How Do Nonbank Mortgage Lenders Shape Bank Small Business Lending? *

Xiyue Li† Dongliang Lu ‡ Keling Zheng§

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Abstract

We investigate the impact of nonbank expansion in the mortgage market on bank's lending portfolios. Employing a difference-in-differences approach based on regulatory changes that reduce nonbank lending costs, we find: 1) Nonbank expansion decreases bank mortgage market share amid no changes in total mortgage lending. 2) Diversified banks increase credit supply and offer lower rates to small business lending in counties with more nonbank expansion. 3) Within bank and county credit reallocation increases local small business entry and employment in the tradable sector. We develop a conceptual framework to show frictions in cross-county capital allocation drive the results. Our results highlight the distributional consequences of nonbank expansion in the small business lending market.

Keywords: Shadow Banks; Small Business Lending; Bank Portfolio Choice; Soft Information; Securitization; Mortgage Lending

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†Sauder School of Business, University of British Columbia. Email: xiyue.li@sauder.ubc.ca.

‡Sauder School of Business, University of British Columbia. Email: dongliang.lu@sauder.ubc.ca.

§Sauder School of Business, University of British Columbia. Email: keling.zheng@sauder.ubc.ca.

1 Introduction

In the last decade, shadow banks have become important players in the U.S. credit market, especially in the U.S. residential mortgage market. As of 2017, shadow banks originated more than 50% of the total volume of conventional mortgages and 70% of mortgages insured by the Federal Housing Administration (FHA) and the Department of Veteran Affairs (VA).[1] As shadow banks increasingly occupy the mortgage market, how do banks react to such competition? Unlike shadow banks, which usually focus on a particular credit market, banks have a lending portfolio consisting of both mortgage and commercial loans. Diversified asset portfolio allows banks to adjust to competition from shadow banks by focusing on business lines which they maintain competitive advantages.

In this paper, we provide an empirical exploration into the effect of the rise of shadow banks in the residential mortgage market on bank small business lending (hereafter SBL). We find that banks increase small business lending when facing expansion of shadow banks in the mortgage market. Counties with a higher shadow bank market share in the mortgage market saw a larger increase in SBL, which leads to startup entry and employment growth. Overall, our findings highlight the distributional consequences of nonbank expansion in the small business lending market through bank portfolio choice channel.

To empirically examine the impact of mortgage market competition on small business lending, we exploit a regulation spillover shock: the U.S. liquidity coverage ratio (LCR). The shock increases secondary market prices for FHA-insured loans by granting them favorable regulatory status once securitized. The shock is particularly beneficial for shadow banks specializing in the FHA market. Since shadow banks' market share in the FHA market before the regulatory shock differs across the U.S., this setting provides substantial variation in shadow bank expansion in the cross-section.

We begin by verifying that the regulation shock increases the size of the shadow banking system in the mortgage market. Following Gete and Reher (2021), we show that counties with ex-ante higher shadow bank market share in the FHA market see higher growth of shadow banks in the mortgage market. These counties have higher shadow bank market share while

[1] Buchak et al. (2018)

not having relatively higher total mortgage origination. This indicates that the shock changes lender composition - banks retreat from the local mortgage market.

We first show the effect of shadow bank expansion on small business lending at the county level. We use a difference-in-differences approach and establish a significantly positive relationship between the expansion of shadow banks and bank small business lending: the small business lending volume increases more in counties with more shadow bank expansion. Such an effect is robust to including county and year fixed effects. At the county level, small business lending increases by 7.39% when shadow banks fully take over the mortgage market.

Two potential concerns arise from the county-level analysis. First, it might be driven by local demand. Shadow banks' entry into the local mortgage market is not random. If shadow banks choose to enter counties with potentially higher expected economic growth, we would observe an increase in small business lending. Second, the county-level results might capture the direct effect of LCR on small business lending. As documented in Sundaresan and Xiao (2022), LCR caused an increase in lending provided by non-LCR banks (banks with assets smaller than 50 million). If the local shadow bank market share is highly correlated with the local non-LCR bank share, then our results are just capturing the spillover effect.

To better identify the causal effect, we run a triple difference regression at the lender-county level. Instead of using the ex-ante shadow bank FHA market share as a treatment, we further interact it with the lender's ex-ante exposure to the local mortgage market. The hypothesis is that banks with more exposure to the local mortgage market will be affected more by the rise of shadow banks caused by LCR shock. The lender-county level specification allows us to address potential endogeneity concerns and confounding effects. First, we add lender-county fixed effects to control for entry of banks in different counties. Second, we add county-year fixed effects to control for local demand. Third, we add lender-year fixed effects to control for lender level lending behavior change, including the redirect regulatory effect from LCR. In other words, after excluding the demand effect, we are observing the cross-sectional small business lending within a lender year. We find that lenders with higher exposure to local shadow bank mortgage expansion extend more small business loans.

To validate the supply side effect, we explore heterogeneity in bank asset diversification. Bank operation is diversified in nature (Gelman et al. (2022)). Diversified business lines allow banks to substitute mortgages in their lending portfolio for small business loans in the local market. Thus we expect a stronger substitution effect for banks that conduct both mortgage and small business lending. Besides, when banks operate in multiple counties, bank internal capital markets could partially immune banks from local shadow bank expansion. Thus we expect a weaker effect of local shadow bank expansion on bank small business lending for banks with a higher level of geographical diversification. Our results support these hypotheses.

Since SBL relies on acquisition of soft information (Rajan (1992); Berger et al. (2005); Chakraborty and Hu (2006), DeYoung et al. (2018)), banks are more likely to substitute mortgage lending using SBL in areas where they can effectively collect soft information. Specifically, we hypothesize that banks extend more small business credit in areas with more branches when facing the same level of nonbank mortgage lender expansion. We find results that support the hypothesis.

To further support the supply side channel, we construct an "except-for-one" type of treatment at the lender-county level. Namely, for each lender-county pair, we aggregate the shadow bank ex-ante FHA market share weighted by bank mortgage market share in counties where the bank operates, except for the current county where the lender extends small business credit. This exercise helps to isolate the local demand factor that drives both small business lending and mortgage lending by using the expansion of shadow banks from other counties.

We also conduct several tests to rule out other possible channels. First, we include the number of qualified small businesses at the county level as a control to address the confounding effect of "Small Business Health Care Tax Credit" in the Affordable Care Act enacted between 2014 and 2015 (He et al. (2022)), which could potentially drive SBL deman. Our results survive this test. Second, we check if banks supply more deposits in counties with more shadow bank expansion. Suppose there is some spurious correlation between bank local funding and nonbank mortgage lender expansion. In that case, the increase in small business lending could be explained by extra deposits that banks received. We do not find that banks increase deposit supply in counties with more nonbank mortgage lender expansion.

After establishing how shadow bank expansion changes banks' small business lending strategy, we discuss the real effects of the expansion of shadow banks through bank lending portfolio adjustment. Small business provides 30% of employment in the U.S. labor market. However, the ability of small businesses to invest, grow and create jobs is often challenged by financial constraints and the lack of credit availability (Evans and Jovanovic (1989); Whited and Wu (2006); Rauh (2006); Kerr and Nanda (2010); Barrot (2016); Adelino et al. (2017)). Even though the nonbank market share has expanded significantly in the last decade in small business lending (Gopal and Schnabl (2022)), banks still play a dominant role in small business lending, with 68% of small businesses that sought financing applied with banks as of 2019[2]. Banks thus play an important role in supporting the growth of local small businesses, with bank branches possessing soft information (Stein (2002), Berger et al. (2005), Chakraborty and Hu (2006), DeYoung et al. (2018)).

We find that counties with such exogenous bank credit supply to small businesses see more growth in entrepreneurship and more employment in the tradable sector. However, we do not observe similar effects in housing price growth and employment in construction and non-tradable sector, which is consistent with our observation that the expansion of shadow banks do not increase overall mortgage lending at the county level and alleviates the concern that our county-level results are mostly driven by the demand spurred by shadow bank expansion.

Our paper contributes to three strands of literature. First, our paper is closely related to the literature that documents the rise of shadow banks in the U.S. credit market. Shadow banks have expanded their market share in consumer credit market (Buchak et al. (2018)). We show that shadow bank expansions in the mortgage market spillover to SBL through bank portfolio choice. The rise of shadow banks in the residential mortgage market cause banks to shift their lending capacity to local small businesses, which impacts local entrepreneurial activities and employment.

Second, our paper speaks to literature related to bank diversification (Gopal and Schnabl (2022)). Bank operation is multi-product by nature (Benetton et al. (2022)). Our paper discusses bank lending portfolio diversification in terms of product and geography. From the product side, bank lending portfolio consists of both mortgage and commercial lending. Our paper adds to the literature that shows the substitution between mortgage lending and commercial lending in

[2]Estimation comes from Small Business Credit Survey by Federal Reserve Bank of Cleveland.

bank portfolios (Chakraborty et al. (2018); Chakraborty et al. (2020)). We show that banks redistribute loan origination to SBL market while facing severe competition from shadow banks in the mortgage market. Furthermore, our findings show within county substitution between mortgage and small business lending but not cross county spillover, suggesing internal capital market frictions of banks.

Third, our paper shows that Liquidity Capital Ratio regulation unintentionally affects bank lending through shadow bank competition in the mortgage market. Liquidity regulation is shown to crowd out bank lending and lead to the migration of liquidity risk to unregulated parties (Sundaresan and Xiao (2022)). Unlike the previous literature, we show that the crowding out effect in the mortgage market, caused by liquidity regulation, leads to *more* bank lending to small businesses.

