The Secular Decline in Interest Rates and the Rise of Shadow Banks*

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Abstract

Over the past two decades, shadow banks have significantly expanded their share of residential mortgage lending, even surpassing pre-financial crisis levels. This surge is often attributed to post-crisis regulatory changes and improvements in shadow banks' technology. In this paper, we document a new driving force: the persistent decline in interest rates. When interest rates are high, cheap deposit funding provides banks with a significant competitive advantage against shadow banks relying on wholesale funding. As interest rates plummet, banks lose this advantage, experience a squeeze in their net interest margin, leading to diminished profitability, weaker growth, and cost-cutting measures such as branch closures. By contrast, shadow banks are able to gain market share. We test this mechanism using a shift-share empirical design based on differences in historical bank balance sheet composition. We find that banks more vulnerable to falling interest rates contracted lending as a response to lower profitability while also scaling back non-interest expenses on their branches. This created a fertile environment for non-banks to expand in areas with banks exposed to declining interest rates.

Keywords: Low interest rates, net interest margin, shadow banks, non-banks, mortgages.

JEL classification: E43, G21, G23, G28.

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1 Introduction

In recent years there has been a marked shift in the U.S. consumer and corporate lending markets, with the bulk of lending migrating from commercial banks to non-depository institutions known as "shadow banks". In the mortgage market, Buchak et al. (2018) documents that the share of originations by shadow banks, such as mortgage companies, grew from less than 30% in 2007 to almost 50% in 2015 (see Figure 1). These trends have raised concerns regarding the stability and the quality of the credit provided by shadow banks.[1] The lighter regulation faced by shadow banks allows them to expand more aggressively than more constrained traditional banks in good times, especially in riskier segments of the market. The downside is that shadow banks depend on uninsured funding that can quickly evaporate during episodes of financial stress. Notably, the 2008 credit crunch was amplified by the prevalence of non-bank lending in the mortgage market, as non-bank intermediaries lost funding liquidity when the securitization market froze.

This evolution makes it crucial to understand the economic drivers behind the rise of shadow banks. Two main factors have been proposed and quantified in recent work (Buchak et al., 2018). Under the "regulatory arbitrage" view, the rise of shadow banks is a byproduct of tighter regulation on traditional banks, especially following post-Great Financial Crisis (GFC) reforms. More stringent constraints in the regulated sector lead to a migration of capital-intensive activities towards the unregulated sphere. Under the technological view, rapid advances in the quality of online platforms and in the processes for automated lending have fueled the expansion of non-bank lenders dependent on these technologies, whereas commercial banks relying on their branch network and loan officers have transitioned more slowly.

We argue that the secular decline in interest rates provides a novel and complementary explanation. Our starting point is that in the same time frame, the low interest rate environment has been recognized as a major challenge to the profitability of commercial banks (e.g., Borio et al., 2017; Claessens et al., 2018). Although the net interest margin (NIM) of U.S. banks has been quite stable historically, Figure 1 displays a clear decline in recent times, in lockstep with the general fall in interest rates. The perils of low interest rates were made especially salient in the decade spent at or around the zero lower bound following the GFC, but the decline in the NIM started in the late 1990s. Low nominal interest rates hurt bank profitability by compressing the spreads they earn between assets and liabilities. A widely recognized mechanism is that deposit rates do not adjust fully with market rates such as the Fed funds rate. As a result the spread

[1] For instance, the Financial Stability Board introduced a November 2021 report on "Enhancing the Resilience of Non-Bank Financial Intermediation" by noting that "*non-bank financial intermediation has grown considerably over the past decade – to almost half of global financial assets – and become more diverse. However, the March 2020 turmoil underscored the need to strengthen resilience in this sector, to ensure a more stable provision of financing to the economy and reduce the need for extraordinary central bank interventions.*"

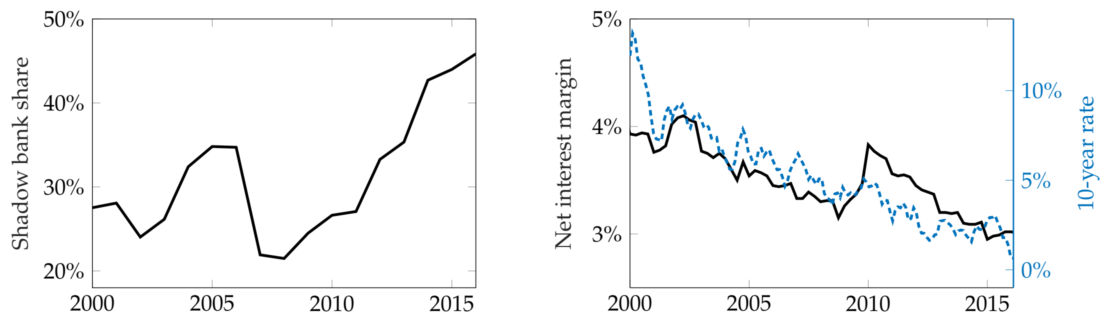


Figure 1: Left panel: Shadow bank value share of residential mortgage originations. Right panel: Average U.S. net interest margin (solid line, left axis) and 10-year nominal rate (dashed line, right axis), 2000-2016. Sources: FRED, HMDA.

between market rates and deposit rates is a major source of profits for banks when interest rates are high, but also a fragile one that vanishes as interest rates approach zero. The longer interest rates stay low, the harder it becomes to use long-term assets to hedge the negative effect on income. Banks have been able to offset some of the lost income from deposits through higher loan spreads (e.g., Wang, 2022) or higher non-interest income in the form of fees (e.g., Boungou and Hubert, 2021), but their adaptation remains partial.

Our paper is the first to study jointly the harmful effects of lower rates on bank lending and the response of non-banks. Our hypothesis is that the decline in interest rates has an asymmetric impact on banks and non-banks. We start with a simple conceptual framework that captures previously known factors behind the rise of shadow banks such as regulation and technology, as well as this new channel. Shadow banks have no access to cheap deposits, hence they must fund themselves at higher rates than their bank competitors. Since the spread between market rates and deposit rates is higher at high interest rates, the competitive disadvantage faced by shadow banks is more severe in a high rate environment. Conversely, as interest rates fall, the funding disadvantage of shadow banks disappears, which helps them grow relative to traditional banks.

The main empirical challenge is to draw a causal chain between the decline in interest rates, the contraction of bank credit, and the rise of shadow banks. To do so we go beyond aggregate data and turn to the cross-section of U.S. banks and counties. The fall in the net interest margin in Figure 1 is at the heart of our empirical strategy. We show that the average decline in the NIM masks an important heterogeneity in banks' exposure to lower interest rates, due to the heterogeneous pass-through of interest rates to the various components of bank balance sheets, both on the asset side and on the liability side. For instance, on average, securities have a lower interest rate pass-through than loans whereas checking and saving deposits have a lower interest rate pass-through than time deposits. As a result, banks with high pass-through assets and low pass-through liabilities are the most susceptible to falling interest rates.

This heterogeneity motivates our shift-share strategy based on banks' historical balance sheet composition. For each bank, we construct a measure of exposure to declining interest rates (henceforth, exposure) by combining lagged balance sheet weights with national trends in the yields of each balance sheet category. Importantly, our exposure measure only relies on historical differences in balance sheet composition (e.g., the share of savings vs. time deposits) and does *not* use differences in bank-specific pricing of assets and liabilities (e.g., how each bank's deposit rates respond differentially to interest rates). Therefore, unlike banks' realized NIM, the exposure is not affected by bank-specific trends such as demand shocks, changes in borrower composition, or changes in loan and deposit market power.

Our first results show that in the cross-section of U.S. banks, more exposed banks earn lower net income between 2003 and 2016. Therefore banks were unable to use fees to offset the compression in spreads implied by their historical balance sheet structure. This, in turn, led to slower equity growth, and ultimately lower asset and loan growth, for both commercial and residential lending. These results are consistent with the class of models in which scarce bank equity constrains lending and banks are reluctant to issue equity in response to lower retained earnings. We also show that exposed banks decrease holdings of mortgage-backed securities; thus the contraction in portfolio lending is not simply a substitution towards other forms of funding mortgages.

