE_t dummy is replaced with dummy variables for each quarter, with 2019Q4 omitted as the reference quarter. Panel (A) shows a gradual increase in credit limits throughout 2020 that tapers off in 2021. Panel (B) shows a similar pattern, with credit limit usage increasing throughout 2020 and peaking in the second half of the year. Panel (C) shows an immediate jump in utilization at the beginning of the pandemic, that remains positive but drops in magnitude in the subsequent quarters. In all three panels, the 2019 coefficients' 90% confidence intervals include zero, suggesting that the estimates are not contaminated by a violation of the parallel underlying trends assumption.

In the Online Appendix, we show that the results for both Table 3 and Table 4 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 2020Q2 rather than 2020Q1; (iii) alternative definitions of the treatment dummy using either the mean or the upper and bottom deciles as cutoff points; (iv) using

Figure 6: The Impact of QE on Bank Wholesale Funding to NFBIs - Dynamic Impact



Note: This figure presents the dynamic effect of QE on the log of total wholesale credit lines (Panel A), the log of total used credit (Panel B), and credit line utilization share (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 the onset of QE in 2021 Q1.

matching techniques to address any lingering concerns of endogeneity stemming from bank selection of MBS holdings; (v) re-estimate the main specifications with bank Treasury-to-asset ratios replacing MBS ratios; and (vi) control for the impact of local exposure to the pandemic and the Paycheck Protection Program (PPP) on bank credit supply.

4.2 Application Level Results: The Bank Channel

In this section, we complement the lender-level results by using confidential HMDA data to examine how lender exposure to QE impacted mortgage application outcomes during the pandemic boom. As in the lender-level estimations, we estimate Eq.(2) separately for banks and NBFIs.

Table 5 presents estimates focusing on bank mortgage applications. The results in Table 5 show that, in general, banks with higher MBS Ratios tend to have higher rejection rates. Specifically, the interpretation of the MBS Ratio variable coefficient is that for every one percentage point increase in MBS ratio, rejections for the bank tend to be between 14 to 17.5 basis points higher. However, the interaction with the QE variable shows that these differences significantly dropped during the QE period, as banks with greater exposure to QE experienced a significant decline in rejection rates. Notably, rejection rates declined at a much larger magnitude for refinance applications compared to home purchases.

Table 5: Bank Channel - Application Rejection Rates

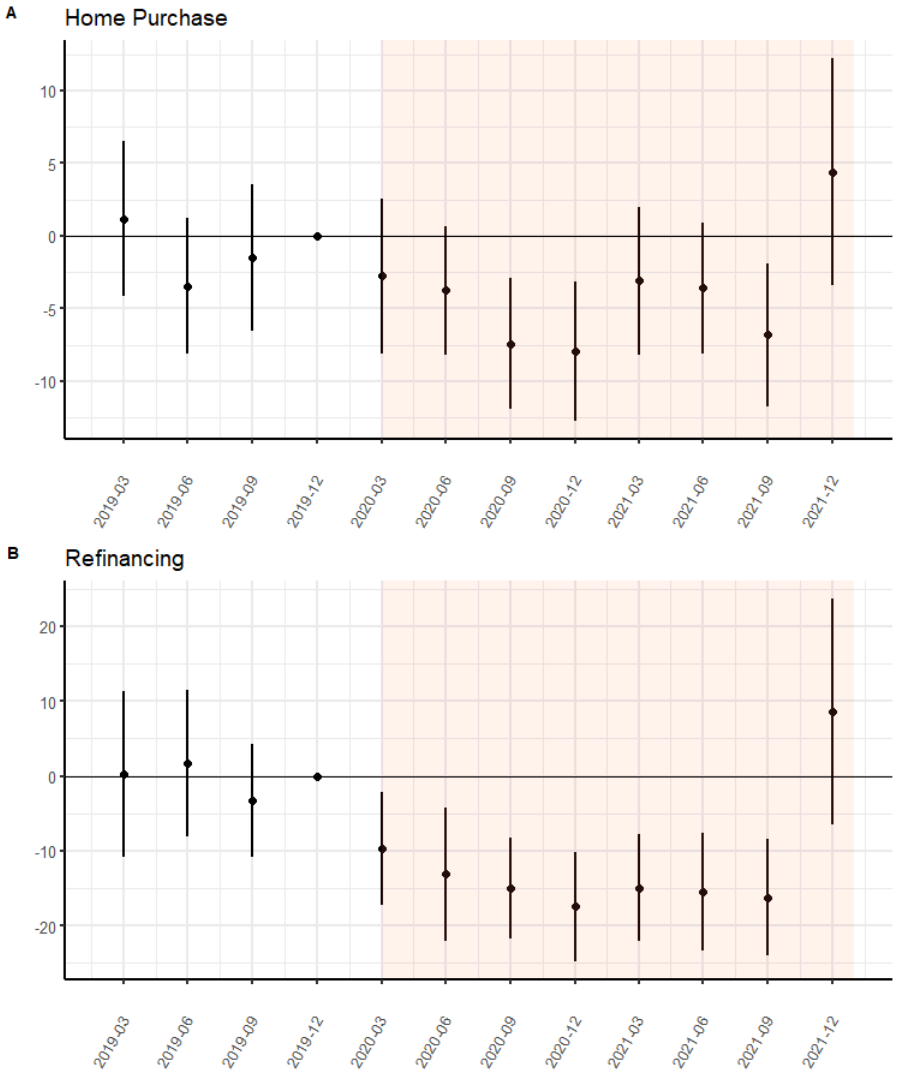
	Rejection Rates		
	(1)	(2)	(3)
Panel A: Home Purchase			
QE	0.901***		
	(0.24)		
MBS Ratio	14.875***	15.288***	
	(1.68)	(1.69)	
MBS Ratio X QE	-3.675*	-4.379**	-3.176**
	(1.88)	(2.01)	(1.35)
Observations	679,173	658,525	658,510
Adjusted R^2	0.181	0.184	0.199
Panel B: Refinancing			
QE	1.463**		
	(0.62)		
MBS Ratio	17.592***	16.119***	
	(4.31)	(4.40)	
MBS Ratio X QE	-10.168**	-9.596**	-10.072***
	(4.52)	(4.74)	(2.14)
Observations	1,058,442	1,039,563	1,039,535
Adjusted R^2	0.281	0.287	0.311
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