The rest of the paper proceeds as follows. Section 2 provides a theoretical framework illustrating banks' portfolio choice problem. Section 3 describes the institutional details related to Liquidity Coverage Ratio shock and its impact on shadow bank expansion, especially in FHA market. Section 4 presents the sources and summary statistics for the data used in the empirical analysis. Section 5 presents our main findings on how expansion of shadow banks increases bank small business lending with heterogeneity tests. Section 6 discusses potential channels for substitution in mortgage and small business lending. Section 7 shows the real effects of shadow bank expansion in the mortgage market on local small business entry and employment through bank portfolio adjustment. Section 8 discuss the robustness tests. Section 9 concludes.

2 Conceptual Framework

Consider a static economy with a representative bank that operates in two counties $j \in \{1, 2\}$. In each county, the bank provides two types of loans: residential mortgage loans and SBL, indexed by $i \in \{m, s\}$. In county 1, the bank competes with a representative nonbank in the mortgage market. In county 2, the bank monopolizes the mortgage market. These assumption captures the significant cross-sectional variation of the market share of the nonbank in the mortgage market across counties. In addition, we assume that the bank is the only supplier in the SBL markets in two counties. This assumption aligns with empirical evidence that SBL is predominantly offered by banks.

We assume the gross rate of each loan in each county is linear in the amount of supply. In particular, the gross rate of loan i in county j satisfies

$$R_{ij} = \alpha_{ij} - \beta_{ij} k_{ij}, \tag{1}$$

where k_{ij} represents the total amount of supply of loan i in county j, and α_{ij} and β_{ij} are constants. In the mortgage market of county 1, where both the bank and the nonbank participate, the total amount of supply is the sum of supply by the two institutions. Specifically, we have

$$k_{m1} = k^b_{m1} + k^n_{m1},$$

where k^b_{m1} and k^n_{m1} denote the mortgage supply by bank and nonbank, respectively. In other market segments the bank monopolies, the total supply (k_{ij}) equals the supply by bank (k^b_{ij}).

For the nonbank, issuing mortgage loans is associated with a cost of c^n_{m1} per unit. This cost represents the effort in screening loan applications and the lending cost from warehouse lenders. The nonbank solves the problem

$$\max_{k^n_{m1} \in R^+_0} k^n_{m1}(R_{m1} - c^n_{m1}) \tag{2}$$

given the bank's choice k^b_{m1} to maximize payoff.

The bank is involved in a cost of c^b_{ij} issuing loan i in county j, which captures the bank's screening and operating costs. The bank allocates capital across market segments to maximize payoffs. For simplification, we assume that the bank has total capital of K_j in county j that can be allocated into either mortgage lending or SBL. The capital constraint represents the deposit of the bank in county j. This assumption simplifies the discussion by setting aside the bank's simultaneous choice of asset (e.g., loans) and liability (e.g., deposits). In section ?, We provide empirical evidence consistent with this assumption.

The bank can choose to allocate capital from one county to the other. However, this cross-county capital allocation is costly. An allocation of $\Delta \in [-K_1, K_2]$ units of capital from county 2 to county 1 is associated with a cost of $q\Delta^2$. The parameter q is a constant that captures frictions in the bank internal capital market. In sum, the banks solves

$$
\begin{aligned}
\max_{k^b_{ij}} \sum_{i\in\{m,s\},j\in\{1,2\},\Delta} & (R_{ij}-c^b_{ij})k^b_{ij} - q\Delta^2 \\
s.t. & \left(k^b_{m1}+k^b_{s1}\right) \le K_1+\Delta \\
& \left(k^b_{m2}+k^b_{s2}\right) \le K_2-\Delta \\
& \Delta \ge -K_1 \\
& \Delta \le K_2.
\end{aligned}
\tag{3}
$$

To simplify our analysis, we focus on the cases that the bank's capital constraint binds. In addition, we assume two counties have identical inverse demand function and the bank's lending cost of the same loan are identical in various counties. Specifically, we assume $\alpha_{i1}=\alpha_{i2}=\alpha_i$, $\beta_{i1}=\beta_{i2}=\beta_i$ and $c^b_{i1}=c^b_{i2}=c^b_i$ for $i\in\{m,s\}$. As the nonbank only operates in county 1, we also ignore the subscript 1 in $c^n_{m,1}$.

Proposition 1. *Assumes the parameters satisfy the conditions in (A). Denote the equilibrium strategies with a superscript $*$. the bank's and the nonbank's equilibrium strategies satisfy the following conditions. For the nonbank:*

$$
k^{n,*}_{m1} = \frac{\alpha_m - c^n_m}{2\beta_m} - \frac{\alpha_m + c^n_m - 2\alpha_s + 4\beta_s K - 2c^b_m + 2c^b_s}{2(3\beta_m+4\beta_s)}
\tag{4}
$$

The equilibrium strategy for the bank is:

$$
\begin{aligned}
k^{b,*}_{m1} &= \frac{\alpha_m + c^n_m - 2\alpha_s + 4\beta_s(K_1+\Delta^*) - 2c^b_m + 2c^b_s}{(3\beta_m+4\beta_s)} \\
k^{b,*}_{s1} &= \frac{3\beta_m(K_1+\Delta^*) - \alpha_m - c^n_m + 2\alpha_s + 2c^b_m - 2c^b_s}{(3\beta_m+4\beta_s)} \\
k^{b,*}_{m2} &= \frac{\alpha_m - \alpha_s + 2\beta_s(K_2-\Delta^*) - c^b_m + c^b_s}{2(\beta_m+\beta_s)} \\
k^{b,*}_{s2} &= \frac{2\beta_m(K_2-\Delta^*) - \alpha_m + \alpha_s + c^b_m - c^b_s}{2(\beta_m+\beta_s)} \\
\Delta^* &= \frac{Z_2}{2q - Z_1}
\end{aligned}
\tag{5}
$$

Where

$$
\begin{aligned}
Z_1 &= -2\beta_s \frac{3\beta_m}{3\beta_m + 4\beta_s} - \beta_s \frac{2\beta_m}{\beta_m + \beta_s} < 0 \\
Z_2 &= -2\beta_s \frac{3\beta_m K_1 - \alpha_m - c_m^n + 2\alpha_s + 2c_m^b - 2c_s^b}{3\beta_m + 4\beta_s} \\
&\quad + \beta_s \frac{2\beta_m K_2 - \alpha_m + \alpha_s + c_m^b - c_s^b}{\beta_m + \beta_s}
\end{aligned} \tag{6}
$$

Proposition 1 gives the equilibrium strategy of the bank and the nonbank. In this paper, we are specifically interested in how the bank's lending portfolio change with frictions faced by the nonbank. More specifically, we investigate the variations in bank lending across various market segments in relation to the cost of nonbank lending within the mortgage market.

Lemma 1. *(Benchmark) If there is no cost of cross-county capital allocation ($q = 0$), we have* $\frac{\partial k_{s1}^{b,*}}{\partial c_m^n} = \frac{\partial k_{s2}^{b,*}}{\partial c_m^n} < 0$.

Lemma 1 concludes bank's SBL supply in two counties without friction in bank's internal capital market. The bank strategically allocate capital to SBL markets which are identical, resulting in the same amount of SBL supply in two counties. Upon an increase (decrease) of lending cost of the nonbank, the bank optimally increases (decreases) the supply of mortgage in county 1 and allocates less (more) capital to SBL in two counties.

Proposition 2. *When $q > 0$, we have $\frac{\partial k_{s1}^{b,*}}{\partial c_{m1}^n} < \frac{\partial k_{s2}^{b,*}}{\partial c_{m1}^n}$ and $\frac{\partial R_{s1}^{b,*}}{\partial c_{m1}^n} > \frac{\partial R_{s2}^{b,*}}{\partial c_{m1}^n}$.*

Proposition 2 concludes bank's SBL supply in two counties when there exists cost of capital allocation across counties. In counties where the bank compete with the nonbank, bank's supply of SBL is more sensitive to the cost of nonbank lending. This is because frictions in the bank's internal capital market results inefficient allocation of capital and deters the spillover of nonbank competition to other counties.

Corollary 1. $\frac{\partial^2 (k_{s2}^{b*} - k_{s1}^{b*})}{\partial c_{m1}^n \partial q} < 0$.

As $\frac{\partial (k_{s2}^{b*} - k_{s1}^{b*})}{\partial c_{m1}^n} < 0$, the negative sign of $\frac{\partial^2 (k_{s2}^{b*} - k_{s1}^{b*})}{\partial c_{m1}^n \partial q}$ shows the differences of bank's supply of SBL in two counties are more pronounced when the cost of internal capital allocation is large. An extreme case is $q = \infty$, which indicates no capital allocation across counties is allowed. The bank is then equivalent to two banks operate in two counties, respectively. According to Corollary 1, banks operating in concentrated county reallocate more to SBL when the lending cost of nonbank decreases.

3 Liquidity Coverage Ratio

The U.S. Liquidity Coverage Ratio was proposed on Oct 24, 2013 and finalized in September 2014, as an effort to ensure that large financial institutions have enough liquid assets to survive a 30-day period of cash outflows. The liquidity coverage ratio (LCR) is defined as the ratio of high-quality liquid assets (HQLA) to total net cash outflows over 30 days.

$$LCR = \frac{\textit{High quality liquid assets}}{\textit{Net expected cash outflows over 30 days}} \geq 100\%$$

is required for banks with a total assets of more than 50 \$billion (LCR banks). The numerator, *High quality liquid assets* is the weighed sum of asset values. The policy assigned different liquidity weight to different assets, with Level 1 liquid assets receiving a liquidity of 100%, Level 2 liquid assets receiving a liquidity weight from 50% to 85%. Loans and other illiquid assets receive a liquidity weight of 0.