In the rest of the paper we focus on the residential mortgage market. Although shadow banking is rising in several credit markets, the mortgage market allows us to use rich county-level data, thus providing a particularly good setting to disentangle the forces behind the rise of shadow banks at a granular level. We first confirm and reinforce the bank-level results with a bank-region analysis: we find that bank mortgage lending fell in counties with more exposed banks. The bank-county level regressions allow us to add county fixed effects to absorb any credit demand shocks operating at the county level.

Our main results show the response of shadow banks to the contraction in traditional bank lending. We find that counties with more exposed banks saw a stronger increase in the shadow bank share, by around 10% for every additional 100 bps in the exposure of banks present in the county, weighted by local lending. This result supports the idea that shadow banks gained significant territory in housing markets where banks were hurt by the decline in interest rates. Crucially, we follow Buchak et al. (2018) and show that the effect of exposure is not due to correlated increases in local banks' regulatory burden or local technological progress in online lending.

We then study separately the rise of shadow banks in two segments of the market: "GSE" loans, defined as mortgages sold after origination to Fannie Mae, Freddie Mac, Ginnie Mae, and Farmer Mac as well as any FHA loan, and "non-GSE" loans (such as "jumbo" loans above the conforming limit), which are either kept on balance sheet or sold on the private market. The quick securitization process for GSE loans reduces their effective required space on banks' balance sheets, which may make GSE lending less sensitive to the lower funding capacity of exposed banks. On the other hand, non-GSE loans are more difficult to originate for shadow banks that lack a long-term funding capacity. This became especially the case after the private label securitization market collapsed in 2008, although the market rebounded partly in more recent years. Interestingly, we find that counties with exposed banks experience a strong shadow bank growth for both GSE and non-GSE loans. We highlight a "cost-cutting channel" that applies to both types of loans: exposed banks respond to lower net interest income by reducing their non-interest expenses, in particular on fixed assets and salaries. Lower interest rates hurt these banks' ability or willingness to maintain and expand their branch network, which lead them to cut back on originating all kinds of loans.

Relation to the literature

Most of the theoretical work on shadow banks, e.g., Plantin (2014), Hanson et al. (2015), and Farhi and Tirole (2020), has focused on regulatory arbitrage. Lightly regulated shadow banks compete against traditional banks that are heavily regulated but benefit from government support in bad times (e.g., deposit insurance and lender of last resort policies). These models contrast the ways banks and shadow banks satisfy the demand for liquid liabilities, and show that the threat of migration of activities to the shadow banking sector may constrain the design of traditional bank regulation. The macro-finance literature, e.g., Gertler et al. (2016), Moreira and Savov (2017), Begenau and Landvoigt (2021), has also highlighted the risks and inefficiencies created by a growing shadow banking sector, and the interesting dynamics arising from its interactions with banks.

Our empirical work builds on the seminal paper by Buchak et al. (2018), focusing on the rise of shadow banks in the residential mortgage market. Buchak et al. (2018) shows the empirical relevance of both regulation and technology, and develops a model to quantify the relative importance of these two drivers. Although we highlight declining interest rates as a new force behind the rise of shadow banks, we emphasize that this is a complementary explanation that does not reduce the relevance of regulatory or technological factors. In fact, our results point to an *interaction* between falling rates and regulation. Tight capital regulation makes the compression in bank net interest margins particularly harmful, since retained earnings are the main source of bank capital. Moreover, we show that lending contracts more for exposed banks with a low equity-to-assets ratio, which can be interpreted as more constrained by regulation.

Several other recent papers study the expansion of shadow banks across several markets: mortgages (Demyanyk and Loutskina 2016, Fuster et al. 2019, Jiang et al. 2020, Jiang 2022, Gete and Reher 2020, Mian and Sufi 2021, Lewellen and Williams 2021, Buchak et al. 2022), small business loans (Gopal and Schnabl, 2022) and syndicated loans (Irani et al., 2020). Besides the role of non-banks as credit providers, there is also a rich literature examining the role of the shadow banking sectors (i.e., money market mutual funds) in liquidity provision (e.g., Xiao 2019, Ma et al. 2022).

A large theoretical and empirical literature has developed around the perverse effects of excessively low interest rates (Abadi et al. 2022, Eggertsson et al. 2020, Heider et al. 2019, Ulate 2021, Wang et al. 2020) with a focus on the short-run effects of low or negative interest rates, notably in the case of accommodative monetary policy (see also the survey of empirical findings across countries by Heider et al. 2020). This paper is closer to Wang (2022), Balloch and Koby (2022) and Supera (2022) which share our emphasis on the *long-run* effects of low interest rates on bank credit supply. Our contribution is twofold. First, we use plausibly exogenous variation in bank exposure to show how falling interest rates affected lending by U.S. banks. Second, unlike the literature that has considered banks in isolation, we document the strong response of the shadow banking sector. One exception is Drechsler et al. (2022), which studies the importance of non-bank lending during the 2003-2006 housing boom at a time of *rising* interest rates, as can be seen in Figure 1. Our paper finds the opposite pattern in the long run, with falling interest rates causing a rise in shadow banking. As discussed in Wang (2022), these two findings can be reconciled by noting that interest rate movements have opposite short-run and long-run effects. In the short run, deposit market power and equity revaluation govern the response of bank lending. The compression in net interest income takes more time to affect bank equity and lending, but dominates in the long run.

2 Conceptual Framework

This section presents a simplified model of the competition between traditional and shadow banks in loan origination, and how it is affected by changes in regulation, technology, and interest rates.

Traditional Banks The first defining feature of traditional banks is that they rely on cheap and stable deposit funding. The safety and convenience of deposits allows banks to pay a below-market rate on their deposit liabilities $r_d = r - s_d$. The deposit spread $s_d \geq 0$ captures both a convenience yield and a potential rent from banks' market power in the provision of liquid assets. Crucially, the deposit spread s_d is not fixed, but varies with the level of interest rates. It is determined by the equilibrium in the deposit market equating deposit supply D^B to deposit demand, given by a function $\mathcal{D}(s_d, r)$ that decreases with s_d and increases with r. A standard microfoundation for this dependence is the stronger competition between cash and deposits at lower nominal rates: as the opportunity of cash falls, it becomes a more attractive alternative to deposits in the market for safe and liquid assets.[2]

On the asset side, banks lend at a rate $r_\ell = r + s_\ell$ and pay an operating cost γ^B per dollar. The loan rate r_ℓ may exceed r; the equilibrium loan spread $s_\ell \geq 0$ reflects both the technological cost of lending and the scarcity of bank and non-bank loan supply relative to loan demand. Bank loan supply is scarce because banks are subject to regulatory constraints.[3] We assume that total bank borrowing D^B cannot exceed a multiple ϕ of bank equity E^B: $D^B \leq \phi E^B$. As a result, total bank lending, financed by bank equity and deposits, must satisfy

$$L^B \leq (1+\phi)E^B. \tag{1}$$

The factor $1+\phi$ should be interpreted as leverage adjusted by how long it takes to securitize the loan; even conforming loans require some balance sheet space as they cannot be sold to GSEs instantaneously (Demyanyk and Loutskina, 2016). For technical reasons we assume $\phi\epsilon_{\mathcal{D}} \geq 1$ where $\epsilon_{\mathcal{D}} = -s_d\mathcal{D}_{s_d}(s_d, r)/\mathcal{D}(s_d, r)$ is the elasticity of deposit demand with respect to the deposit spread. In practice this condition is mild since ϕ is between 5 and 10 and $\epsilon_{\mathcal{D}}$ is around 5 (Drechsler et al., 2017).

Finally, banks target a long-run gross return on equity $r + \rho$ (e.g., Pennacchi and Santos, 2021). For simplicity, and consistent with the empirical evidence, we assume equity grows out of retained earnings and banks cannot raise equity to overcome the leverage constraint; less extreme frictions to equity issuance would lead to the same results.