Figure 7 shows the dynamic effects from estimating Eq.(2), replacing the QE_t dummy with dummy variables for each quarter, with 2019Q4 omitted as the reference quarter. Panel (A) shows a significant decrease in home purchase rejection rates,

with the strongest effects coming in the second half of 2020. Panel (B) shows a much more persistent effect for refinancing, with rejection rates immediately decreasing in 2020Q1 and remaining significantly lower well into 2021. In both panels, the 2019 coefficients' 90% confidence intervals include zero, once again implying that the estimates are not biased by a violation of the parallel underlying trends assumption.

Figure 7: Bank Channel - Application Rejection Rates - Dynamic Impact



Note: 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 parenthesis. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

4.3 Application Level Results: The Nonbank Channel

Next, we examine the role of QE in impacting nonbank mortgage lending. The regression results for Eq.(2) when using the sample of NBFI mortgage applications are presented in Table 6. Here, we measure each NBFI pre-pandemic QE exposure by using a weighted average of all the MBS ratios of the banks from which the NBFI receives funding, weighted by the amount of utilized credit from each credit line.

Table 6 presents the results for the NBFI mortgage sample. Panel (A) suggests that QE exposure is not significantly associated with rejection rates for home purchases before the QE program. The interaction between the QE dummy and the QE exposure measure (MBS Ratio) is negative but only marginally significant when applying all controls and fixed effects. This suggests that for home purchases, QE, at most, had a modest impact of reducing NBFI home purchase rejection rates.

Table 6: Nonbank Channel - Application Rejection Rates

	Rejection Rates		
	(1)	(2)	(3)
Panel A: Home Purchase			
QE	0.556		
	(0.47)		
MBS Ratio	2.730	4.236	
	(4.09)	(3.82)	
MBS Ratio X QE	-3.039	-4.552	-4.673*
	(5.09)	(4.97)	(2.51)
Observations	1,289,446	1,270,816	1,270,814
Adjusted R^2	0.124	0.131	0.163
Panel B: Refinancing			
QE	0.523		
	(1.40)		
MBS Ratio	-37.759***	-38.206***	
	(9.55)	(9.25)	
MBS Ratio X QE	-6.623	-6.819	-13.414**
	(12.63)	(12.26)	(5.49)
Observations	2,062,788	2,044,388	2,044,385
Adjusted R^2	0.184	0.193	0.255
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 NBFI-month level are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

The impact is more pronounced in the refinancing market in Panel (B), however. While the interaction coefficient between the MBS Ratio and QE dummy is insignificant in the first two columns, when applying all controls and fixed effects in our preferred specification (column 3), the interaction coefficient becomes negative, significant, and

economically meaningful. Specifically, it suggests that a one percentage point increase in an NBFI's weighted MBS ratio leads to a 13 basis point reduction in refinance application rejection rates. Overall, the evidence in Table 6 indicates that NBFIs with greater indirect exposure to QE through their bank financing relationships reduced mortgage rejection rates, particularly for refinancing.

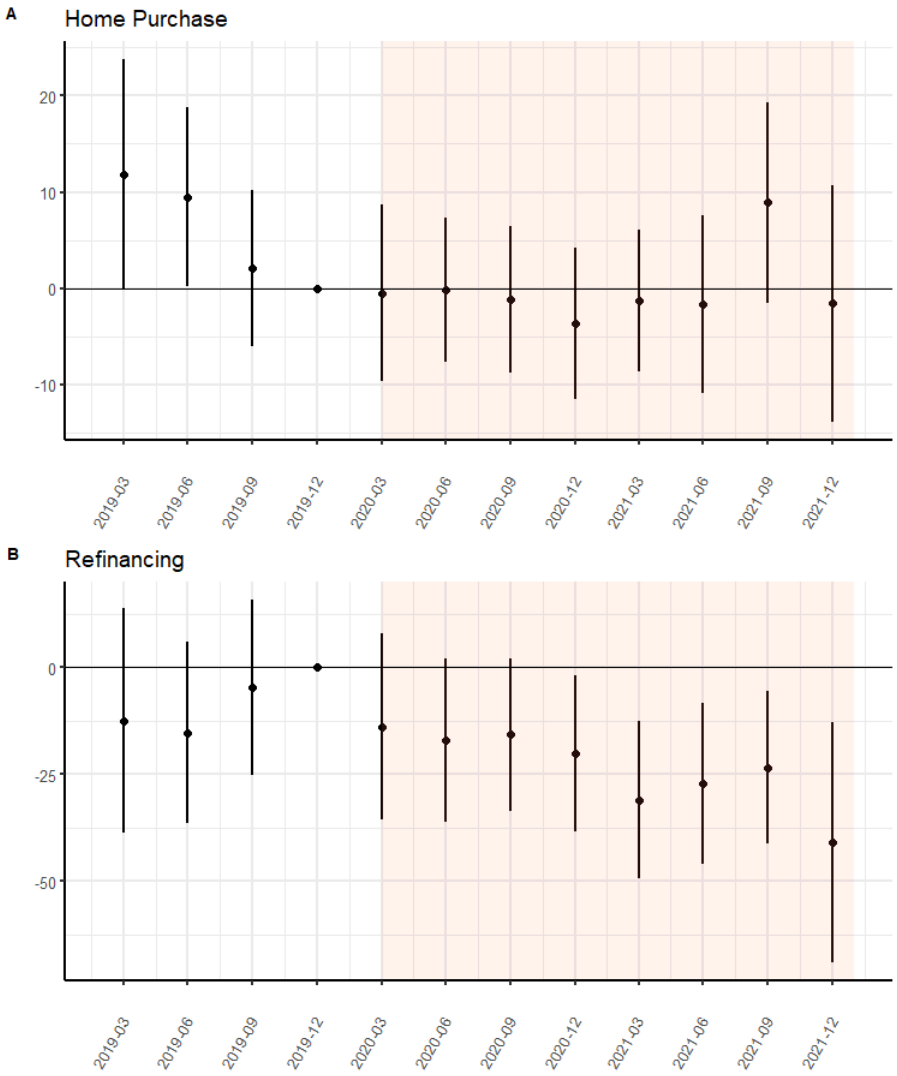
Figure 8 shows the dynamic effects from estimating Eq.(2) with the NBFI sample. Panel (A) shows a weak effect on home purchase rejection rates, with none of the post-treatment coefficients being statistically significant. Panel (B), on the other hand, shows a negative, mostly significant, and highly persistent effect on refinancing applications, with rejection rates remaining significantly lower throughout 2021.