Ginnie Mae (GNMA) MBS is classified as Level 1 liquid assets because it is issued by an U.S. government agency whose obligations are fully and explicitly guaranteed by the full faith and credit of the U.S. government. Compared to Fannie Mae (FNMA) and Freddie Mac (FHLMC) MBS, which are classified as Level 2, GNMA MBS get a favorable regulatory treatment. As documented in Gete and Reher (2022), the favorable regulatory treatment for GNMA MBS accounted for 22% of nonbanks' growth in overall mortgage market share over 2013-2015. Such effect is driven by the growing demand and increasing liquidity of GNMA MBS, which in particular benefit the shadow banks that operate in the FHA market. Importantly, banks affected by LCR prefer purchasing GNMA MBS on the secondary market to satisfy the regulatory requirement instead of originating more FHA loans themselves and sell them as GNMA MBS[3].

Following Gete and Reher (2021), we use the implementation of LCR as a shock to shadow bank expansion to observe bank lending behavior when facing shadow bank competition in the

[3] As documented in Gete and Reher (2022), the strategy would be unprofitable because originating new loans entails additional operating costs

mortgage market. One might worry that LCR affects bank lending directly. Existing literature has shown some evidence on the effect of LCR on bank balancesheet composition (Banerjee and Mio (2018)) and lending (Sundaresan and Xiao (2022)). Considering the U.S. implementation of LCR, which gives the same liquidity weight to mortgage and business loans, we do not expect banks change the relative supply of mortgages and small business loans under the direct impact of LCR. Besides, we control for bank-year fixed effects by utilizing the cross sectional variation in bank local mortgage exposure. The effect of LCR would have been absorbed by the bank-year fixed effects if there is a direct effect on lending.

4 Data

4.1 Small business loan data

The Community Reinvestment Act (CRA), enacted by the Congress in 1977, requires regulated depository institutions that meet the asset size threshold[4] to report information on small business lending, which are commercial and industrial (C&I) loans with size below $1 million. Each institution that is subject to the data collection requirements reports annually the aggregated amount and number of small business loans originated in each county.

In addition to these aggregations, the CRA data also reports the amount and number of loans issued to the very small enterprises whose gross annual revenue is less than or equal to $1 million. Small business borrowers are also categorized based on the owners' relative family income. For each income group, the amount and number of loans are reported. This allows us to estimate the loans distributed to the smaller-size or lower-income borrowers due to the rise of shadows banks in the mortgage market.

We use both the county level aggregated small business lending data and the lender-county level data to analyze the causal effect of the rise of shadow banks on bank small business lending.

Additionally, we get the small business lending data from U.S. small business administration (SBA). The data contains variables include initial interest rate, loan term, program, default

[4] The threshold is $250 million before 2005 and $1 billion after 2005, then adjusted year by year. Any depository institution with total asset size above the threshold is subject to the CRA regulation to report the related information.

status, lender, county, etc at the loan level. We aggregate the data at the lender county level or county level to analyze the effect of the rise of shadow banks on bank small business lending.

4.2 Mortgage data

The Home Mortgage Disclosure Act(HMDA), enacted by the Congress in 1975, requires regulated all financial institutions that meet the asset size threshold[5] to report loan level information on mortgage applications and originations to the Federal Reserve. The HMDA data provides information on the year and location of application, the lender, loan characteristics include amount, type, purpose, etc and borrower characteristics include gender, race, income etc.

In this paper, we construct the local shadow bank FHA market share using the lender identifier and loan type. We define a shadow bank as either an "independent mortgage bank" following the "Avery file."[6]. We collapse the loan level data at the county level and use either application share or origination share in 2013 as a measure of shadow bank FHA market share prior to the treatment.

4.3 Summary statistics

To provide a description of the variables used in our analysis, Table 1 reports the summary statistics from small business loan data, mortgage data and county level characteristics. Our sample period is 2010–2017. Panel A of Table 1 summarizes the variables used in the county level analysis. On average, each county has 277 and 65 million small business loans per year. A median county has 57% of FHA loans originated by shadow banks back in 2013.

Panel B of Table 1 reports the summary statistics for variables used in the lender county level analysis. An average lender in a county originate 7 and 0.25 million small business loans. Around 23 percent of the counties where the lenders operate have at least one branch. On average, a branch receives 573 thousands deposts per year.

[5] The threshold is $30 million before 2000 and then adjusted year by year. Any depository institution with total asset size above the threshold is subject to the CRA regulation to report the related information.

[6] See https://sites.google.com/site/neilbhutta/data

5 Empirical analysis

we begin by presenting evidence that counties with higher ex-ante FHA market share saw an increase in small business lending after the implementation of liquidity coverage ratio. Next, we document bank county level evidence that a lender provides more small business lending to a county with higher ex-ante shadow bank FHA market share and higher mortgage market exposure. We provide further validation tests by constructing "except-for-one" type of treatment and controlling for potential confounding factors.

5.1 Shadow bank expansion and small business lending

5.1.1 County level analysis

Due to technology development and regulatory arbitrage, shadow banks have take up the market share of banks in the mortgage market. Compared to mortgage, originating small business loans requires more soft information. Besides, small business loans are not widely securitized like mortgages. The competition from shadow banks and comparative advantage of banks in processing small business loans lead banks to originate more small business loans when they face more expansion of shadow banks in the mortgage lending market.

To test this hypothesis, we start our analysis with county level data from HMDA and CRA to study whether the rise of shadow banks affect mortgage and small business lending at the county level. The data allows us to control for county-specific economic conditions and macroeconomic conditions that may affect demand for loans. Specifically, we estimate the regression equation

$$\begin{aligned} Y_{c,t} =& \beta_1 \text{Treatment}_c \times \text{Post}_t + \beta_2 \text{Treatment}_c + \gamma X_{c,t} \\ &+ FE_c + FE_t + \epsilon_{c,t}. \end{aligned} \tag{7}$$

$Y_{c,t}$ is a dependent variable aggregated at a county c in year t. We use shadow bank mortgage market share, total mortgage amount and small business lending count or amount. Treatment_c is the shadow bank FHA market share, calculated as the number of FHA applications submitted to shadow banks and the total number of FHA applications in 2013.[7] Post_t is a dummy variable that

[7] We also tried FHA origination share of shadow banks and the results are similar.

takes value 1 if the year is 2014 onwards. $X_{c,t}$ is a vector of county-level controls.[8] We saturate the model with county fixed effects (FE_c) to control for differences in time-invariant county characteristics and with time fixed effects (FE_t) to control for other time-varying macroeconomic shocks. FE_t represents year fixed effect. We cluster standard errors at the county level. The main coefficient of interest is β_1, which captures the differential response of counties to the rise of shadow banks. We expect the coefficient to be positive for shadow bank market share and small business loan origination by banks. The former one shows that counties with ex-ante higher shadow bank FHA market share indeed have more shadow bank market share subsequently. The latter one shows that these counties with higher shadow bank FHA market share also see higher small business lending growth.

We begin by looking at change in mortgage market following the passage of LCR in the U.S. Table 2 reports the results. Columns 1–3 and 4–6 contain regression estimates using total mortgage origination count and shadow bank mortgage origination share as the dependent variable, respectively. The coefficient on the interaction term between the shadow bank ex-ante FHA market share and post dummy is negative and statistically significant for total mortgages originated but positive and statistically significant across all specifications for nonbank mortgage market share. This indicates that the counties with ex-ante higher shadow bank FHA market share do not necessarily have more mortgage origination but have a higher shadow bank market share. The estimated coefficients imply that, a 1% increase in ex-ante nonbank FHA market origination share leads to 2.4% increase in nonbank mortgage market share after the policy shock.

We then show our main results, the effect of shadow bank expansion in mortgage market on bank small business lending. Table 3 reports the results. Columns 1–3 and 4–6 contain regression estimates using log small business lending count and amount, respectively. The coefficient on the interaction term between the shadow bank ex-ante FHA market share and post dummy is positive and statistically significant across all specifications and both dependent variables. This indicates that the counties with ex-ante higher shadow bank FHA market share witness more small business credit extension. The estimated coefficients imply that, a 1% increase in ex-ante nonbank FHA

[8]These include the fraction of white, the fraction of population over 65 and the fraction of population below 16, log income per capita, the fraction of female etc.

market origination share leads to 5% increase small business loan count and 11.4% increase in loan amount.

5.1.2 Bank-county level analysis

The county level analysis face two concerns. First, the results might be driven by unobserved demand factors at the county level. Counties with a high ex-ante shadow bank FHA market share might have a high growth potential and economic growth drives the increase in bank small business lending. Second, the result might reflect a direct regulation effect of Liquidity Coverage Ratio if the county level ex-ante shadow bank FHA market share is positively correlated with the local small bank market share.

The key set of controls are the bank-time fixed effects, which absorb all time-varying differences between banks. Intuitively, we are comparing branches of the same bank and asking whether, following an increase in the shadow bank market share, the bank's branches in counties where their mortgage origination are squeezed out more increase small business lending more relative to its branches in counties with less shadow bank expansion. Doing so controls for any changes in banks' lending opportunities under our identifying assumption that banks are able to allocate funds internally.

To address these two concerns, we present bank county level analysis. We first estimate the following empirical model following Drechsler et al. (2017):

$$\begin{aligned} Y_{l,c,t} =&\beta_1 \text{Treatment}_c \times \text{Post}_t + \beta_2 \text{Treatment}_c + \beta_3 \text{Post}_t + \gamma X_{c,t} \\ &+ FE_c + FE_t + FE_{l,t} + FE_{s,t} + \epsilon_{l,c,t}. \end{aligned} \tag{8}$$

$Y_{l,c,t}$ is log small business lending count or amount originated by bank l aggregated at a county c in year t. Treatment_c is the shadow bank FHA market share, calculated as the number of FHA mortgages originated by shadow banks and the total number of FHA origination in 2013.[9] Post_t is a dummy variable that takes value 1 if the year is 2014 onwards.