Shadow Banks Shadow bank lenders have a different business model and cost structure. Shadow banks do not face any regulatory constraint, but they have no deposit base and so must fund themselves on the wholesale funding market, which comes at an increasing marginal cost above and beyond the market rate r, due to, e.g., information asymmetry (Stein, 1998; Hanson et al., 2015). They solve the same problem each period

$$\max_L\, (1+r_\ell)L - (1+r)L - \tau(L) - \gamma^{SB}L$$

where $\tau(L)$ is the increasing convex cost of wholesale funding relative to r, and γ^{SB} is shadow banks' technological cost of lending, which includes both origination and servicing (Kim et al., 2022) and may be lower than banks' cost γ^B. Defining $L^{SB}(\cdot) = \tau'^{-1}(\cdot)$, the optimal shadow bank loan supply is thus given by an increasing function $L^{SB}\left(s_\ell - \gamma^{SB}\right)$ of the spread s_ℓ net of

[2] What matters is the nominal interest rate $i = r + \pi$ where π is inflation; we hold long-run inflation fixed and thus only need to express the dependence of $\mathcal{D}$ in r.

[3] As Farhi and Tirole (2020) argue, the two key features of banks that we focus on come hand in hand: the main reason banks are able to issue safe deposits is that they benefit from the explicit and implicit government guarantees extended to institutions complying with regulatory constraints.

technological cost γ^{SB}.

Loan Demand Households cannot access public markets and can only borrow through bank or non-bank intermediaries. Their loan demand is given by a decreasing function of the loan spread $\mathcal{L}(s_\ell)$.[4] Banks will never lend at a spread below γ^B hence we assume $\mathcal{L}(\gamma^B) > L^{SB}(\gamma^B - \gamma^{SB})$, which means that shadow banks' technological advantage is not strong enough for them to take over the entire market.

Long-Run Equilibrium Denote $\bar{r}$ the solution to

$$\mathcal{L}(\gamma^B) - L^{SB}(\gamma^B - \gamma^{SB}) = (1 + 1/\phi)\,\mathcal{D}(\rho/\phi, \bar{r}). \tag{2}$$

Lemma 1. *The equilibrium loan spread s_ℓ is equal to γ^B if $r \geq \bar{r}$ and strictly above γ^B if $r < \bar{r}$.*

For $r \geq \bar{r}$, deposit spreads s_d are sufficiently high to sustain banks' required return on equity without any income from lending, hence the equilibrium loan spread s_ℓ is equal to the technological cost of lending γ^B. We focus on the low-rate regime $r < \bar{r}$, in which competition from cash forces deposit spreads to fall below ρ/ϕ, hence an equilibrium loan spread s_ℓ above γ^B is required to sustain banks' required return on equity. In that case bank loan supply is given by the binding constraint (1), $L^B = (1+\phi)E^B$.

Equilibrium spreads must clear the deposit and loan markets:

$$\mathcal{D}(s_d, r) = \underbrace{\phi E^B}_{D^B} \tag{3}$$

$$\mathcal{L}(s_\ell) = \underbrace{(1+\phi)E^B}_{L^B} + L^{SB}\left(s_\ell - \gamma^{SB}\right) \tag{4}$$

In addition, spreads must satisfy the following "bank profitability" condition:

$$\rho = \phi s_d + (1+\phi)(s_\ell - \gamma^B) \tag{5}$$

which states that banks must be able to generate their target excess return on equity ρ through a combination of deposit and loan spreads.

Equation (3) yields an equilibrium deposit spread s_d that decreases with deposit supply ϕE^B. Equation (4) yields an equilibrium loan spread s_ℓ that decreases with bank loan supply $(1+\phi)E^B$. Plugging the two spreads into (5) determines the equilibrium size of the banking sector E^B. Therefore the equilibrium $\left(s_d, s_\ell, E^B\right)$ is characterized by the system (3)-(5), which

[4] In Appendix A.3 we extend the results to a richer setting in which loan demand can be shifted by the same drivers that cause the secular decline in r, e.g., lower potential output growth and demographic factors that increase the propensity to save.

leads to our main result regarding the response to *shocks* to regulation, technology, and interest rates:

Proposition 1 (Response to shocks)**.** *Suppose that $r < \bar{r}$. Then*:

1. *A tightening of regulation $\Delta\phi < 0$ increases the loan spread s_ℓ, reduces bank lending L^B, and increases shadow bank lending L^{SB}.*

2. *An improvement in shadow banks' lending technology $\Delta\gamma^{SB} < 0$ lowers the loan spread s_ℓ, reduces L^B, and increases L^{SB}.*

3. *A decline in interest rates $\Delta r < 0$ leads to lower deposit spreads s_d and higher loan spreads s_ℓ, a decline in L^B, and a rise in L^{SB}.*

While stylized, our model is able to capture the three leading factors shaping the competition between banks and non-banks: regulation, technology, and interest rates. Shadow banks' market share increases in response to tighter bank regulation and improved shadow bank technology, as in Buchak et al. (2018). The third and novel prediction is about the role of the interest rate r. A lower interest rate r makes cash more attractive which acts as a negative shifter for deposit demand $\mathcal{D}$. In equilibrium, the deposit spread s_d must fall together with r. The bank profitability condition (5) then implies that the loan spread s_ℓ must rise to offset the lost income from deposits. The higher loan spread spurs lending by shadow banks L^{SB}. Intuitively, the funding advantage that banks obtain from deposits is reduced as rates fall, and this benefits shadow banks that rely on a different funding technology.

The three negative shocks $\Delta\phi$, $\Delta\gamma^{SB}$, Δr affect quantities similarly hence a combination of these shocks unambiguously increases shadow bank lending and hurts bank lending. The net effect on the loan spread is ambiguous and depends on the relative size of the shocks. Note that from Lemma 1 a decline in rates increases shadow bank lending only once rates are already sufficient low, $r < \bar{r}$, which may explain why most of the rise in shadow banks took place in the 2000s even though interest rates started falling in the late 1980s.

Extension: the Cost-Cutting Channel. The deposit spreads earned by banks do not come for free: depositors are willing to forego returns in exchange for services that require banks to spend operating costs, say c per dollar of deposits, for instance on branches (premises, salaries, etc.) and apps. Thus banks earn income $s_d - c$ on deposits. These costs can be measured as part of the "non-interest expenses" category in the data. In Appendix A.4 we consider an extension of the model that endogenizes banks' operating costs and the effect on bank credit supply.

Banks' investment in their branch network is endogenous and depends on both past and future profitability. Given the financial constraints we have emphasized, lower realized net interest income (e.g., due to low interest rates) forces banks to reduce their expenses c. In addition, standard q-theory logic implies that banks may cut back if they expect their deposit franchise to be less valuable in the future, for instance because interest rates are permanently lower.

There is a natural complementarity between loans and deposits: a better branch network also allows banks to lend more. This can be viewed as an effective bank loan supply $L^B = \alpha(c)(1 + \phi)E$ where $\alpha(c) \in [0, 1]$ increases with c. This additional "cost-cutting channel" *amplifies* the net worth channel of lower rates highlighted in Proposition 1. In Section 6.2 we find empirical evidence supporting this mechanism.

3 Empirical Strategy: Shift-Share Exposure to Declining Rates

The main testable prediction arising from the model is that shadow banks will tend to expand more agressively in markets where incumbent banks are especially hurt by the decline in r. The rest of the paper examines these implications empirically.

After describing the data, we present our empirical strategy relying on a Bartik shift-share instrument capturing banks' exposure to declining interest rates, and explore what drives the variation in the exposure measure across banks. We then give an overview of the various specifications used in the paper.

3.1 Data Sources

Bank income and balance sheets The bank-level data are from the Consolidated Reports of Condition and Income, better known as Call Reports, hosted by the Federal Financial Institutions Examination Council (FFIEC) Central Data Repository's Public Data Distribution. This data contains quarterly information on income statements and balance sheets for every national bank, state member bank, insured state non-member bank, and savings association in the U.S.