5 Mechanism: QE Transmission to NBFIs

This section examines the mechanism through which QE impacts the credit supply to NBFIs more formally. Our suggested mechanism implies that QE improves overall credit line conditions by improving banks' lending capacity. Credit line contracts specify the credit limit, interest rate, commitment period, commitment fees, and other covenants. As conditions change, these contracts may be renegotiated. Thus, to the extent that QE during the pandemic impacted banks' credit supply, we expect QE to impact credit line usage by NBFI positively. That is, all else equal, we expect NBFIs to shift to credit lines supplied by banks with greater QE exposure. It is important to note that credit line substitution during the COVID-19 pandemic may result from improved conditions in certain credit lines, worsening conditions in others, or both.

To test these predictions, we use the credit line-level MCR data to examine how bank providers' exposure to QE impacted the NBFI credit line amount and usage during the pandemic. If our predictions are correct, and QE induced banks to extend credit and improve credit line conditions, we would expect to see a larger increase in the use and magnitude 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:

Figure 8: Nonbank Channel - Application Rejection Rates - Dynamic Impact



Note: 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 NBFI-month level are reported in parenthesis. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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

where i is the NBFI with a credit line with bank j in quarter t. $y_{i,j,t}$ is one of three dependent variables: (i) the log of the credit line at quarter-end; (ii) the log of the credit being used by NBFI i; (iii) the credit line utilization defined as the ratio of the credit used and the total available credit line.[13] $MBSRatio_j$ 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 first quarter of 2020. $\alpha_{i,t}$ is the NBFI-time fixed effects that absorb all time-varying differences within each NBFI, including credit demand conditions. $\omega_{i,j}$ is NBFI-Bank fixed effects, which control for constant relation 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.[14] 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) to capture these additional bank characteristics that may impact bank performance during the pandemic.

In this specification, our main coefficient of interest is β, which estimates the relation between the specific credit line provider exposure to QE and the credit line size and usage in the post-treatment period. Table 7 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 total credit usage and for credit utilization, while being positive but statistically insignificant for total credit line limit, suggesting that the credit provider's exposure to QE is positively associated with an increase in credit supply to NBFI borrowers.

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

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

Table 7: Credit line estimation level

	Dependent variable:		
	Log(Credit Limit)	Log(Credit Usage)	Utilization
	(1)	(2)	(3)
MBS Ratio x *QE*	0.257	1.286***	0.232**
	(0.293)	(0.450)	(0.117)
NBFI x Time F.E.	Y	Y	Y
NBFI x Bank F.E.	Y	Y	Y
Observations	10,967	10,967	10,967
R^2	0.900	0.834	0.691
Adjusted R^2	0.837	0.731	0.498

Notes: This table presents the results of estimating Eq.(3). Quarterly variables from 2019Q1 - 2021Q2. QE in a dummy variable that takes the value of one for every quarter from 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 NBFI level, are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