We saturate the model with an extensive set of fixed effects to address potential confounding concerns. First, we add lender year fixed effects ($FE_{l,t}$). This allows us to tease out the direct

[9] We also tried FHA application share of shadow banks and the results are similar. See robustness test.

effect of Liquidity Coverage Ratio on bank level small business lending. Second, we add county FE_c fixed effects to control for county-related time-invariant components. Third, we add year fixed effects FE_t to control for the common factors that may affect all counties. Finally, we add state-time fixed effects in combination with county time varying controls, including county demographics, economic conditions, income, poverty rate, etc, to control for regional specific demand factors. The standard errors are clustered at the county level.

The main coefficient of interest is β_1, which captures the differential responses of counties to the rise of shadow banks with bank heterogeneous mortgage portfolio exposure. We expect the coefficient to be positive for bank small business lending in the county where it faces more competition from shadow bank mortgage market expansion. Table 4 shows the results. The coefficient of interest is positive and significant for all specifications. Besides, the coefficient indicates that a 1% increase in ex-ante nonbank FHA market origination share leads to 7.69% increase small business loan count and 11.35% increase in loan amount. The magnitude is similar to the county level results.

To further validate the baseline results, we construct an "except for one" type of treatment in 2013 as following:

$$\text{LendingExposure}_{l,c} = \sum_{c_j \neq c} \frac{MortgageCount_{l,c_j}}{\sum_{c_j} MortgageCount_{l,c_j}} \times Treatment_{c_j}, \tag{9}$$

where $Treatment_{c_j}$ is the ex-ante shadow bank FHA market share of county c_j in 2013. County c_j is any county that bank l operates except for county c. This treatment measure is constructed for a lender l in county c but uses the shadow bank expansion in all other counties except for county c, which potentially rule out the possibility that the results are driven by *local* demand.

After constructing the new treatment measure, we estimate the following empirical model:

$$Y_{l,c,t} = \beta_1 \text{LendingExposure}_{l,c} \times \text{Post}_t + FE_{c,t} + FE_{l,t} + \epsilon_{l,c,t}. \tag{10}$$

We saturate the model with county year fixed effects and lender year fixed effects. The county year fixed effects control for the lending opportunities driven by local demand. The lender year fixed effects help tease out the direct effect of Liquidity Coverage Ratio on bank level small business lending. All standard errors are clustered at the county level. Table 5 shows that coefficients are positive and significant in all specifications, which provide addtional support that our results are not driven by local demand factors, but the adjustments that lender make in reponse to the expansion of shadow banks in the mortgage market.

To further verify that the effect on loan amount or loan count is driven by supply side factors, we use the new treatment variable to test the effect on small business loan interest rate and default status. If the result is more likely driven by supply side factors, we expect to see a negative effect on interest rate and positive effect on default. Table 6 shows that coefficients. The effect is negative and significant for interest rate, providing additional evidence on the supply side effect.

6 Channels

In this section, we discuss the potential channels that lead banks to supply more small business loans to areas with more shadow bank expansion in the mortgage market. We examine two possible explanations. First, we check if the banks supply more small business loans through collecting more deposits in the counties with more shadow bank expansion. Second, we focus on bank asset composition and exmaine if the effect is driven by banks substitute mortgage lending using small business loans.

6.1 Funding channel

One explanation for the increase in the supply of small business loans is the increase in bank funding. Shadow bank expansion in the mortgage market could lead to easier access to credit and more incentives for saving, thus banks may have more deposits in areas with more shadow bank expansion, which enable banks to provide more small business loans.

To test this channel, we re-estimate Equation 7, using log amount of deposits of a county as dependent variable. Table 7 shows the estimates of the coefficients. We find that counties with more shadow bank expansion do not necessarily have higher level of deposits - the coefficient is positive but not significant. This indicates that the increase in funding cannot explain the increase in small business lending that we observe in the results.

6.2 Substitution effect

One potential channel to explain our results is that banks substitute SBL for mortgages as a response to shadow bank expansion in the mortgage market. Assuming that banks solve a portfolio choice problem to allocate capital into either SBL or mortgage. Competition on the mortgage market reduces banks' expected profit from the mortgage market, banks thereby retreat from mortgage market and provides a higher amount of SBL.

Existing literature finds that commercial loans and mortgage lending are substitutes for banks. For example, Chakraborty et al. (2018) find banks that housing prices booms leads to an increase in mortgage and lending and crowds out commercial lending. Chakraborty et al. (2020) provide evidences that banks shift resources away from commercial lending while the mortgage market provides more capital gains.

In our context, SBL and mortgages can substitute each other mainly because they are comparable in terms of size and liquidity. First, SBL in our sample have a size below $1 million, which is comparable to mortgages. Second, both SBL and mortgage lending are classified as illiquid under LCR regulation. When banks make portfolio choices within the pool of illiquid assets, SBL and mortgages are substitutes. Examining the impact on SBL also helps to understand the spillover effect of LCR regulation on different counties. SBL is a key source of financial support for small businesses in local areas. Through affecting SBL supply, LCR impacts different counties differently, depending on the market share of shadow banks in local mortgage market.

Banks can increase SBL due to their specialization in obtaining soft information of local businesses. Different from small business loans, over half of the mortgages are sold to government sponsored enterprises, i.e. Fannie Mae and Freddie Mac, and shadow banks securitize over 95% of the mortgages originated in the U.S. market. Since GSEs mainly consider loan to value ratio, debt to income ratio and FICO score when purchasing mortgages, mortgages are originated and priced mostly rely on hard information, which is easy to obtain and automated.

Originating small business loans rests on collecting soft information. If banks substitute mortgages using small business loans, such substitution effect should be stronger in areas where banks can collect more soft information. A proxy for the collection of soft information is the presence of bank branches. We hypothesize that the increase in small business loans is stronger in areas where banks have branches, given the same level of shadow bank expansion in the mortgage market.

To test the hypothesis, we estimate the following empirical model:

$$\begin{aligned} Y_{l,c,t} = &\beta_1 \text{Treatment}_c \times \text{Branch}_{l,c} \times \text{Post}_t \\ &+ FE_{c,t} + FE_{l,t} + FE_{l,c} + \epsilon_{l,c,t}. \end{aligned} \tag{11}$$

$Y_{l,c,t}$ is log small business lending count originated by bank l aggregated at a county c in year t. $\text{ShadowShare}_{c,2013}$ is the shadow bank FHA market share, calculated as the number of FHA mortgages originated by shadow banks and the total number of FHA origination in 2013. Post_t is a dummy variable that takes value 1 if the year is 2014 onwards. $\text{Branch}_{l,c}$ is a dummy variable which takes value 1 if the bank has a branch in the county c in year 2013. Similar to previous specifications, we saturate the model with an extensive set of fixed effects to address potential confounding concerns, which include county year fixed effects ($FE_{c,t}$), lender year fixed effects ($FE_{l,t}$), and county lender fixed effects ($FE_{l,c}$). We cluster the standard errors at the bank-county level.

The main coefficient of interest is β_1, which captures the differential responses of counties to the rise of shadow banks with bank branch presence. We expect the coefficient to be positive for bank small business lending in the county where it has a branch, where it has more comparative advantages in originating small business loans.

Table 8 shows the results. We find that the coefficient of the tripple interaction term is positive and significant. It indicates that banks' response to the expansion of shadow banks are stronger in counties where banks have branches. Since banks have an advantage in collecting soft information from customers through face to face interactions, the presence of bank branches increase the amount of small business lending face the same level of shadow bank expansion in the mortgage market.

7 Real effects

In this section, we examine if the expansion of shadow banks in mortgage market has real effects on local entrepreneurship entry and employment growth. If the expansion of shadow banks leads to more small business lending through bank lending portfolio adjustment, we expect to observe more entrepreneurship entry and employment growth. The increase in small business lending could spur more entry because it loose financial constraints faced by new born firms.

We test the above hypothesis by re-estimating Equation 7, but entrepreneurial entry, and the number of employments as the dependent variables. Entrepreneurial entry comes from the Startup Cartography Project, which offers a new set of entrepreneurial statistics for the United States from 1988-2016 (Andrews et al. (2022)). We use the Startup Formation Rate (SFR) as our main dependent variable. It represents the quantity of for-profit, new business registrants within a given population. The number of employments comes from Census Business Pattern survey. We follow Mian and Sufi (2014) and construct the number of employees in tradable, non-tradable, construction and other sectors. We also check the effects on housing prices and GDP growth.

Table 9 presents the results. In the panel A, columns 1-4 show the effect of shadow bank expansion on total establishments, new firm formation, housing price growth and GDP growth respectively. In the panel B, columns 1-4 show the effect of shadow bank expansion on employment by sectors. We find that the expansion of shadow banks leads to increase in start up formation rate and tradable sector employment growth. However, we do not find a significant impact on housing price growth non-tradable and construction sector employment growth. The results alleviate the concern that the increase in small business lending is driven by local demand. If shadow bank expansion enables households to get more mortgages at a lower price, we would expect an increase in total mortgage origination, local housing price, and more employment in construction and non-tradable sector. We fail to detect a significant impact of shadow bank expansion on these dependent variables, which indicate that our results are more likely driven by the increase in the supply of small business loans through bank lending portfolio adjustment.