Mortgage lending The U.S. residential mortgage lending data comes from the Home Mortgage Disclosure Act (HMDA) dataset. The HMDA data is provided annually at the loan-level and contains information on the size and purpose of the loan, the lender that provided the loan and in what county, the regulating agency, who the loan was sold to, and demographic information on the borrower. We do not include home improvement loans, focusing only on home purchase and refinancing loans. We further restrict our sample to originated loans as HMDA includes purchased and denied loans as well. Lenders in the HMDA data are identified based on a unique HMDA ID. We match lenders to their balance sheet data by linking the HMDA ID to their unique RSSD ID in the Call Reports using the Avery file constructed by Robert Avery.[5] Table 14 in the Appendix shows the top lenders in 2016 for both banks and non-banks. Wells Fargo, JPMorgan Chase, and Bank of America are the largest banks in the market with respective market shares of 6.7%, 4.3%, and 2.8%. Quicken Loans, Loandepot.com , and Caliber Home Loans are the largest shadow banks in the market with respective market shares of 4.3%, 1.7%, and 1.3%.

Branch-level deposits The branch-level deposits data comes from the FDIC's Summary of Deposits. This data contains annual information on the amount of deposits for all FDIC-insured institutions.

Demographics We collect county-level demographics data from various sources. Employment, income, and population data are from the Bureau of Economic Analysis (BEA). Data on age, sex, race, and hispanic origin shares are from the Census Bureau's U.S. Intercensal County Population data, hosted by the National Bureau of Economic Research (NBER). Education data is from the Census Bureau's Censuses of Population and the American Community Survey's (ACS) 5-year average county level estimates, prepared by the U.S. Department of Agriculture's (USDA) Economic Research Service. Until 2013 education data is only available at ten year intervals at the start of each decade, so data for years in between was linearly interpolated as 2003 was our primary year of interest for demographics controls. Broadband access data are estimates from the Arizona State University Center on Technology, Data and Society as exact county level data was not provided until the 2013 ACS. These estimates are only available for about 330 counties. Population density was calculated using 2011 land area data from the U.S. Census Bureau. Sometimes county designations change either by merging or splitting existing FIPS codes, primarily in Alaska and Virginia. In those instances we always aggregate these cases up to a single stable county.

Interest rates The data on the Federal Funds Effective Rate and the 10-year rate comes from the Federal Reserve Economic Data (FRED) maintained by the Federal Reserve Bank of St. Louis.

Fintech classification To classify lenders as FinTech or non-FinTech we combine the classifications of Fuster et al. (2019) and Buchak et al. (2018). Both follow similar procedures, manually classifying a lender as FinTech or non-FinTech based on whether the majority of the mortgage application process can be completed online without human participation from the lender. We take a liberal approach and classify a lender as FinTech if it is classified as FinTech in either of the

[5] This dataset was downloaded from Neil Bhutta's website. Please see therein for a full description of the data.

previous papers. We note that in applying this criterion no traditional banks end up being classified as FinTech. As shown in Table 14, the two largest shadow banks in 2016 (Quicken Loans and Loandepot.com) are fintech lenders, but 7 of the 10 largest non-banks are not classified as fintech.

3.2 Heterogeneous Bank Exposure to Declining Rates

The aggregate evidence in the introduction shows that the sharp increase in the shadow bank share of mortgage lending over the last two decades coincided with a decline in the aggregate net interest margin of banks. In order to draw a causal link between the compression in spreads and the response of banks' and shadow banks' lending, we turn to cross-sectional data, both at the bank level and at the regional level. The key idea is that the secular decline in interest rates had a more negative impact on banks holding assets whose yield declined by more, or funded by liabilities whose yield declined by less. We use a shift-share research design, based on the heterogeneous exposure of banks to declining interest rates stemming from historical difference in their balance sheet composition.

We construct a novel measure of each bank's exposure to declining rates and the resulting compression in spreads, as a Bartik or shift-share instrument that takes into account the persistence of the decline. Specifically, for each bank b, we construct

$$\tilde{e}_{bt} = \sum_{i \in I_A} \omega^i_{bt_0} \times \int_{t_0}^{t} \left[r^i_s - r^i_{t_0} \right] ds - \sum_{i \in I_D} \omega^i_{bt_0} \times \int_{t_0}^{t} \left[r^i_s - r^i_{t_0} \right] ds,$$

where $\omega^i_{bt_0}$ is bank b's balance sheet weight of category i, and r^i_t is the national average of category's i yield at time t. For instance, for transaction deposits r^i_t corresponds to the ratio of aggregate interest expense on these deposits over their aggregate amount. We use three asset categories in I_A: loans, securities, other assets (total assets minus loans and securities), and four liability categories in I_D: transaction deposits, saving deposits, time deposits, other liabilities (total liabilities minus the former three items). Therefore, $\tilde{e}_{bt}$ captures the predicted change in net interest income for a bank earning and paying the national average interest rate on each category, holding the initial balance sheet composition fixed. A compression of spreads between t_0 and t makes the exposure measure negative, and we will refer to a "larger" exposure when a bank has a larger $\tilde{e}_{bt}$ in absolute value.

Integrating over the path of the decline in rates, as opposed to just taking the difference between the end points, is important, as it allows us to take into account differences in the speed at which rates fall across categories. For instance, for a given 100 bps decline in the yield on some asset i between 2003 and 2016, the measure captures the fact that a bank would be more affected if most of the decline happened around 2003, and less affected if most of the decline occurred closer to 2016.

The measure $\tilde{e}_{bt}$ departs from the actual net interest income in two ways that are crucial for identification of causal effects: it is constructed using changes in *national* rates r_t^i and thus ignores differences in rates across banks, and it holds the balance sheet composition fixed. These two features largely mitigate concerns about bank-specific shocks that would affect their interest income or expenses, such as deposit or loan demand shocks, or changes in market power. For instance, all else equal, negative bank-level loan demand shocks contract both lending and loan rates, thereby inducing a positive correlation across banks between lending and realized net interest margins. Our exposure measure is not affected by such shocks because it does not use bank-specific loan or deposit rates. Using pre-determined balance sheet weights, instead of time-varying weights, corrects for the fact that balance sheets could endogenously change in response to lower rates, due to bank decisions or shifts in the demand for different savings products.

To further aid in identification we also adjust $\tilde{e}_{bt}$ and rely instead on a measure e_{bt} which lags the balance sheet weights by T years:

$$e_{bt} = \sum_{i \in I_A} \omega_{ibt_0 - T} \times \int_{t_0}^{t} \left[r_{is} - r_{it_0}\right] ds - \sum_{i \in I_D} \omega_{ibt_0 - T} \times \int_{t_0}^{t} \left[r_{is} - r_{it_0}\right] ds. \tag{6}$$

Thus, for our main specifications we regress bank-level outcomes (e.g., equity and lending growth) between 2003 and 2016 ($t_0 = 2003, t = 2016$) on e_{b2003}, which we construct using 1990 balance sheet weights ($T = 13$), and a set of 2003 controls.[6] Using lagged weights helps us capture the historical differences in banks' business models that expose them randomly to the declining rates trends two decades later. In particular, it addresses concerns that 2003 balance sheets could already be affected by the anticipation of the future decline in interest rates.

We are after a *long-run* effect of low rates on banks, hence we choose 2003 as initial year to start as early as possible in the declining interest rate trend after the 2001 recession. We end in 2016 to have a long enough period of falling rates before the hiking cycle beginning in 2017. Using a long horizon is helpful on several fronts. First, in in the short run, a fall in rates has potential counterveiling effects: for instance, lending could increase if revaluation gains on long-duration assets help relax some of banks' financial constraints.[7] Second, the impact of low rates on banks should take time to materialize and become detectable in the data. As one might be concerned

[6] We use lagged balance sheet weights from 1990 because the quality of transaction deposits data in the Call Reports improves substantially after 1987. Thus, 1990 is a long enough lag to plausibly help in identification, while allowing for an adjustment period following 1987.

[7] In principle we could control for banks' duration mismatch by using data on repricing maturity of assets and liabilities available after 1997, as in, e.g., English et al. (2018). The issue is that this measure would overestimate banks' exposure to interest rates if the effective duration of deposits exceeds the contractual duration (Drechsler et al., 2021).

though that the period 2003-2016 contains both the housing boom and the financial crisis, we also show that all the main results in the paper hold for the post-crisis 2010-2016 period.