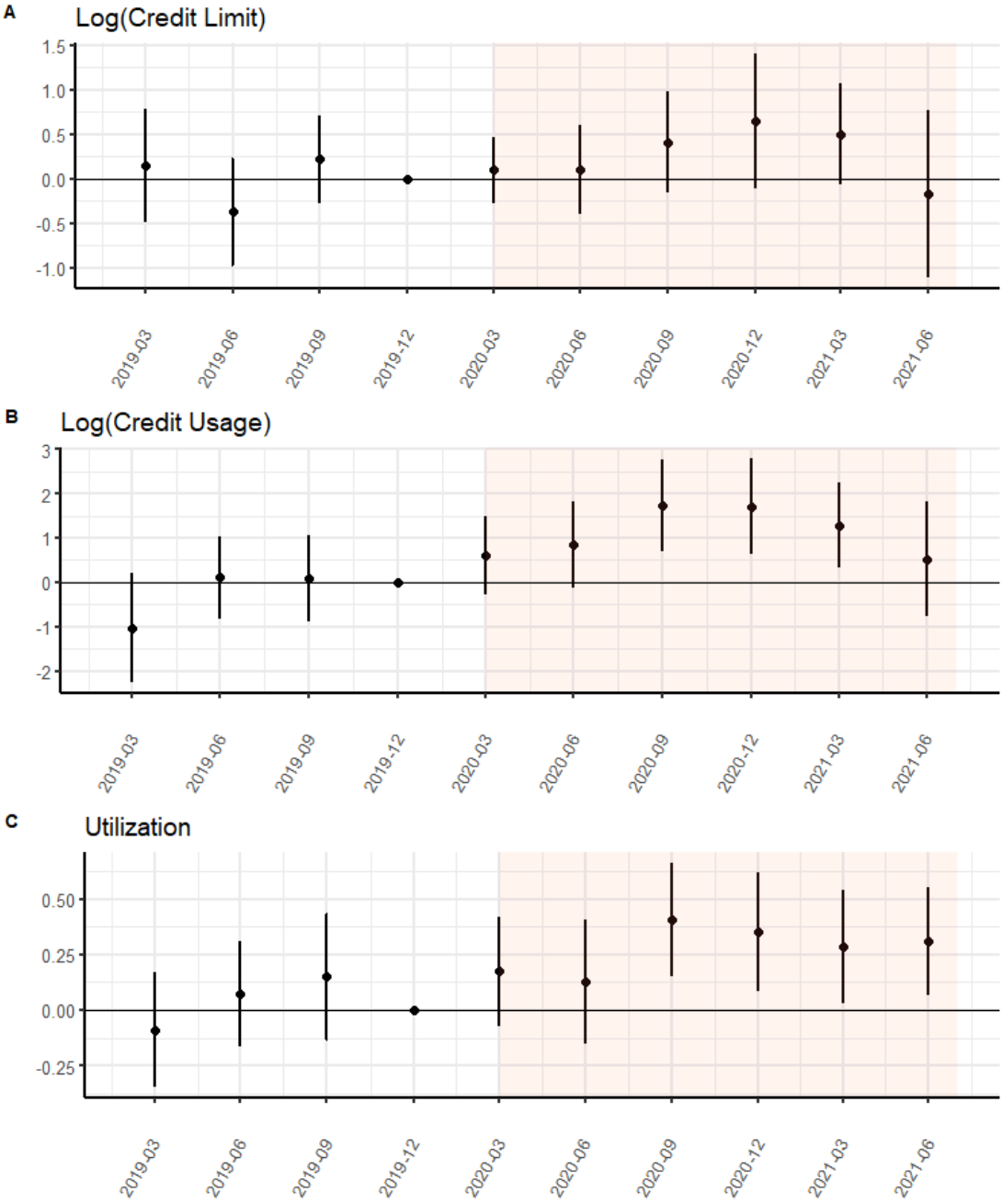
The interpretation of the coefficients is as follows. In column 1, the β coefficient implies that for every percentage point increase in MBS ratio, the credit limit in the QE period is, on average, 26 basis points higher relative to the pre-QE period. For column 2, the coefficient implies that for every percentage point increase in MBS ratio, the credit usage in the QE period is on average 130 basis points higher. The coefficient in column 3 indicates that for every percentage point increase in MBS ratio, the utilization rate of the credit line is, on average, 23 basis points higher after the onset of QE.

We also estimate Eq. (3) as a dynamic specification by replacing the QE dummy with a set of dummy variables for each quarter, except for 2019Q1, which is omitted as the benchmark quarter. The dynamic specification allows us to examine pre-existing trends in the relationship between the credit line providers' MBS ratio and the various dependent variables. Figure 9 presents the dynamic specification results, which plots the time-varying point estimates of the interaction between the credit line provider MBS ratio and the quarter dummies along with 90% confidence bands.

The figure shows a clear jump in credit usage and utilization, particularly in the second half of 2020 and the first quarter of 2021. While only marginally significant, there is also an immediate increase in magnitude detectable in the first two quarters of 2020. Overall, the increase in usage and utilization is largely stable over the sample period, with a slight decline appearing in credit usage in 2021Q2. The increase in credit line size in Panel (A) is more weakly significant, but nevertheless exhibits a clear jump in magnitude during 2020Q3 - 2021Q1.

A growing literature shows that firms drew down heavily from existing credit lines in a rush to increase cash-holding during the pandemic outbreak (Acharya and Steffen 2020; Li et al. 2020; Acharya et al. 2021; Greenwald et al. 2024). There are two points, however, in which the mortgage-related credit lines examined here seems to

Figure 9: Credit Line Estimation - Dynamic Impact



Note: This figure presents the dynamic effect of banks' QE exposure (MBS ratio) on the log of total credit lines provided to non-bank mortgage lenders (Panel A), the log of credit usage by the NBFIs (Panel B), and the utilization ratio (Panel C). The figure plots the regression coefficients from estimating Eq. (3) with dummy variables for each quarter instead of the QE dummy along with 90% confidence intervals. The coefficient for 2019 Q1 is normalized to zero. The shaded area represents the period from 2021 Q1.

diverge from other corporate credit lines observed by the literature. First, while in most cases, credit line draw-downs peaked by the third quarter of 2020 and then quickly normalized to pre-pandamic levels, the increase in draw-downs observed for the NBFI mortgage lenders appears to be more persistent. This suggests that while the overall increase in credit line usage at the beginning of the pandemic was mostly due to an increase in credit demand and not an expansion of credit supply (Berger and Demirgüç-Kunt 2021), the fact that there is a strong positive relationship between bank provider exposure to QE and the increase in draw-downs for mortgage originating NBFIs suggests that the spike observed in Figure 9 was supply related. Second, the fact that we observe a positive, significant, and persistent relation between the credit line provider exposure to QE (the MBS ratio) and our various measures of credit line usage points to the important role that QE may have played in supporting credit supply by banks during the pandemic. Specifically, while other studies have shown that the credit-line draw-downs may have reduced bank credit supply to other sectors (Kapan and Minoiu 2021; Greenwald et al. 2024), our results suggest that this crowding out effect may have been mitigated through QE, which increased bank liquidity, improved balance sheet strength and boosted credit supply.