8 Robustness tests

8.1 Confounding events

A potential concern with our baseline result is that the result might be driven by other confounding events. For example, the "Small Business Health Care Tax Credit" in the Affordable Care Act enacted between 2014 and 2015, which incentivize local small business to take out small business loans (He et al. (2022)). To address for this confounding demand effect, we follow He et al. (2022) to use the number of establishments with employees less than 20 as the number of qualified small businesses (QSB). A county with more small business with less than 20 small businesses may take out more small business loans after 2013. This can potentially drive our results observed at the county level.

We add the interaction term $Ln(QSB) \times Post_t$ as the control variable and see if our main interaction term is still positive and significant. The results in 10 show that the coefficient on our main interaction term is significicant and positive, and with similar magnitude. This indicates that our results are unlikely driven by the demand effect induced by the confounding event.

8.2 Alternative treatments

In previous tests, we use the shadow bank origination share in FHA market prior to 2013 at the county level as a treatment. The treatment should measure how likely a county would be affected by the LCR shock. Since LCR shock increases the demand for GNMS, the shock should be particularly beneficial for a county with high demand for shadow bank FHA mortgages. If the underwriting standard is the same across banks and shadow banks, then the application share and origination share should be perfectly correlated. However, banks and shadow banks may vary in their underwriting standards and costs in originating FHA mortgages. An alternative measure for shadow bank market share is to use the application share of shadow banks in the FHA market. The applications of FHA mortgages measure the demand for shadow banks. If shadow banks has higher FHA market share, as measured by the number of FHA mortgage applications submitted to shadow banks scaled by the total number of mortgages, then we should expect higher small business loan origination volume.

Using the new treatment measure as our proxy for a county's exposure to LCR shocks, we re-estimate Equation 7. Table 11 shows the results. Columns 1-3 show the effect on the . The standard errors are clustered at the county level. The effect of shadow bank expansion on small business lending is robust to the choice of treatment measure. The coefficients of the interaction term between ex-ante shadow bank market share and post dummy are positive and statistically significant in all specifications. This indicates that our results are not sensitive to the choice of treatment measure.

8.3 Alternative definition of small business loans

Small business loans are usually defined as commercial and industrial loans less than 1 million. However, this does not necessarily mean that the loans goes to "small business". To examine if our results are valid for small firms, we subset the lending volume and amount to the small business loans provided to firms with less than 1 million dollar annual revenue. We use the shadow bank origination share as our proxy for treatment and re-estimate Equation . Again, our standard errors are clustered at the county level.

Table 12 shows the results. Columns 1-3 show the effect of shadow bank expansion on the small business lending to firms with less than 1 million annual revenue. The coefficients of the interaction term are positive and significant. It indicates that our results are valid for small business loans for small firms. It also provides additional support for the real effect results that entrepreneurship entry increases in counties with more shadow bank expansion.

9 Conclusion

The past decade saws a fast expansion of shadow banks in the mortgage market. This paper examines how traditional banks react to the competition with shadow banks. Using the implementation of Liquidity Capital Ratio regulation as a shock to shadow bank expansion, we find that banks decrease mortgage lending and increase small business loans in counties with severe competition.

Further analyses support the explanation that banks substitute small business loans for mortgage lending as a reaction to shadow bank expansion. The substitution is stronger in areas where banks have at least one branch. The result indicates that banks utlize their advantage in obtaining soft information to expand in the small business credit market.

Our results highlight the distributional role of shadow bank growth, but through a bank portfolio choice channel. In areas with more sahdow bank expansion, increase credit supply to small business encourage local encourage local entrepreneurial entry and employment. Though shadow bank expansion in the mortgage market does not lead to direct increase credit supply and housing price, it unexpectedly increases the bank credit supply to small business. As shadow banks are taking an increasing market share in the market, our results show that financial innovation in one sector could spillover to another sector through portfolio allocation decision of incumbent financial intermediation.

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Figures and Tables

Figure 1: **Shadow bank FHA market share in 2013**

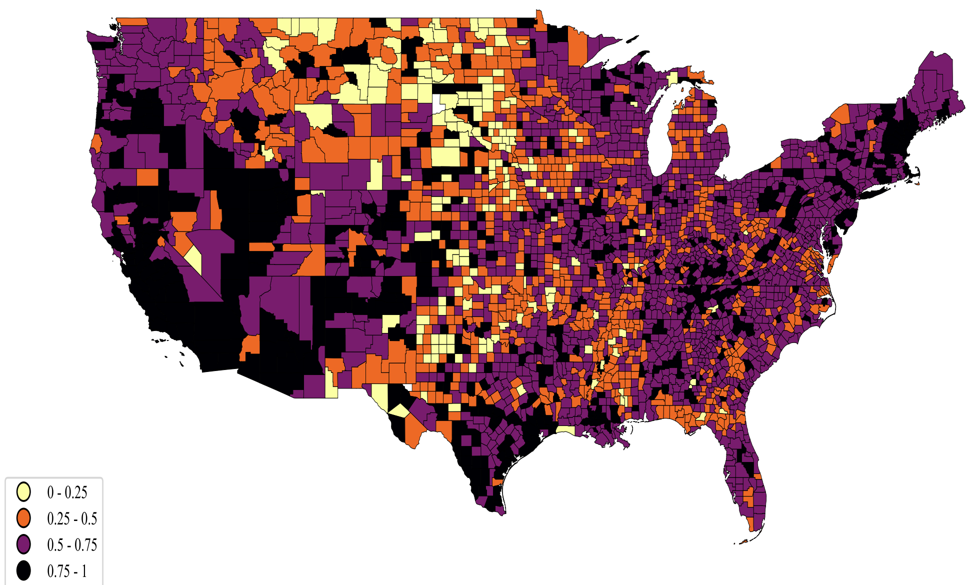
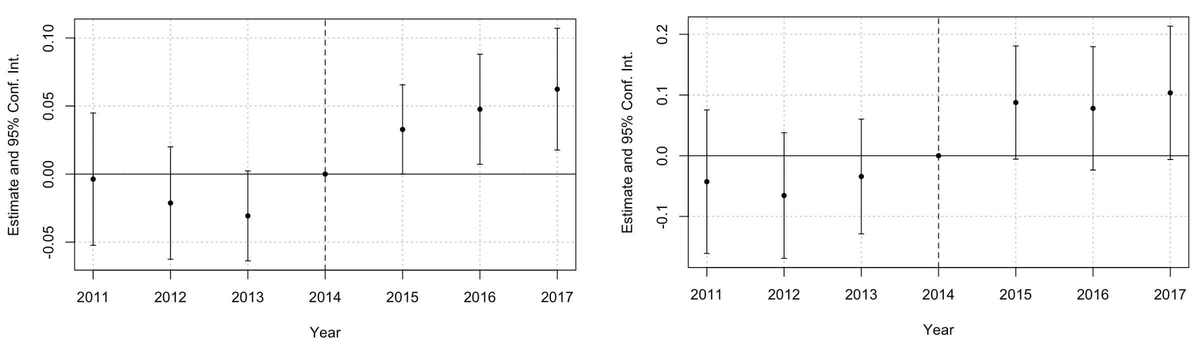


Figure 2: **The rise of shadow banks and bank small business lending**

This figure plots the γ_t coefficients from the following equation.

$$\log(\text{ loans })_{c,t} = \sum_t \gamma_t (\text{ Treated }_c \times \mathbf{T}_t) + \sum_{x \in \text{ controls}} \eta_x X_{c,t-1} + FE_c + FE_t + \epsilon_{c,t} \quad (12)$$
$$\forall t \in \{2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017\} \backslash 2014$$

The dependent variable is log small business loan count or amount in county c at time t. FE_c captures county fixed effects. T_t is a dummy variable for each time period (year) in the sample (2014 is the omitted year). Treated is a continuous variable that measures the county level shadow bank FHA market share before the implementation of LCR, $Treated_c \times T_t$ is an interaction term between time dummies and county level treatment variable. $X_{c,t-1}$ is a set of lagged county-level controls. County level controls include the fraction of female, the fraction of white, the fraction of population below 16 years old, the fraction of population above 65 years old, log income per capita, log population. Standard errors are clustered at the county level. The black circles represent the point estimates and the vertical lines around them reflect 95 percent confidence bands. The black dashed line marks the beginning of the LCR requirement. The left panel shows the coefficients for log small business loan origination count and the right panel shows coefficients for log small business loan origination amount.



(a) Log Loan Count

(b) Log Loan Amount

Table 1: Summary statistics

This table reports the summary statistics for the variables used in our regression analysis. Panel A reports the summary statistics for the county level analysis and Panel B reports the summary statistics for the lender county level analysis.