3.3 Overview of the Specifications

We vary the level of aggregation and the data sources on lending to show that our results hold in a range of settings. We start with bank-level regressions using Call Reports data, before incorporating mortgage data from HMDA to run bank-county and county-level regressions.

Bank-level regressions For the bank-level results, we first estimate equations of the form:

$$\Delta y_{bt} = \alpha + \beta e_{bt} + controls_{bt_0} + u_{bt}, \tag{7}$$

where Δy_{bt} is a bank-level outcome, such as portfolio lending growth from t_0 to t. For our main analysis, we use long differences from 2003 to 2016. We also show robustness results where we change the period of analysis. The variables in $controls_{bt_0}$ help control for banks' different business models and sectors, which can potentially experience demand shocks correlated with our exposure variable e_{bt}. For convenience, the exact set of controls is discussed when we present the results.

Bank-region regressions We then incorporate regional, loan-level, mortgage data to run bank-region level regressions. The main advantage of the regional data relative to the bank-level analysis (7) is that it allows us to add granular region fixed effects to absorb any credit demand shock operating at the regional level, as in Khwaja and Mian (2008). Specifically, we estimate equations of the form:

$$\Delta y_{cbt} = \alpha_c + \beta e_{bt} + controls_{bt_0} + u_{cbt}, \tag{8}$$

where Δy_{cbt} is a bank-county level outcome, such as the growth in portfolio origination counts of bank b in region c between t_0 and t, and α_c is a region fixed effect. The latter absorbs any credit demand shock at geographic level c between t_0 and t. Thus, in this specification β is identified from the comparison of banks serving the same narrowly defined housing market but differentially exposed to declining interest rates.[8]

County-level regressions For the regional, county-level, regressions we use a "nested Bartik" strategy. We aggregate bank exposures up to the county level to construct a county-level

[8] This is in the same spirit as Mian and Sufi (2021); see also Mian et al. (2022) for a more detailed analysis of the relationship between bank and bank-region level specifications.

exposure e_{ct}. This allows us to run regressions of the form:

$$\Delta y_{ct} = \alpha + \beta e_{ct} + controls_{ct_0} + u_{ct}, \tag{9}$$

where Δy_{ct} is a county-level outcome, such as the change in the shadow bank share of residential mortgage lending between t_0 to t, and:

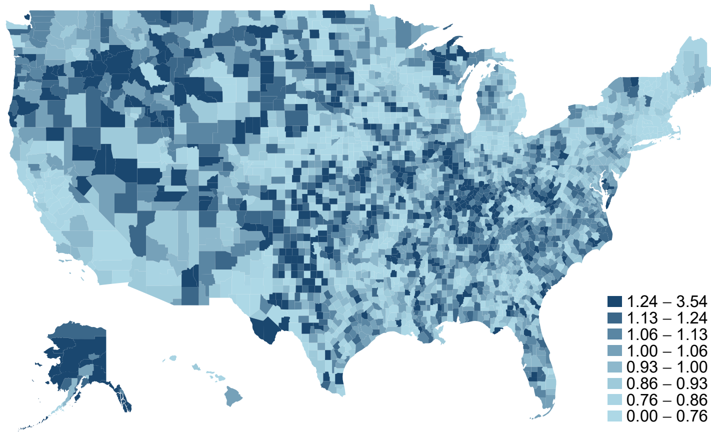
$$e_{ct} = \sum_{b \in B_{ct_0}} l_{cbt_0} e_{bt}, \tag{10}$$

is the county-level exposure, with l_{cbt_0} bank b's share of total mortgage lending in region c at time t_0. Given that shadow banks are already present at t_0, the initial total bank share of a region's lending does not sum up to one so we include $\sum_{b \in B_{ct_0}} l_{cbt_0}$ in $controls_{ct_0}$.

The identification assumption is that banks' balance sheets in 1990 are orthogonal to local credit supply and demand shocks in 2003-2016 in their main counties of activity. This is similar in spirit to the arguments in Borusyak et al. (2021) and Goldsmith-Pinkham et al. (2020), but because of the nested Bartik structure of the instrument it does not fit exactly within those frameworks. These regressions do not rely on the exogeneity of the l_{cbt_0} shares (Goldsmith-Pinkham et al., 2020) nor on the exogeneity of the aggregate shocks $\int_{t_0}^{t} [r_{is} - r_{it_0}]\, ds$ (Borusyak et al., 2021), but on the exogeneity of the lagged balance sheet weights, ω_{ibt_0-T}.

Figure 2 shows a heat map of the county-level exposure e_{ct} for the period 2003-2016. To make it easier to follow we multiply the generally negative exposure e_{ct} by -1, so that higher positive values represent larger exposures. As the figure shows, there is significant variation across the U.S., both within and across states. Even though many of the more exposed counties are located towards the midwest, west and southeast, there are highly exposed counties outside those regions as well.

Reduced-form strategy The main specifications in this paper are "reduced-form", in the sense that outcomes are regressed directly on the exposure measure. The reason is that it is not clear exactly which variable (e.g., net income, unweighted or risk-weighted capital, etc.) should mediate the variation of the instrument on the outcomes. Moreover, it is likely that multiple variables are involved, hence identifying the separate channels, or attempting to single out one of them as the main one, would impose unnecessarily strong assumptions. We do however study in depth the variation coming from the exposure measure and provide a number of results that help understand where the variation is coming from. Among other variables, we look at the direct effect on profitability through the cumulative decline in net income, which is likely involved in mediating the effect of the exposure measure according to standard models of financially constrained banks.



Note: The figure shows the heat map of the county-level exposure e_{ct} for the period 2003-2016. The county-level exposure is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003. For simplicity, the e_{bt} are multiplied by -1, so higher values represent larger exposures.

Figure 2: Distribution of exposures.

Summary statistics Table 1 presents summary statistics at the bank (Panel A) and county (Panel B) levels. Columns (1) and (2) show the mean and standard deviations for all the observations in the sample, respectively. Columns (3) and (4) report the means for the cross-sectional units whose exposure is below and above the median exposure, respectively.

Panel A shows that the average exposure at the bank level, e_{bt} in equation (6), is -1.2% with a standard deviation of 0.6% (i.e., roughly 9.25 basis points per year) in line with the decrease in the aggregate net interest margin over the same period. Among the banks in the more exposed half of the sample, the exposure climbs to -1.7% (13 basis points per year) versus -0.7% (5.4 basis points per year) in the less exposed half.

The panel also shows that equity, assets, and its main components (loans, securities, and all other assets) all experienced similar growth, roughly doubling between 2003 and 2016. This is also true for real estate loans and commercial & industrial (C&I) loans, but not for personal loans which remained largely stagnant, and holdings of mortgage backed securities, which increased much more aggressively. As columns (3) and (4) show, with the exception of personal loans, all the growth rates are lower for banks that were more exposed to the compression in spreads. For example, the equity growth rate was 124% for banks with an exposure below the median, but only 111% for banks with an exposure above the median.[9] In Section 4 we examine these patterns more systematically.

Panel B shows that the average exposure at the county level, e_{ct} in equation (10), is -1% with a standard deviation of 0.2%. This amounts to an average compression of 7.7 basis points per year. The exposure equals 9.2 basis points per year in counties with above median exposure, and falls

[9] Of course much of the growth is coming from the growth of the economy, as we show raw numbers for growth rates instead of normalizing by GDP.