6 Conclusion

The Fed's QE program aims to support the flow of credit to households, and, by purchasing large quantities of mortgage-backed securities, particularly aims at supporting the residential mortgage market. Our evidence shows that the Fed's pandemic-era QE program supported the mortgage market by directly increasing bank lending and indirectly increasing NBFI lending. Specifically, banks with greater exposure to QE increased both C&I and real estate lending, although, in contrast to previous rounds of QE, the increase in C&I lending was larger. Within C&I lending, banks particularly increased warehouse funding to nonbank mortgage originators. At the mortgage application-level, banks with greater direct exposure to QE and nonbank lenders with greater indirect exposure, through their bank funding relationships, both reduced rejection rates. The decline in rejection rates was notably larger for refinance applications than new home purchases, as refinancing became the primary driver of the mortgage boom. We establish a direct line of QE transmission from banks to NBFIs, as NBFI warehouse line of credit limits, use, and utilization all increased for credit lines provided by banks with more exposure to Fed asset purchases.

These results are important for both monetary policymakers and financial regulators. First, they show in precise fashion how the effects of QE are transmitted from banks to other financial institutions, resulting in easier liquidity conditions throughout

the financial sector. 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 non-bank 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.

References

Acharya, Viral V, Robert F Engle III, and Sascha Steffen (2021). *Why did bank stocks crash during COVID-19?* Tech. rep. National Bureau of Economic Research.

Acharya, Viral V and Sascha Steffen (2020). "The risk of being a fallen angel and the corporate dash for cash in the midst of COVID". *The Review of Corporate Finance Studies* 9.3, pp. 430–471.

Aldasoro, Iñaki, Sebastian Doerr, and Haonan Zhou (2023). "Non-bank lending during crises". *Available at SSRN 4008248*.

Allen, Linda, Yu Shan, and Yao Shen (2023). "Do fintech mortgage lenders fill the credit gap? Evidence from natural disasters". *Journal of Financial and Quantitative Analysis* 58.8, pp. 3342–3383.

Bao, Zhengyang and Difang Huang (2021). "Shadow banking in a crisis: Evidence from FinTech during COVID-19". *Journal of Financial and Quantitative Analysis* 56.7, pp. 2320–2355.

Beck, Thorsten and Jan Keil (2022). "Have banks caught corona? Effects of COVID on lending in the US". *Journal of Corporate Finance* 72, p. 102160.

Ben-David, Itzhak, Mark J Johnson, and René M Stulz (2021). *Why Did Small Business FinTech Lending Dry Up During the COVID-19 Crisis?* Tech. rep. National Bureau of Economic Research.

Berg, Tobias, Andreas Fuster, and Manju Puri (2022). "Fintech lending". *Annual Review of Financial Economics* 14, pp. 187–207.

Berger, Allen N and Asli Demirgüç-Kunt (2021). "Banking research in the time of COVID-19". *Journal of Financial Stability* 57, p. 100939.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru (2018). "Fintech, regulatory arbitrage, and the rise of shadow banks". *Journal of financial economics* 130.3, pp. 453–483.

— (2024). "Beyond the balance sheet model of banking: Implications for bank regulation and monetary policy". *Journal of Political Economy* 132.2, pp. 616–693.

Chakraborty, Indraneel, Itay Goldstein, and Andrew MacKinlay (2020). "Monetary stimulus and bank lending". *Journal of Financial Economics* 136.1, pp. 189–218.

Colak, Gönül and Özde Öztekin (2021). "The impact of COVID-19 pandemic on bank lending around the world". *Journal of Banking & Finance* 133, p. 106207.

Di Maggio, Marco, Amir Kermani, and Christopher J Palmer (2020). "How quantitative easing works: Evidence on the refinancing channel". *The Review of Economic Studies* 87.3, pp. 1498–1528.

Diamond, William, Zhengyang Jiang, and Yiming Ma (2024). "The reserve supply channel of unconventional monetary policy". *Journal of Financial Economics* 159, p. 103887.

Drechsler, Itamar, Alexi Savov, Philipp Schnabl, and Dominik Supera (2024). "Monetary Policy and the Mortgage Market". In: Working Paper, presented at Jackson Hole Economic Policy Symposium.

Erel, Isil and Jack Liebersohn (2020). *Does fintech substitute for banks? evidence from the paycheck protection program*. Tech. rep. National Bureau of Economic Research.

— (2022). "Can FinTech reduce disparities in access to finance? Evidence from the Paycheck Protection Program". *Journal of Financial Economics* 146.1, pp. 90–118.

Fleckenstein, Quirin, Manasa Gopal, German Gutierrez Gallardo, and Sebastian Hillenbrand (2020). "Nonbank lending and credit cyclicality". *NYU Stern School of Business*.

Fuster, Andreas, Aurel Hizmo, Lauren Lambie-Hanson, James Vickery, and Paul S Willen (2021). *How resilient is mortgage credit supply? Evidence from the COVID-19 pandemic*. Tech. rep. National Bureau of Economic Research.

Fuster, Andreas, Matthew Plosser, Philipp Schnabl, and James Vickery (2019). "The role of technology in mortgage lending". *The Review of Financial Studies* 32.5, pp. 1854–1899.

Greenwald, Daniel L, John Krainer, and Pascal Paul (2024). "The credit line channel". *the Journal of Finance*.

Griffin, John M, Samuel Kruger, and Prateek Mahajan (2023). "Did FinTech lenders facilitate PPP fraud?" *The Journal of Finance* 78.3, pp. 1777–1827.

Jiang, Erica, Gregor Matvos, Tomasz Piskorski, and Amit Seru (2020). *Banking without deposits: Evidence from shadow bank call reports*. Tech. rep. National Bureau of Economic Research.