Panel A: County level						
Variables	count	mean	std	25%	50%	75%
SBL Num Orig	24832	1,702.62	7,247.84	107.00	277.00	867.00
SBL Amt Orig (000s)	24832	65,808.00	245,291.00	2,890.00	9,776.00	37,300.00
NonBankApplShare	24832	0.32	0.15	0.21	0.31	0.42
NonBankOriShare	24792	0.29	0.17	0.16	0.27	0.40
NonBankFHAApplShare2013	24483	0.58	0.19	0.48	0.60	0.71
NonBankFHAOriShare2013	24035	0.55	0.23	0.41	0.57	0.71
Frac White	24819	0.87	0.16	0.82	0.94	0.97
Frac Male	24819	0.50	0.02	0.49	0.50	0.50
Frac Below 19	24819	0.26	0.03	0.23	0.25	0.27
Frac Over 65	24819	0.17	0.04	0.14	0.17	0.19
Population (000s)	24819	100.00	322.00	11.00	25.00	67.00
Median Household Income	24832	45,633.32	11,857.57	37,677.75	43,642.50	51,040.25
Frac Subprime	18138	31.59	9.55	24.39	30.70	38.34
Total Establishments	21729	2,421.71	8,366.63	226.00	546.00	1,468.00
SFR	20904	541.38	2,636.92	17.00	51.00	186.65
Housing Price Growth	18914	0.02	0.05	-0.01	0.02	0.05
GDP Growth	24413	0.04	0.11	0.00	0.03	0.07
Employment - Tradable Growth	22523	0.98	0.25	0.92	1.00	1.05
Employment - Construction Growth	24152	0.99	0.20	0.91	1.00	1.06
Employment - Nontradable Growth	23976	0.93	0.17	0.84	0.98	1.03
Employment - Other Growth	24131	0.97	0.14	0.94	1.00	1.04
Panel B: Lender-County level						
Variables	count	mean	std	25%	50%	75%
SBL Num Orig	377556	59.43	437.08	3.00	7.00	24.00
SBL Amt Orig (000s)	377556	3268.00	15695.00	50.00	251.00	1322.00
NonBankFHAApplShare2013	376526	0.61	0.16	0.50	0.63	0.72
NonBankFHAOriShare2013	374474	0.58	0.20	0.45	0.60	0.73
Frac White	377373	0.85	0.15	0.79	0.91	0.96
Frac Male	377373	0.50	0.02	0.49	0.49	0.50
Frac Below 19	377373	0.26	0.03	0.24	0.26	0.27
Frac Over 65	377373	0.16	0.04	0.13	0.16	0.18
Population (000s)	377373	269.00	699.00	23.00	59.00	209.00
Median Household Income	377556	50005.29	13922.29	40687.00	47253.00	55686.00
Frac Subprime	275585	31.06	8.58	24.64	30.13	36.94
Branch Dummy	377556	0.23	0.42	0.00	0.00	0.00
Deposits (000s)	86149	573.00	5082.00	38.00	89.00	262.00

Table 2: Effect of LCR on Mortgage Origination

This table reports estimates from Equation (8) at the county level from 2011–2017. The dependent variables are the total number of mortgages originated (columns 1–3) or shadow bank mortgage market share (columns 4–6) in a given county and year. The main independent variable is $\text{Treatment}_c \times \text{Post}$, the interaction between the shadow bank FHA market share prior to LCR shock (Treatment_c) and post dummy (Post_t). The shadow bank FHA market share is measured using the fraction of FHA mortgages originated by shadow banks. The post dummy is 1 for years after 2013. County controls include the fraction of female, the fraction of white, the fraction of population below 16 years old, the fraction of population above 65 years old, log income per capita, log population, poverty rate, fraction of subprime borrowers. Columns 2 and 5 include county fixed effects, columns 3 and 6 include county and year fixed effects. Standard errors clustered at the county level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variables:	Total Mortgage Origination			NonBank Origination Share		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treatment}_c \times \text{Post}_t$	-0.1407	-0.2419***	-0.1965**	0.0353***	0.0180**	0.0242***
	(0.0943)	(0.0910)	(0.0883)	(0.0071)	(0.0073)	(0.0071)
Post_t	-0.5589***	-0.3753***		0.1010***	0.0727***	
	(0.0472)	(0.0488)		(0.0043)	(0.0044)	
Treatment_c	0.9561***			0.2410***		
	(0.2616)			(0.0090)		
Controls						
County controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
County		Yes	Yes		Yes	Yes
Year			Yes			Yes
Fit statistics						
Observations	21,019	21,019	21,019	21,016	21,016	21,016
R^2	0.36904	0.96346	0.96454	0.41996	0.85384	0.85934
Within R^2		0.03171	0.01042		0.54022	0.02152

Table 3: County Level Analysis - Nonbank Expansion and Small Business Lending

This table reports estimates from Equation (8) at the county level from 2011–2017. The dependent variables are the log loan count (columns 1–3) or loan amount (columns 4–6) of small business loans originated by banks in a given county and year. The main independent variable is $\text{Treatment}_c \times \text{Post}$, the interaction between the shadow bank FHA market share prior to LCR shock (Treatment_c) and post dummy (Post_t). The shadow bank FHA market share is measured using the fraction of FHA mortgages originated by shadow banks. The post dummy is 1 for years after 2013. County controls include the fraction of female, the fraction of white, the fraction of population below 16 years old, the fraction of population above 65 years old, log income per capita, log population, poverty rate, fraction of subprime borrowers. Columns 2 and 5 include county fixed effects, columns 3 and 6 include county and year fixed effects. Standard errors clustered at the county level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variables:		Log(Count)			Log(Amt)	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treatment}_c \times \text{Post}_t$	0.0649***	0.0541***	0.0539***	0.0874**	0.1036**	0.1140***
	(0.0177)	(0.0174)	(0.0174)	(0.0401)	(0.0403)	(0.0404)
Post_t	-0.0645***	0.0163		-0.0535**	-0.0369	
	(0.0120)	(0.0107)		(0.0256)	(0.0246)	
Treatment_c	-0.1158***			-0.4024***		
	(0.0404)			(0.0682)		
Controls						
County controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
County		Yes	Yes		Yes	Yes
Year			Yes			Yes
Fit statistics						
Observations	15,390	15,390	15,390	15,390	15,390	15,390
R^2	0.94540	0.99317	0.99354	0.88211	0.97362	0.97370
Within R^2		0.14248	0.04821		0.03728	0.00589

Table 4: Lender County Level Analysis - Nonbank Expansion and Small Business Lending

This table reports estimates from Equation (8) at the county level from 2011–2017. The dependent variables are the log loan count (columns 1–4) or loan amount (columns 5–8) of small business loans originated by banks in a given county and year. The main independent variable is $\text{Treatment}_c \times \text{Post}$, the interaction between the shadow bank FHA market share prior to LCR shock (Treatment_c) and post dummy (Post_t). The shadow bank FHA market share is measured using the fraction of FHA mortgages originated by shadow banks. The post dummy is 1 for years after 2013. The post dummy is 1 for years after 2013. County controls include the fraction of female, the fraction of white, the fraction of population below 16 years old, the fraction of population above 65 years old, log income per capita, log population, poverty rate, fraction of subprime borrowers. Columns 2 and 6 include county and year fixed effects, columns 3 and 7 include lender-year fixed effects, columns 4 and 8 include state-year fixed effects. Standard errors clustered at the county level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variables:	Log(Count)				Log(Amt)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Treatment}_c \times \text{Post}_t$	0.1029***	0.0445**	0.0850***	0.0769***	0.1301***	0.0872***	0.1133***	0.1135***
	(0.0201)	(0.0184)	(0.0190)	(0.0191)	(0.0278)	(0.0274)	(0.0277)	(0.0295)
Post_t	0.1454***				-0.0161			
	(0.0122)				(0.0173)			
Treatment_c	-0.2114***				-0.2300***			
	(0.0271)				(0.0432)			
Controls								
County controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects								
County		Yes	Yes	Yes		Yes	Yes	Yes
Year		Yes	Yes	Yes		Yes	Yes	Yes
Lender-Year			Yes	Yes			Yes	Yes
State-Year				Yes				Yes
Fit statistics								
Observations	273,209	273,209	273,209	273,209	273,209	273,209	273,209	273,209
R^2	0.12530	0.14933	0.45192	0.45286	0.24322	0.26804	0.53621	0.53689

Table 5: Lender County Level Analysis - Except for One Treatment

This table reports estimates from Equation (10) at the county level from 2011–2017. The dependent variables are the log loan count (columns 1–3) or loan amount (columns 4–6) of small business loans originated by banks in a given county and year. The main independent variable is $\text{LendingExposure}_{l,c} \times \text{Post}_t$, the interaction between the lender exposure to shadow bank expansion prior to LCR shock ($\text{LendingExposure}_{l,c}$) and post dummy ($\text{Post}_t$). $\text{LendingExposure}_{l,c}$ is constructed following Equation (9). The post dummy is 1 for years after 2013. The post dummy is 1 for years after 2013. County controls include the fraction of female, the fraction of white, the fraction of population below 16 years old, the fraction of population above 65 years old, log income per capita, log population, poverty rate, fraction of subprime borrowers. Columns 2 and 6 include county and year fixed effects, columns 3 and 7 include lender-year fixed effects, columns 4 and 8 include state-year fixed effects. Standard errors clustered at the county level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variables:	Log(Count)				Log(Amt)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{LendingExposure}_{l,c} \times \text{Post}_t$	0.5444***	0.4993***	0.6589***	0.9237***	0.2236***	0.1730***	0.8532***	1.171***
	(0.0126)	(0.0128)	(0.1384)	(0.1420)	(0.0229)	(0.0230)	(0.1725)	(0.1826)
$\text{LendingExposure}_{l,c}$	-0.7267***	-0.7059***	-12.09***	-12.22***	1.013***	1.038***	-13.82***	-13.97***
	(0.0236)	(0.0234)	(0.4799)	(0.4842)	(0.0297)	(0.0291)	(0.5908)	(0.5951)
Post_t	-0.0447***				-0.0955***			
	(0.0077)				(0.0121)			
Controls								
County controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects								
County		Yes	Yes			Yes	Yes	
Year		Yes	Yes			Yes	Yes	
Lender-year			Yes	Yes			Yes	Yes
County-year				Yes				Yes
Fit statistics								
Observations	275,402	275,402	275,402	275,402	275,402	275,402	275,402	275,402
R^2	0.13651	0.16048	0.50367	0.51121	0.26324	0.28799	0.56700	0.57726
Within R^2		0.01012	0.09485	0.09416		0.02132	0.06196	0.06184