Table 1: Summary Statistics

Panel A: Bank-level Variables	All		Low Exposure	High Exposure
	Mean	St. Dev.	Mean	Mean
	(1)	(2)	(3)	(4)
Exposure (e_{bt})	-0.012	0.006	-0.007	-0.017
Equity Growth	1.181	0.935	1.240	1.107
Asset Growth	0.975	0.764	1.003	0.941
Loans Growth	1.117	0.993	1.136	1.095
Securities Growth	0.828	1.192	0.854	0.798
Other Assets Growth	1.243	1.138	1.244	1.242
Real Estate Loans Growth	1.462	1.336	1.482	1.437
Consumer/Industrial Loans Growth	1.134	1.590	1.191	1.065
Personal Loans Growth	−0.067	0.608	−0.080	−0.051
Mortgage Backed Securities Growth	4.190	11.586	4.450	3.855
Observations	4,185	4,185	2,092	2,093

Panel B: County-level Variables	All		Low Exposure	High Exposure
	Mean	St. Dev.	Mean	Mean
	(1)	(2)	(3)	(4)
Exposure (e_{ct})	−0.010	0.002	−0.008	−0.012
Outcome Variables				
Change in Shadow Bank Share - All Loans	0.165	0.140	0.145	0.185
Change in Shadow Bank Share - GSE Loans	0.373	0.177	0.358	0.388
Change in Shadow Bank Share - NonGSE Loans	0.011	0.162	−0.008	0.029
Demographic Controls				
Hispanic share	0.069	0.124	0.073	0.065
Native American share	0.020	0.076	0.017	0.023
Black share	0.088	0.145	0.087	0.089
Asian share	0.010	0.025	0.012	0.008
Male share	0.497	0.020	0.497	0.498
Below age 35 share	0.455	0.057	0.458	0.452
Above age 65 share	0.149	0.041	0.147	0.151
Only a high school share	0.342	0.069	0.341	0.342
Some college share	0.266	0.053	0.265	0.268
Bachelor's degree or more share	0.169	0.072	0.171	0.168
Economic Indicators				
Total Lending	1,067,051	5,283,643	1,551,226	583,189
Employment	53,454	184,230	66,578	40,296
Personal Income	3,057,794	10,987,527	3,972,330	2,140,898
Population	93,463	302,912	119,123	67,736
Observations	3,096	3,096	1,548	1,548

The table reports summary statistics on measures at the bank-level in Panel A and at the county-level in Panel B. Column (1) reports the mean for all the observations in the sample. Column (2) reports the standard deviation for all the observations in the sample. Column (3) restricts the sample to the banks (counties) with exposure measures e_{bt} (e_{ct}) less than the median in absolute value terms and reports the mean. Column (4) restricts the sample to the banks (counties) with exposure measures e_{bt} (e_{ct}) greater than or equal to the median in absolute value terms and reports the mean. In Panel B, all Demographic Controls and Economic Indicators variables are in 2003. The period considered for growth/change variables in both panels is 2003-2016.

to 6.2 basis points per year for counties with below median exposure. During the 2003-2016 period, we see that the shadow bank market share of residential mortgage lending increased by 16.5 percentage points on average, with a standard deviation of 14 percentage points. In more exposed counties, the shadow bank share rises by 18.5 percentage points, but only by 14.5 percentage points in less exposed counties. In Section 5 we look at these relationships in depth.

Panel B also shows that high-exposure and low-exposure counties share very similar demographic characteristics, but counties with a higher exposure tend to have smaller populations, with lower incomes and lending. To avoid any bias coming from these differences, we include these demographic variables as controls in all our specifications. Our results are also robust to omitting these controls.

4 The Decline in Bank Lending

The persistent decline in interest rates over the last decades led to a compression in spreads and thus a negative exposure e_{bt} for the vast majority of banks. Recent studies argue that the compression in spreads can force banks to contract lending in the long run due to the negative impact of lower spreads on their equity (Abadi et al., 2022; Wang, 2022). In this section we show that affected banks indeed contracted their portfolio lending relative to less exposed banks.

To test this mechanism we first conduct a bank-level analysis and estimate equation (7) using the growth rates of various balance sheet items in the Call Reports as dependent variables. This allows us to look directly at the reaction of banks' portfolio lending and its different components.

After the bank-level analysis, we turn to the geographical cross-section and conduct a bank-region level analysis in the context of the mortgage market. The bank-region level analysis confirms the bank-level results. It requires us to focus on a particular product (mortgages); the advantage is that we can compare banks that serve the same housing market but differ in their exposure, alleviating concerns about unobserved demand shifters that might be correlated with the exposure measure.

4.1 Bank-level Results

Table 2 presents the results of estimating equation (7):

$$\Delta y_{bt} = \alpha + \beta e_{bt} + controls_{bt_0} + u_{bt},$$

on the asset side of the balance sheet during the period 2003-2016, and presents the main asset classes separately. In all the bank-level regressions we control for banks' equity ratio (equity divided by assets), bank size (log assets), the ratio of loans to assets, and the expense beta.[10][11] The first three variables help control for banks' different business models, which could potentially be correlated with loan demand. The expense beta allows us to control for the "deposit channel" (Drechsler et al., 2017). Since we are looking at the effects of a decline in rates, the deposit channel would predict that banks with deposit market power would reduce the spreads they charge on deposits, increase their stable and cheap deposit funding, and increase their portfolio lending as a result. If the expense beta is correlated with our exposure variable the deposit channel would bias our results. Moreover, we weight regressions by total loans in 2003 to be consistent with the bank and bank-region regressions that follow, as well as with the regional regressions of Section 5. This is also important for the aggregate relevance of our results given the highly skewed bank size distribution.

Column (1) shows a very strong and positive relationship between asset growth and the exposure measure, meaning that more exposed banks experienced lower asset growth over the period. The coefficient, at 20.772, is highly significant and, in terms of magnitudes, it implies that the asset growth of a bank that suffered a 100 basis point compression in spreads was approximately 21 percentage points lower than that of an unexposed bank. Thus, conditional on starting with the same balance sheet size, more exposed banks saw smaller balance sheets by the end of the period.

Columns (2)-(4) look at total loans, securities holdings and other assets (total assets minus the two former items). Column (3) shows that more exposed banks also had lower portfolio lending growth, at a magnitude that is higher than the one observed for overall assets and for equity. In this case, the portfolio lending of a bank that suffered a 100 basis point cumulated decline in spreads over the period grew 56 percentage points less compared to that of a bank that had no exposure. Column (4) shows that this trend also holds for securities holdings, which decreased by 22 percentage points for each 100 basis point cumulated decline. Column (5) shows a picture for the remaining assets that is in between portfolio lending and securities holdings, with a 44 percentage point decline.

Table 3 dives deeper in the balance sheet and looks at subcategories from various items in Table 2. Columns (1) through (3) focus on the different loan subcategories: real estate, commercial and industrial, and personal loans. Column (4) looks within securities holdings and focuses on MBS holdings in particular. Finally, column (5) looks at the change in the ratio of loans to assets.

Column (1) shows that the overall decline in portfolio lending is roughly matched by what happened with real estate loans. The point estimate is 60.846 for the latter, against 56.321 for

[10] See Appendix A.5 for a detailed description of the expense beta.

[11] Since the betas are estimated, we are running regressions such as (7) with generated regressors. We adjust the standard errors to account for the uncertainty involved in estimating the betas by using the same block bootstrap approach as Drechsler et al. (2021), and show results based on 1,000 samples.

Table 2: Exposure and bank-level outcomes 2003-2016

	Asset Growth (1)	Loans Growth (2)	Securities Growth (3)	Other Assets Growth (4)
Exposure (e_{bt})	20.772***	56.321***	22.671***	43.804***
	(3.719)	(6.363)	(3.800)	(4.296)
	Covariates			
Balance Sheet Controls	Yes	Yes	Yes	Yes
Expense Beta	Yes	Yes	Yes	Yes
N	3,407	3,414	3,407	3,415
R-sq	0.129	0.188	0.086	0.085

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the bank level, with weights equal to the loans in dollar amounts of each bank in 2003, relating the change in balance sheet item to the exposure measure e_{bt}. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results on the bank-level asset growth. Column (2) reports results on the bank-level loans growth. Column (3) reports results on the bank-level securities growth. Column (4) reports results on the bank-level other assets growth. All specifications include controls for balance sheet measures (equity to assets ratio, log assets, and loan to assets ratio), and the expense beta. All outcome variables, as well as the exposure measure e_{bt}, were trimmed at the 5% level. The expense beta was trimmed at the 1% level. The period considered is 2003-2016. Bootstrap standard errors based on 1,000 simulations are below the coefficients in parentheses.