Jiang, Erica Xuewei (2023). "Financing competitors: Shadow banks' funding and mortgage market competition". *The Review of Financial Studies* 36.10, pp. 3861–3905.

Kandrac, John and Bernd Schlusche (2021). "Quantitative easing and bank risk taking: evidence from lending". *Journal of Money, Credit and Banking* 53.4, pp. 635–676.

Kapan, Tumer and Camelia Minoiu (2021). "Liquidity insurance vs. credit provision: Evidence from the COVID-19 crisis". *Credit Provision: Evidence from the COVID-19 Crisis (September 30, 2021)*.

Kapoor, Supriya and Oana Peia (2021). "The impact of quantitative easing on liquidity creation". *Journal of Banking & Finance* 122, p. 105998.

Karakaplan, Mustafa U (2021). "This time is really different: The multiplier effect of the Paycheck Protection Program (PPP) on small business bank loans". *Journal of Banking & Finance* 133, p. 106223.

Khwaja, Asim Ijaz and Atif Mian (2008). "Tracing the impact of bank liquidity shocks: Evidence from an emerging market". *American Economic Review* 98.4, pp. 1413–1442.

Krishnamurthy, Arvind and Annette Vissing-Jorgensen (2011). *The effects of quantitative easing on interest rates: channels and implications for policy*. Tech. rep. National Bureau of Economic Research.

— (2013). "The ins and outs of LSAPs". In: *Kansas City federal reserve symposium on global dimensions of unconventional monetary policy*. Federal Reserve Bank of Kansas City Kansas City, pp. 57–111.

Kurtzman, Robert, Stephan Luck, and Tom Zimmermann (2022). "Did QE lead banks to relax their lending standards? Evidence from the Federal Reserve's LSAPs". *Journal of Banking & Finance* 138.C.

Li, Lei and Philip E Strahan (2021). "Who supplies PPP loans (and does it matter)? Banks, relationships, and the COVID crisis". *Journal of Financial and Quantitative Analysis* 56.7, pp. 2411–2438.

Li, Lei, Philip E Strahan, and Song Zhang (2020). "Banks as lenders of first resort: Evidence from the COVID-19 crisis". *The Review of Corporate Finance Studies* 9.3, pp. 472–500.

Lopez, Jose A and Mark M Spiegel (2023). "Small business lending under the PPP and PPPLF programs". *Journal of Financial Intermediation* 53, p. 101017.

Luck, Stephan and Tom Zimmermann (2020). "Employment effects of unconventional monetary policy: Evidence from QE". *Journal of Financial Economics* 135.3, pp. 678–703.

Neef, H Özlem Dursun-de and Alexander Schandlbauer (2021). "COVID-19 and lending responses of European banks". *Journal of Banking & Finance* 133, p. 106236.

Neef, H Özlem Dursun-de, Alexander Schandlbauer, and Colin Wittig (2023). "Countercyclical capital buffers and credit supply: evidence from the COVID-19 crisis". *Journal of Banking & Finance* 154, p. 106930.

Newton, Natalie and James I Vickery (2022). "The Pandemic Mortgage Boom". *Economic Insights, Federal Reserve Bank of Philadelphia*, Q3–Q4.

Rodnyansky, Alexander and Olivier M Darmouni (2017). "The effects of quantitative easing on bank lending behavior". *The Review of Financial Studies* 30.11, pp. 3858–3887.

Schaffer, Matthew and Nimrod Segev (2023). "Quantitative Easing, Bank Lending, and Aggregate Fluctuations". *Bank Lending, and Aggregate Fluctuations (January 5, 2023)*.

A Online Appendix

A.1 Robustness tests - Lender level results

Here, we present a number of robustness tests for estimation Eq. (1) using either bank-level call report data or the NBFI-level MCR database.

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 impact of other bank characteristics on the responses to QE and the impact on the credit line supply to NBFIs. In Panel A we present results for the bank level specification using call report data, while panel B presents the results for the NBFI specification using the NBFI level aggregated Washington State mortgage call reports database.

While some of the significance is lost, especially when using the continuous MBS ratio measure, the overall results are consistent, suggesting a weak positive relation between QE during the COVID-19 pandemic and bank real estate lending, a stronger relation to banks' C&I loans, and an even more robust connection to NBFI mortgage credit supply.

A.1.2 Timing

Table A.2 presents the results when starting the QE dummy from 2020 Q2 instead of Q1.

A.1.3 Alternative treat threshold

We consider two alternative classifications of the treat dummy: using the entire sample and comparing lenders with an MBS ratio above the distribution median or comparing the upper tercile of the exposure distribution to the lower tercile.

Table A.3 shows the results when the treat dummy equals one for lenders whose MBS Ratio is above the distribution mean or in the upper tercile.

A.1.4 Alternative exposure

In general, prior literature on the relationship between QE and bank lending has found that the mechanism works primarily through the Fed purchase of MBS, which raises the price and liquidity of banks' MBS holdings. Additionally, treasuries tend to have a much smaller share of banks' securities than MBS's. Thus, the literature has argued

Table A.1: Additional Interactions

Panel A: Bank Level (call reports)

	log(Loans)		log(RE Loans)		log(C&I Loans)	
MBS Ratio X QE	0.056*		0.073		0.179	
	(0.032)		(0.046)		(0.137)	
treat X QE		0.019***		0.010		0.068***
		(0.007)		(0.008)		(0.023)
Observations	44,670	22,210	44,484	22,119	43,424	21,416
R^2	0.997	0.998	0.997	0.998	0.976	0.981
Adjusted R^2	0.997	0.998	0.997	0.998	0.973	0.979

Panel B: NBFI Level (mortage call reports)