Table 6: Lender County Level Analysis - Except for One Treatment - Interest rate

This table reports estimates from Equation (10) at the county level from 2011–2017. The dependent variables are the default dummy (columns 1–3) or initial interest rate (columns 4–6) of small business loans originated by banks in a given county and year. The main independent variable is $\text{LendingExposure}_{l,c} \times \text{Post}_t$, the interaction between the lender exposure to shadow bank expansion prior to LCR shock ($\text{LendingExposure}_{l,c}$) and post dummy ($\text{Post}_t$). $\text{LendingExposure}_{l,c}$ is constructed following Equation (9). The post dummy is 1 for years after 2013. The post dummy is 1 for years after 2013. County controls include the fraction of female, the fraction of white, the fraction of population below 16 years old, the fraction of population above 65 years old, log income per capita, log population, poverty rate, fraction of subprime borrowers. Columns 2 and 6 include county and year fixed effects, columns 3 and 7 include lender-year fixed effects, columns 4 and 8 include state-year fixed effects. Standard errors clustered at the county level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variables:	Default				InitialInterestRate			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{LendingExposure}_{l,c} \times \text{Post}_t$	0.0159^{*}	-0.0146	-0.0030	-0.0083	0.5285^{***}	-0.1944^{***}	-0.2718^{***}	-0.3476^{***}
	(0.0094)	(0.0111)	(0.0162)	(0.0151)	(0.1677)	(0.0615)	(0.0764)	(0.0670)
$\text{LendingExposure}_{l,c}$	0.0219^{***}	0.0035	0.0229^{*}	0.8099	2.230^{***}	0.1742^{***}	0.2602^{***}	1.961
	(0.0073)	(0.0085)	(0.0129)	(1,790.4)	(0.1207)	(0.0441)	(0.0558)	(7,270.4)
Post_t	-0.0127^{**}			-2.595	-0.1523			-1.592
	(0.0057)			(5,557.4)	(0.1079)			(15,534.1)
Fixed-effects								
Program	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-year		Yes	Yes	Yes		Yes	Yes	Yes
County-year			Yes	Yes			Yes	Yes
County-lender				Yes				Yes
Fit statistics								
Observations	235,605	235,605	235,605	235,605	235,605	235,605	235,605	235,605
R^2	0.01215	0.02759	0.07964	0.12087	0.36180	0.56579	0.59577	0.62072

Table 7: Channel - Deposits

This table reports estimates from Equation (8) at the county level from 2011–2017. The dependent variables are the log deposits in a given county and year. The main independent variable is $\text{Treatment}_c \times \text{Post}$, the interaction between the shadow bank FHA market share prior to LCR shock (Treatment_c) and post dummy (Post_t). The shadow bank FHA market share is measured using the fraction of FHA mortgages originated by shadow banks. The post dummy is 1 for years after 2013. The post dummy is 1 for years after 2013. County controls include the fraction of female, the fraction of white, the fraction of population below 16 years old, the fraction of population above 65 years old, log income per capita, log population, poverty rate, fraction of subprime borrowers. Columns 2 includes county fixed effects, columns 3 includes county and year fixed effects. Standard errors clustered at the county level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variable:	Log(Deposits)		
Model:	(1)	(2)	(3)
$\text{Treatment}_c \times \text{Post}_t$	0.0578	0.0570	0.0655
	(0.0470)	(0.0419)	(0.0433)
Post_t	-0.0486*	-0.0113	
	(0.0294)	(0.0198)	
Treatment_c	-0.2775***		
	(0.0916)		
Controls			
County controls	Yes	Yes	Yes
Fixed-effects			
County		Yes	Yes
Year			Yes
Fit statistics			
Observations	15,390	15,390	15,390
R^2	0.80047	0.98330	0.98337
Within R^2		0.06025	0.02757

Table 8: Channel - Soft Information

This table reports estimates from Equation (11) at the county level from 2011–2017. The dependent variables are the log deposits in a given county and year. The main independent variable is $\text{Treatment}_c \times \text{Branch}_{l,c} \times \text{Post}_t$, the interaction between the shadow bank FHA market share prior to LCR shock (Treatment_c), post dummy (Post_t) and a branch presence dummy ($\text{Branch}_{l,c}$). The shadow bank FHA market share is measured using the fraction of FHA mortgages originated by shadow banks. The post dummy is 1 for years after 2013. The branch presence dummy is 1 if a bank l has a branch in county c in year 2013. County controls include the fraction of female, the fraction of white, the fraction of population below 16 years old, the fraction of population above 65 years old, log income per capita, log population, poverty rate, fraction of subprime borrowers. Columns 2 includes county fixed effects, columns 3 includes county and year fixed effects. Standard errors clustered at the county level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variable:	Log(Count)			
Model:	(1)	(2)	(3)	(4)
$\text{Treatment}_c \times \text{Branch}_{l,c} \times \text{Post}_t$	0.2621***	0.2451***	0.1546***	0.1694***
	(0.0422)	(0.0413)	(0.0319)	(0.0317)
$\text{Treatment}_c \times \text{Post}_t$	0.0689***	0.0102	0.0465***	0.0312**
	(0.0165)	(0.0160)	(0.0154)	(0.0157)
$\text{Branch}_{l,c} \times \text{Post}_t$	-0.2187***	-0.2195***	-0.2289***	-0.2443***
	(0.0256)	(0.0251)	(0.0197)	(0.0197)
$\text{Treatment}_c \times \text{Branch}_{l,c}$	0.1458*	0.2737***	0.1301*	0.1217
	(0.0828)	(0.0877)	(0.0757)	(0.0755)
Treatment_c	-0.2361***			
	(0.0249)			
Post_t	0.1595***			
	(0.0099)			
Controls				
County controls	Yes	Yes	Yes	Yes
Fixed-effects				
County		Yes	Yes	Yes
Year		Yes	Yes	Yes
Lender-Year			Yes	Yes
State-Year				Yes
Fit statistics				
Observations	374,291	374,291	374,291	374,291
R^2	0.30870	0.32842	0.66584	0.66651
Within R^2		0.21080	0.39773	0.39782

Table 9: Real Effects

This table reports estimates from Equation (8) at the county level from 2011–2017. Panel A reports the results for log number of total establishments, SFR, housing price growth, GDP growth; Panel B reports the results for employment growth by sector. The main independent variable is $\text{Treatment}_c \times Post_t$, the interaction between the shadow bank FHA market share prior to LCR shock (Treatment_c) and post dummy (Post_t). The shadow bank FHA market share is measured using the fraction of FHA mortgages originated by shadow banks. The post dummy is 1 for years after 2013. County controls include the fraction of female, the fraction of white, the fraction of population below 16 years old, the fraction of population above 65 years old, log income per capita, log population, poverty rate, fraction of subprime borrowers. All columns include county and year fixed effects. Standard errors clustered at the county level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Panel A: Real effects on Firm Formation and Macroeconomic Variables				
Dependent Variables:	Log(Total Establishments)	SFR	Housing Price Growth	GDP Growth
Model:	(1)	(2)	(3)	(4)
$\text{Treatment}_c \times Post_t$	0.0071	218.9***	-0.0010	0.0211*
	(0.0048)	(55.62)	(0.0032)	(0.0123)
Fixed-effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	15,390	12,781	12,534	15,089
R^2	0.99963	0.98919	0.62076	0.21635
Within R^2	0.29458	0.07771	0.01863	0.03592

Panel B: Real effects on Employment Growth				
Dependent Variables:	Construction	NonTradable	Other	Tradable
Model:	(1)	(2)	(3)	(4)
$\text{Treatment}_c \times Post_t$	-0.0128	0.0103	0.0089	0.0361**
	(0.0160)	(0.0083)	(0.0075)	(0.0171)
Fixed-effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	15,012	14,884	14,971	14,056
R^2	0.21157	0.68324	0.56193	0.34042
Within R^2	0.01820	0.02018	0.04627	0.00575

Table 10: Confounding Events - Tax Credit for Small Business

This table reports estimates from Equation (8) at the county level from 2011–2017. The dependent variables are the log loan count (columns 1–3) or loan amount (columns 4–6) of small business loans originated by banks in a given county and year. The main independent variable is $\text{Treatment}_c \times \text{Post}$, the interaction between the shadow bank FHA market share prior to LCR shock (Treatment_c) and post dummy (Post_t). The shadow bank FHA market share is measured using the fraction of FHA mortgages originated by shadow banks. The post dummy is 1 for years after 2013. To account for the effect from the confounding event, we control for the interaction term $\text{Ln}(1 + \text{QSB}) \times \text{Post}_t$, where QSB is the number of qualified small businesses in a county in 2013. We follow He et al. (2022) to construct the measure from Census Business Pattern (CBP) survey data. County controls include the fraction of female, the fraction of white, the fraction of population below 16 years old, the fraction of population above 65 years old, log income per capita, log population, poverty rate, fraction of subprime borrowers. Columns 2 and 5 include county fixed effects, columns 3 and 6 include county and year fixed effects. Standard errors clustered at the county level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variables:		Log(Count)			Log(Amt)	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treatment}_c \times \text{Post}_t$	0.0741***	0.0502***	0.0500***	0.1377***	0.1241***	0.1348***
	(0.0174)	(0.0175)	(0.0174)	(0.0402)	(0.0407)	(0.0407)
$\text{Ln}(1 + \text{QSB}) \times \text{Post}_t$	0.0146***	0.0049**	0.0049**	-0.0208***	-0.0260***	-0.0263***
	(0.0024)	(0.0024)	(0.0024)	(0.0052)	(0.0056)	(0.0055)
Post_t	-0.0974***	-0.0129		0.1301***	0.1184***	
	(0.0187)	(0.0186)		(0.0416)	(0.0429)	
Treatment_c	-0.0603*			-0.3590***		
	(0.0326)			(0.0621)		
Ln(1 + QSB)	0.7724***			0.9374***		
	(0.0231)			(0.0408)		
Controls						
County controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
County		Yes	Yes		Yes	Yes
Year			Yes			Yes
Fit statistics						
Observations	15,390	15,390	15,390	15,390	15,390	15,390
R^2	0.96362	0.99317	0.99354	0.90100	0.97369	0.97378
Within R^2		0.14293	0.04875		0.03997	0.00874