Table 3: Exposure and bank-level outcomes 2003-2016

	Real Estate Loans Growth (1)	Commercial/Industrial Loans Growth (2)	Personal Loans Growth (3)	Mortgage Backed Securities Growth (4)	Loans-Assets Ratio Growth (5)
Exposure (e_{bt})	60.846***	77.202***	-10.159	247.788***	0.781
	(7.448)	(16.519)	(6.971)	(45.602)	(0.593)
	Covariates				
Balance Sheet Controls	Yes	Yes	Yes	Yes	Yes
Expense Beta	Yes	Yes	Yes	Yes	Yes
N	3,404	3,408	3,421	2,924	3,280
R-sq	0.078	0.229	0.340	0.098	0.275

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the bank level, with weights equal to the loans in dollar amounts of each bank in 2003, relating the change in balance sheet item to the exposure measure e_{bt}. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results on the bank-level real estate loans growth. Column (2) reports results on the bank-level commercial and industrial loans growth. Column (3) reports results on the bank-level personal loans growth. Column (4) reports results on the bank-level mortgage backed securities growth. Column (5) reports results on the bank-level change in loan to asset ratio. All specifications include controls for balance sheet measures (equity to assets ratio, log assets, and loan to assets ratio), and the expense beta. All non-ratio outcome variables, as well as the exposure measure e_{bt}, were trimmed at the 5% level. The expense beta was trimmed at the 1% level. The period considered is 2003-2016. Bootstrap standard errors based on 1,000 simulations are below the coefficients in parentheses.

loans overall, and highly significant. This large decrease in portfolio real estate lending growth of more exposed banks is one of the closest points of contact between the bank level results in this section and the results in Section 5, which focus on the increase in market share of shadow banks in the residential mortgage market. Column (2) shows that the decrease in real estate lending growth for more exposed banks is also present in C&I loans. The coefficient is slightly larger at 77.202. Column (3) shows that for personal loans the picture is different, with a negative coefficient but much smaller and statistically indistinguishable from zero.

Column (4) looks deeper within securities and focuses on MBS holdings. Given that banks could choose between how much portfolio real estate lending to do directly vis-a-vis how much to fund indirectly through MBS, the contraction in lending in column (1) could be partly counterbalanced by increased holdings of MBS. However, the coefficient in column (4) shows that MBS holdings also fell for more exposed banks. Thus, these results indicate that as a result of the declining rates, affected banks decreased funding for real estate loans across the board.

Finally, column (5) shows the impact of the exposure variable in the loans to assets ratio. Consistent with the results from Table 2, which estimated a sharper decline for portfolio lending than for the size of the balance sheet, column (5) shows that the loans to assets ratio decreased for more exposed banks. However, the estimate is not statistically significant.

4.2 Bank-Region Results

In this section we take a first look at the cross-sectional data coming from HMDA on residential mortgage originations. The bank-county level regressions allow us to add granular region fixed effects as in (8):

$$\Delta y_{cbt} = \alpha_c + \beta e_{bt} + controls_{bt_0} + u_{cbt},$$

to absorb any credit demand shocks operating at the county level. Thus, these results reinforce the previous bank-level results using the Call Reports, by controlling for potential confounders in a more direct manner and showing that the results hold for a different dataset. Thus, in this specification β is identified from the comparison of banks serving the same narrowly defined housing market but differentially exposed to the declining spreads.

Table 4 presents the results of estimating equation (8) for the period 2003-2016. Column (1) focuses on overall lending, while Column (2) zooms in on portfolio lending. In order to difference out the correct county-level demand shock, we follow Mian and Sufi (2021) and weigh each bank-county observation within a county by its origination share in 2003.[12] Moreover, to focus exclusively on quantities we work with origination counts, although the exact same

[12] We also follow them in restricting attention to bank-counties with at least 10 mortgage originations. Given that we apply the cutoff at the county-level, instead of at the census-tract-level, the cutoff is more conservative.

Table 4: Bank-County Growth 2003-2016

	All Loans Growth (1)	Portfolio Loans Growth (2)
Exposure (e_{bt})	3.257***	8.034***
	(0.595)	(2.321)
	Covariates	
County FE	Yes	Yes
Balance Sheet Controls	Yes	Yes
Expense Beta	Yes	Yes
N	45,017	36,902
R-sq	0.191	0.063

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the bank-county level, with weights equal to the banks' l_{cb} used in the exposure measure e_{ct}, relating the change in the origination counts to the exposure measure e_{bt}. The bank level exposure e_{bt} is derived from Call Report data following equation (6). All specifications include county fixed effects, controls for balance sheet measures (equity to assets ratio, log assets, and loan to assets ratio), and the expense beta. The period considered is 2003-2016. Robust standard errors are below the coefficients in parentheses.

patterns hold for dollar amounts.

Column (1) shows a significant point estimate of 3.257. Thus, in line with the results in the previous section, two banks that serve the same narrowly defined housing market behaved very differently depending on their exposure to the compression in spreads. In particular, more exposed banks grew their overall originations by less during the period. Moreover, the county fixed effects ensure that this difference is not driven by demand shocks at the county level. Turning to column (2), we see that the point estimate is larger at 8.034 and also highly significant. That is, within a county, more exposed banks also grew their originations of portfolio loans by less during the period, and the effect is stronger than that of overall originations.

5 The Rise of Shadow Banks

The results in the previous section show that the decline in spreads forced banks to contract portfolio lending and their overall balance sheet. The literature on the harmful effects of low interest rates has focused on commercial banks, without examining the reaction of non-bank intermediaries. In this section, we turn to the residential mortgage market and show that the lower lending capacity of exposed banks triggered a strong positive response from their shadow bank competitors.

We look at originations in the HMDA dataset and focus on the shadow bank share of residential mortgage lending:

$$(11) \qquad y_{ct} = \frac{\text{SB originations}_{ct}}{\text{All originations}_{ct}}.$$

Following Mian and Sufi (2021) we classify lenders as banks or shadow banks based on their regulatory agency.[13]

We estimate equation (9):

$$\Delta y_{ct} = \alpha + \beta e_{ct} + controls_{ct_0} + u_{ct},$$

using the change in this share $y_{c2016} - y_{c2003}$ as the dependent variable. Given that the dependent variable is a change in a share, we include the initial shadow bank share in 2003, y_{c2003}, as a control. We use dollar amounts to measure originations (number of loans times size of loans) but, as we show below, focusing on counts instead delivers the same overall picture. This is to be expected, since the variables involved are ratios.

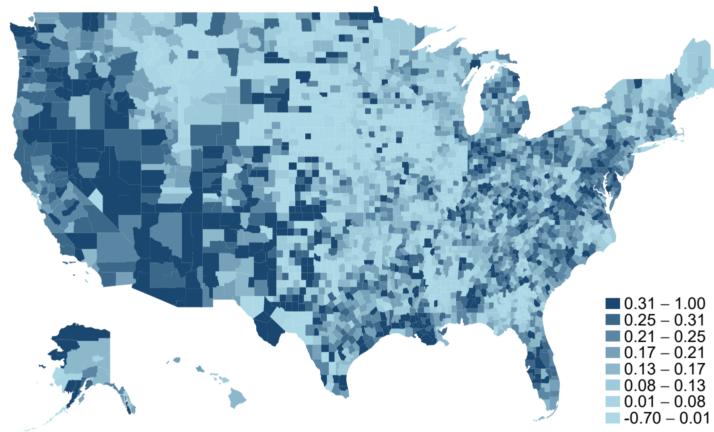
5.1 Overall Shadow Bank Share

We start by looking at the overall shadow bank share, including both refinancing and home purchases loans, and not distinguishing between "GSE loans", e.g. those sold to Fannie Mae and Freddie Mac, and other "non-GSE" loans. Figure 3 presents a heat map of the change in the overall shadow bank share at the county level between 2003 and 2016. As with the county-level exposure, there is significant variation both within and across U.S. states. Counties towards the west, midwest and southeast tend to see the larger increases in the shadow bank share, but many counties experienced increases in the northeast and southwest as well.