	$log(CreditLim)$		$log(Credit)$		$Utilization$	
MBS Ratio X QE	0.668**		0.511		9.966	
	(0.287)		(0.324)		(7.709)	
treat X QE		0.211**		0.208*		1.042
		(0.096)		(0.123)		(2.598)
Observations	4,445	2,169	4,445	2,169	4,445	2,169
R^2	0.929	0.936	0.894	0.892	0.614	0.652
Adjusted R^2	0.920	0.927	0.881	0.877	0.565	0.604
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. Panel A presents results using Bank level variables from Call Reports, and Panel B uses NBFI level variables from Washington State mortgage call reports. The time period is 2019Q1 - 2021Q2. 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 parentheses. *p<0.1; **p<0.05; ***p<0.01

Table A.2: Alternative QE starting date

Panel A: Bank Level (call reports)

	log(Loans)		log(RE Loans)		log(C&I Loans)	
MBS Ratio X QE	0.088***		0.072*		0.259*	
	(0.032)		(0.040)		(0.138)	
treat X QE		0.022***		0.010		0.075***
		(0.008)		(0.008)		(0.023)
Observations	44,670	22,210	44,484	22,119	43,424	21,416
R^2	0.997	0.998	0.997	0.998	0.976	0.981
Adjusted R^2	0.997	0.998	0.997	0.997	0.973	0.979

Panel B: NBFI Level (mortage call reports)

	$log(CreditLim)$		$log(Credit)$		$Utilization$	
MBS Ratio X QE	0.549*		0.585*		4.949	
	(0.295)		(0.353)		(6.599)	
treat X QE		0.270***		0.401***		1.380
		(0.103)		(0.134)		(2.305)
Observations	4,445	2,169	4,445	2,169	4,445	2,169
R^2	0.929	0.935	0.893	0.891	0.613	0.650
Adjusted R^2	0.920	0.926	0.880	0.876	0.564	0.602
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 Q2. Panel A presents results using Bank level variables from Call Reports, and Panel B uses NBFI level variables from Washington State mortgage call reports. The time period is 2019Q1 - 2021Q2. 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

Table A.3: Alternative treat thresholds

Panel A: Bank Level (call reports)

	log(Loans)		log(RE Loans)		log(C&I Loans)	
$\text{treat}^{tercile}$ X QE	0.017***		0.011		0.052***	
	(0.006)		(0.007)		(0.017)	
treat^{median} X QE		0.013***		0.008*		0.027*
		(0.004)		(0.005)		(0.014)
Observations	29,640	44,670	29,522	44,484	28,688	43,424
R^2	0.998	0.997	0.997	0.997	0.979	0.976
Adjusted R^2	0.997	0.997	0.997	0.997	0.977	0.973

Panel B: NBFI Level (mortage call reports)

	$log(CreditLim)$		$log(Credit)$		$Utilization$	
$\text{treat}^{tercile}$ X QE	0.155*		0.214**		1.279	
	(0.081)		(0.100)		(1.839)	
treat^{median} X QE		0.122*		0.147*		1.473
		(0.064)		(0.076)		(1.461)
Observations	2,947	4,445	2,947	4,445	2,947	4,445
R^2	0.926	0.929	0.886	0.893	0.639	0.613
Adjusted R^2	0.916	0.920	0.871	0.880	0.591	0.564
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). Panel A presents results using Bank level variables from Call Reports, and Panel B uses level variables from Washington State mortgage call reports. The time period is 2019Q1 - 2021Q2. 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

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.4 we use the 2019 average share of US treasuries to total assets as an alternative QE exposure measure (Rodnyansky and Darmouni 2017). Consistent with previous literature we find very little effect for the treasury exposure on bank lending supply and mortgage market NBFIs.

Table A.4: Alternative Exposure

Panel A: Bank Level (call reports)

	log(Loans)		log(RE Loans)		log(C&I Loans)	
Treasury Ratio X QE	0.081		0.198		−0.214	
	(0.135)		(0.157)		(0.278)	
treat X QE		0.010**		0.007		−0.023
		(0.004)		(0.006)		(0.019)
Observations	44,670	22,320	44,484	22,265	43,424	21,332
R^2	0.997	0.998	0.997	0.997	0.976	0.977
Adjusted R^2	0.997	0.998	0.997	0.997	0.973	0.975

Panel B: NBFI Level (mortage call reports)

	$log(CreditLim)$		$log(Credit)$		$Utilization$	
Treasury Ratio X QE	−0.423		−0.756		−69.079	
	(1.436)		(1.918)		(46.613)	
treat X QE		0.179**		0.026		−5.631**
		(0.086)		(0.111)		(2.359)
Observations	4,128	2,094	4,128	2,094	4,128	2,094
R^2	0.928	0.943	0.899	0.910	0.595	0.609
Adjusted R^2	0.919	0.936	0.886	0.898	0.542	0.557
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). Panel A presents results using Bank level variables from Call Reports, and Panel B uses level variables from Washington State mortgage call reports. The time period is 2019Q1 - 2021Q2. 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.1.5 Matching

Following Rodnyansky and Darmouni (2017), Kapan and Minoiu (2021), and Kandrac and Schlusche (2021) we also employ propensity score matching to reduce the bias associated with the selection of banks to low and high MBS exposure. Specifically, we

take the upper and bottom quartiles of banks 2019 average MBS ratio and use a probit model to estimate the probability that the bank is in the upper quartile by the other banks' 2019 average characteristics (size, capital-assets ratio, Return on Assets (ROA), deposits over total assets ratio). In the next step we use the propensity scores from the probit model to construct a nearest-neighbor matching between each upper quartile bank (treated bank) and lower quartile (control) with replacment.[15] For the NBFI database, matching is done in the same manner, using the bank credit line providers' weighted pre-pandemic characteristics for matching.