Table 11: New Treatment - Shadow Bank Ex-ante Application Share

This table reports estimates from Equation (8) at the county level from 2011–2017. The dependent variables are the log loan count (columns 1–3) or loan amount (columns 4–6) of small business loans originated by banks in a given county and year. The main independent variable is Alt Treatment$_c$ × Post, the interaction between the shadow bank FHA market share prior to LCR shock (Treatment$_c$) and post dummy (Post$_t$). The shadow bank FHA market share is measured using the fraction of FHA mortgage applications submitted to shadow banks. The post dummy is 1 for years after 2013. County controls include the fraction of female, the fraction of white, the fraction of population below 16 years old, the fraction of population above 65 years old, log income per capita, log population, poverty rate, fraction of subprime borrowers. Columns 2 and 5 include county fixed effects, columns 3 and 6 include county and year fixed effects. Standard errors clustered at the county level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variables:	Log(Count)			Log(Amt)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Alt Treatment$_c$ × Post$_t$	0.0960***	0.0731***	0.0714***	0.0504	0.0600	0.0745
	(0.0228)	(0.0221)	(0.0220)	(0.0500)	(0.0497)	(0.0499)
Post$_t$	-0.0864***	0.0030		-0.0351	-0.0139	
	(0.0153)	(0.0136)		(0.0324)	(0.0313)	
Alt Treatment$_c$	-0.2605***			-0.5645***		
	(0.0498)			(0.0867)		
Controls						
County controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
County		Yes	Yes		Yes	Yes
Year			Yes			Yes
Fit statistics						
Observations	15,691	15,691	15,691	15,691	15,691	15,691
R^2	0.94651	0.99313	0.99349	0.88387	0.97331	0.97341
Within R^2		0.13669	0.04735		0.03398	0.00444

Table 12: New Dependent Variables - Small Business Loans to Small Firms

This table reports estimates from Equation (8) at the county level from 2011–2017. The dependent variables are the log loan count (columns 1–3) or loan amount (columns 4–6) of small business loans originated by banks in a given county and year. Different from Table 3, only small business loans to firms with gross annual revenue (GAR) less than 1 million are counted in the dependent variables. The main independent variable is $\text{Treatment}_c \times \text{Post}$, the interaction between the shadow bank FHA market share prior to LCR shock (Treatment_c) and post dummy (Post_t). The shadow bank FHA market share is measured using the fraction of FHA mortgages originated by shadow banks. The post dummy is 1 for years after 2013. County controls include the fraction of female, the fraction of white, the fraction of population below 16 years old, the fraction of population above 65 years old, log income per capita, log population, poverty rate, fraction of subprime borrowers. Columns 2 and 5 include county fixed effects, columns 3 and 6 include county and year fixed effects. Standard errors clustered at the county level are reported in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Dependent Variables:	Log(Count) w. GAR<1m			Log(Amt) w. GAR<1m		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Treatment}_c \times \text{Post}_t$	0.0987***	0.0822***	0.0926***	0.1566***	0.1770***	0.1873***
	(0.0244)	(0.0244)	(0.0242)	(0.0521)	(0.0521)	(0.0520)
Post_t	-0.0221	0.0156		-0.1188***	-0.0914***	
	(0.0162)	(0.0151)		(0.0331)	(0.0325)	
Treatment_c	-0.2147***			-0.5513***		
	(0.0515)			(0.0834)		
Controls						
County controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
County		Yes	Yes		Yes	Yes
Year			Yes			Yes
Fit statistics						
Observations	15,390	15,390	15,390	15,390	15,390	15,390
R^2	0.92004	0.98737	0.98790	0.83847	0.95273	0.95293
Within R^2		0.21587	0.02778		0.01849	0.00800

Internet Appendix to
How Nonbank Mortgage Lenders Shaped Bank Small Business Lending?

Xiyue Li, Dongliang Lu, Keling Zheng
University of British Columbia

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A Proofs

Proof of Proposition 1. Assume the parameters satisfy the following conditions:

1) $\alpha_i > 0$, $\beta_i > 0$, $c_i^b > 0$, $c_m^n > 0$ for all $i \in \{m, s\}$.

2)

$$\begin{aligned} -2\beta_s \frac{3\beta_m(K_1+\Delta^*) - \alpha_m - c_m^n + 2\alpha_s + 2c_m^b - 2c_s^b}{(3\beta_m + 4\beta_s)} + \alpha_s - c_s^b > 0 \\ -\beta_s \frac{2\beta_m(K_2 - \Delta^*) - \alpha_m + \alpha_s + c_m^b - c_s^b}{\beta_m + \beta_s} + \alpha_s - c_s^b > 0 \end{aligned} \tag{A.1}$$

Where Δ^* is defined later.

3) $\Delta^* > -K_1$ and $\Delta^* < K_2$.

4) assume that the cost c_m^b, c_s^b, c_m^n are small enough such that the equilibrium allocations are all non-negative.

The nonbank's strategy k_{m1}^n given the bank's strategy can be solved by FOC:

$$-\beta_m k_{m1}^{n,*} + \alpha_m - \beta_m(k_{m1}^{b,*} + k_{m1}^{n,*}) - c_m^n = 0 \tag{A.2}$$

Denote the Lagrange multipliers of the optimizing problem as L_l where $l \in \{1,2,3,4\}$ respectively. Taking first order conditions with respect to k_{ij}^b and L_l for $i \in \{m, s\}$, $j \in \{1,2\}$m and $l \in \{1,2,3,4\}$ respectively:

$$\begin{aligned} -\beta_n k_{m1}^{b,*} + (\alpha_m - \beta_m(k_{m1}^{n,*} + k_{m1}^{b,*}) - c_m^b) - L_1 = 0 \\ -\beta_s k_{s1}^{b,*} + (\alpha_s - \beta_s k_{s1}^{b,*} - c_s^b) - L_1 = 0 \\ -\beta_n k_{m2}^{b,*} + (\alpha_m - \beta_m k_{m2}^{b,*} - c_m^b) - L_2 = 0 \\ -\beta_s k_{s2}^{b,*} + (\alpha_s - \beta_s k_{s2}^{b,*} - c_s^b) - L_2 = 0 \\ -2q\Delta^* + L_1 - L_2 - L_3 + L_4 = 0 \end{aligned} \tag{A.3}$$

Solving the nonbank and bank's optimal strategy together, we have the solution given in the Proposition (1). What's more, given the parameter conditions, we have $L_1 > 0$, $L_2 > 0$, and $-K_1 < \Delta^* < K_2$, which gives us the interior solution.

■

Proof of Lemma 1. From Proposition 1, we have

$$\begin{aligned} \frac{\partial k_{s1}^b}{\partial c_m^n} &= \frac{3\beta_m}{3\beta_m + 4\beta^s} \frac{1}{2q - Z_1} \frac{2\beta_s}{3\beta_m + 4\beta_s} - \frac{1}{3\beta_m + 4\beta_s} \\ \frac{\partial k_{s2}^b}{\partial c_m^n} &= -\frac{\beta_m}{\beta_m + \beta_s} \frac{1}{2q - Z_1} \frac{2\beta_s}{3\beta_m + 4\beta_s} \end{aligned} \tag{A.4}$$

It is easy to verify that $\frac{\partial k_{s1}^b}{\partial c_m^n}|_{q=0} - \frac{\partial k_{s2}^b}{\partial c_m^n}|_{q=0} = -\frac{2q}{(3\beta_m+4\beta_s)(2q-Z_1)}|_{q=0} = 0$. Therefore $\frac{\partial k_{s1}^b}{\partial c_m^n}|_{q=0} = \frac{\partial k_{s2}^b}{\partial c_m^n}|_{q=0}$.

Notice that $Z_1 < 0$, so it is easy to see that $\frac{\partial k_{s2}^b}{\partial c_m^n}|_{q=0} < 0$. Therefore $\frac{\partial k_{s1}^b}{\partial c_m^n}|_{q=0} = \frac{\partial k_{s2}^b}{\partial c_m^n}|_{q=0} < 0$.

■

Proof of Proposition 2. It can be shown that when $q > 0$,

$$\frac{\partial k_{s1}^b}{\partial c_m^n} - \frac{\partial k_{s2}^b}{\partial c_m^n} = -\frac{2q}{(3\beta_m + 4\beta_s)(2q - Z_1)} < 0 \tag{A.5}$$

And

$$\frac{\partial R_{s1}}{\partial c_m^n} - \frac{\partial R_{s2}}{\partial c_m^n} = -\beta_s(\frac{\partial k_{s1}^b}{\partial c_m^n} - \frac{\partial k_{s2}^b}{\partial c_m^n}) = \beta_s \frac{2q}{(3\beta_m + 4\beta_s)(2q - Z_1)} > 0 \tag{A.6}$$

■

Proof of Corollary 1. It is easy to check that

$$\frac{\partial^2 (k_{s1}^b - k_{s2}^b)}{\partial c_m^n \partial q} = \frac{2Z_1}{(3\beta_n + 4\beta_s)(2q - Z_1)^2} < 0 \tag{A.7}$$

■