Table A.5: Matching

Panel A: Bank Level (call reports)

	log(Loans)		log(RE Loans)		log(C&I Loans)	
MBS Ratio X QE	0.185***		0.154***		0.342**	
	(0.049)		(0.049)		(0.162)	
treat X QE		0.031***		0.020***		0.033
		(0.008)		(0.007)		(0.025)
Observations	22,370	22,370	22,290	22,290	21,724	21,724
R^2	0.997	0.997	0.997	0.997	0.978	0.978
Adjusted R^2	0.996	0.996	0.997	0.997	0.976	0.976

Panel B: NBFI Level (mortage call reports)

	$log(CreditLim)$		$log(Credit)$		$Utilization$	
MBS Ratio X QE	0.620**		0.504		11.267	
	(0.251)		(0.352)		(7.892)	
treat X QE		0.188**		0.268**		3.616
		(0.085)		(0.122)		(2.489)
Observations	2,182	2,182	2,182	2,182	2,182	2,182
R^2	0.946	0.946	0.906	0.907	0.601	0.602
Adjusted R^2	0.940	0.940	0.896	0.896	0.556	0.557
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) using a propensity scores based matched samples. Panel A presents results using Bank level variables from Call Reports, and Panel B uses level variables from Washington State mortgage call reports. The time period is 2019Q1 - 2021Q2. 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.1.6 Impact of Covid-19 and other policies

Our identification strategy follows most of the previous literature, which uses a dummy variable equal to one in the period when the Fed conducted large-scale asset purchases to capture the impact of QE. However, during our sample period, a number of addi-

[15] As in Kandrac and Schlusche (2021) we limit to up to two replacements for each control.

tional pandemic-related factors may have impacted bank credit supply. Thus, our QE dummy variable might capture other forces impacting bank credit that happened at the same time as the Fed QE progrem.

We focus specifically on two factors that the literature has identified as significantly impacting bank lending during the pandemic. First, studies have shown that the Paycheck Protection Program (PPP), had a significant impact on bank credit supply (Li and Strahan 2021; Karakaplan 2021; Erel and Liebersohn 2022; Lopez and Spiegel 2023). Second, local exposure to the pandemic has also been found to have negatively impacted bank lending (Colak and Öztekin 2021; Neef and Schandlbauer 2021; Beck and Keil 2022).

To control the additional factors we add to our baseline regression, during each quarter of the pandemic, the share of PPP loan to total assets for each bank and bank-specific weighted average local COVID-19 cases.[16]. For both the PPP ratio and the COVID-19 cases measure, we also add an interaction with the lender exposure to QE. Table A.6 presents the results.

[16]To measure bank-level exposure to the pandemic, we take the number of new COVID-19 cases per 1000 people in every state in each quarter during the sample period. We then measure the bank-level weighted average of new cases in every quarter using the number of branches each bank has in every state from the Summary of Deposits data as weights.

Table A.6: COVID-19

Panel A: Bank Level (call reports)

	log(Loans)		log(RE Loans)		log(C&I Loans)	
COVID-19	−0.787	−1.801	1.901**	−0.915	−8.335***	−2.108
	(0.760)	(1.157)	(0.961)	(1.400)	(2.360)	(3.394)
PPP	0.008***	0.009***	−0.003***	−0.004***	0.036***	0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.005)
MBS Ratio X QE	0.084***		0.061		0.269**	
	(0.026)		(0.040)		(0.118)	
MBS Ratio X COVID-19	−8.597		−14.756**		−21.333	
	(6.310)		(7.052)		(20.347)	
MBS Ratio X PPP	0.017***		0.022**		0.022	
	(0.006)		(0.009)		(0.023)	
treat X QE		0.021***		0.008		0.074***
		(0.005)		(0.006)		(0.018)
treat X COVID-19		−1.429		−1.599		−9.890***
		(1.425)		(1.600)		(3.280)
treat X PPP		0.0003		0.003***		−0.00003
		(0.001)		(0.001)		(0.005)
Observations	44,670	22,210	44,484	22,119	43,424	21,416
R^2	0.997	0.998	0.997	0.998	0.978	0.982
Adjusted R^2	0.997	0.998	0.997	0.997	0.975	0.980

Panel B: NBFI Level (mortage call reports)

	$log(CreditLim)$		$log(Credit)$		$Utilization$	
PPP	−0.044***	−0.023**	−0.032***	−0.020*	−0.084	0.011
	(0.012)	(0.011)	(0.012)	(0.012)	(0.249)	(0.299)
COVID-19	0.074**	0.036	0.065	0.020	−0.352	−0.783
	(0.033)	(0.042)	(0.052)	(0.078)	(1.690)	(2.582)
MBS Ratio X QE	0.364**		0.694**		14.530*	
	(0.185)		(0.299)		(8.300)	
MBS Ratio X PPP	0.435***		0.345***		−2.462	
	(0.114)		(0.130)		(3.185)	
MBS Ratio X COVID-19	−0.146*		−0.294**		−3.125	
	(0.075)		(0.134)		(3.299)	
treat X QE		0.134*		0.295***		4.860*
		(0.072)		(0.110)		(2.660)
treat X PPP		0.023		0.023		0.152
		(0.019)		(0.024)		(0.488)
treat X COVID-19		−0.013		−0.049		−1.466
		(0.030)		(0.043)		(1.054)
Observations	4,128	1,878	4,128	1,878	4,128	1,878
R^2	0.929	0.936	0.900	0.901	0.596	0.615
Adjusted R^2	0.919	0.927	0.886	0.886	0.542	0.558
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) with additional COVID-19 related lender level controls. Panel A presents results using Bank level variables from Call Reports, and Panel B uses level variables from Washington State mortgage call reports. The time period is 2019Q1 - 2021Q2. 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