Figure 4 shows a binned scatter plot of the change in the overall shadow bank share against the county-level exposure e_{c2016}, controlling for the initial shadow bank share in 2003. There is a strong negative relationship between the two variables: counties with more exposed banks saw a stronger increase in the shadow bank share, by around 10% for every additional 100 bps in the exposure over the period. This result supports the idea that shadow banks gained significant territory in housing markets where banks were hurt by the decline in interest rates.

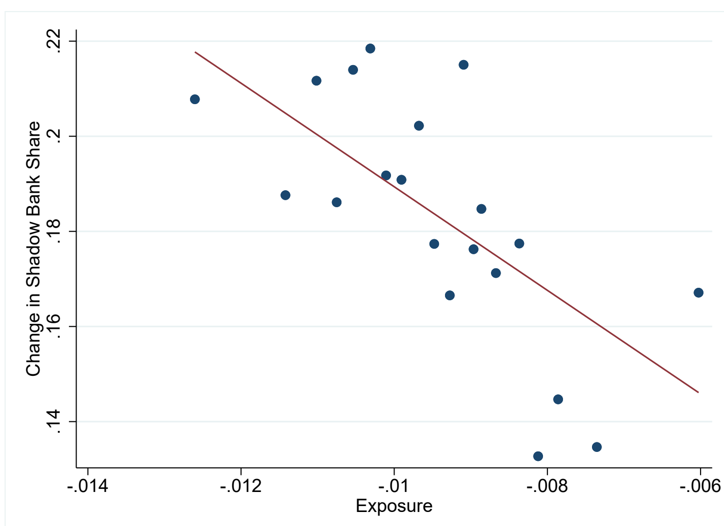
Table 5 shows the regression results behind Figure 4 in column (1), as well as more stringent

[13] Loans regulated by the Office of the Comptroller of the Currency (OCC, agency code 1), Federal Reserve System (FRS, agency code 2), the Federal Deposit Insurance Corporation (FDIC, agency code 3), and the Consumer Financial Protection Bureau (CFPB, agency code 9) are considered bank loans. Loans regulated by the U.S. Department of Housing and Urban Development (HUD, agency code 7) are considered shadow bank loans. Loans from thrifts and credit unions, regulated by the Office of Thrift Supervision (OTS, agency code 4) and the National Credit Union Administration (NCUA, agency code 5) respectively, were considered separately.



Note: The figure shows the heat map of the county-level change in the overall shadow bank share for the period 2003-2016. For each county c, the change is computed following equation (11).

Figure 3: Distribution of change in shadow bank shares.



Note: The figure shows a binned scatter plot of the change in the overall shadow bank share against the county-level exposure e_{ct} for the period 2003-2016, controlling for the initial shadow bank share in 2003. The county-level exposure is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003.

Figure 4: Exposure and shadow bank share.

specifications in columns (2) and (3). We weight regressions by population in our preferred specifications, and show robustness results for other weighting schemes below. In column (1) we estimate a parsimonious specification in which we only include the 2003 shadow bank share as a control. Columns (2) and (3) show that these results are robust to including an increasingly stringent set of controls. In column (2) we add the following demographic controls: the population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelors degree or more. In column (3) we add indicators for the economic conditions in 2003: we control for log population, total lending in dollar amounts, personal income, and employment, all dated in 2003. These set of variables help control for characteristics that could be correlated with local demand and supply shocks during the period. Comparing columns (2) and (3) with column (1), we see that the effect of the exposure is almost unchanged by these characteristics.

Table 5: Change in Shadow Bank Share 2003-2016

	Shadow Bank Share		
	(1)	(2)	(3)
Exposure (e_{ct})	-10.890***	-9.557***	-11.846***
	(2.553)	(2.192)	(1.653)
	Covariates		
Initial SB share	Yes	Yes	Yes
Demographics		Yes	Yes
Economic Indicators			Yes
N	3,099	3,098	3,098
R-sq	0.034	0.151	0.235

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the county level, with weights equal to the population of each county, relating the change in shadow bank market share to the exposure measure e_{ct}. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results controlling only for the initial shadow bank share in 2003. Column (2) reports results with the addition of 2003 demographic controls (population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelor's degree or more). Column (3) reports results further controlling for economic indicators in 2003 (total lending in dollar amounts, employment, personal income, and population). The period considered is 2003-2016. Robust standard errors are below the coefficients in parentheses.

Controlling for regulation The first factor behind the large increase in the shadow bank share documented in the literature (Buchak et al., 2018) is the increased regulatory burden faced by banks after the GFC. One potential issue could be that our exposure variable would actually be picking up variation coming from the increase in regulation. To rule out this concern we follow Buchak et al. (2018) in Table 6 and present tests using various measures of regulatory burden. In all of these tests we keep the whole set of demographic and economic indicators from the more stringent specification in column (3) of Table 5.

Table 6: Change in Shadow Bank Share 2003-2016

	Shadow Bank Share			
	(1)	(2)	(3)	(4)
Exposure (e_{ct})	-13.022***	-12.996***	-10.854***	-12.936***
	(1.781)	(1.759)	(1.719)	(1.891)
	Covariates			
OTS	Yes			Yes
T1RBC		Yes		Yes
MSR			Yes	Yes
N	3,098	3,098	3,098	3,098
R-sq	0.236	0.242	0.240	0.249

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the county level, with weights equal to the population of each county, relating the change in shadow bank market share to the exposure measure e_{ct}. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results controlling for the share of originated loans regulated by the Office of Thrift Supervision (OTS) in 2003. Column (2) reports results controlling for the change in the county-level tier 1 risk-based capital ratio (T1RBC) between 2003 and 2016. Column (3) reports results controlling for the county-level mortgage servicing rights (MSR) as a percentage of tier 1 capital in 2003. Column (4) reports results controlling for all three measures. All specifications include controls for the initial shadow bank share, demographics, and economic indicators. The period considered is 2003-2016. Robust standard errors are below the coefficients in parentheses.

Column (1) in Table 6 adds the county-level share of originations regulated by the Office of Thrift Supervision (OTS) in 2003 as a control. In the early 2000s the OTS became increasingly linked with initiatives that relaxed the regulatory standards imposed upon the depositary institutions it regulated (Granja and Leuz, 2017). This motivates Buchak et al. (2018) to use the OTS share as a measure of the regulatory shock received by a county after the OTS was dissolved during the financial crisis, when its duties were passed on to stricter agencies: the Office of Comptroller and Currency (OCC), Federal Deposit Insurance Corporation (FDIC), Federal Reserve, and Consumer Financial Protection Bureau (CFPB). Comparing the estimates in column

(1) with the results in Table 5 we see that the coefficient on exposure is almost unchanged.

In column (2) we control for the change in the county-level tier 1 risk-based capital ratio (T1RBC) between 2003 and 2016. We compute the county-level T1RBC by first computing the bank-level change in T1RBC, and then averaging those using the l_{cbt_0} weights as in (10). The 2010 Dodd-Frank Act imposed minimum risk-based capital requirements on traditional banks, which resulted in an increase in the average T1RBC of US banks. Buchak et al. (2018) argue that counties with a larger increase in T1RBC saw larger increases in shadow bank shares, because banks retracted from lending in order to increase their T1RBC. Column (2) shows that controlling for the change in T1RBC has practically no effect on the exposure coefficient.

In column (3) we control for the county-level mortgage servicing rights (MSR) as a percentage of tier 1 capital in 2003. As before, we first compute for each bank in a county their MSR as a percentage of tier 1 capital, and then take a weighted average using the l_{cbt_0} loan weights as in (10). Following Basel III guidelines, the Federal Reserve Board increased the risk weight on MSR assets which forced banks to hold more capital against MSR. Buchak et al. (2018) argue that counties with banks that had a high initial share of MSR saw a larger impact from the increased regulation, which led to a stronger growth of shadow banks. Comparing the coefficient in column (3) with the previous columns we see that the point estimate is now slightly below the value in column (3) of Table 5, instead of slightly above, but is practically unchanged.

In column (4) we include all these variables simultaneously and find that again, the exposure coefficient barely changes. Thus, we conclude that the variation of our measure of exposure to the decline in spreads is unlikely to simply capture the increased regulatory burden experienced by traditional banks after the financial crisis.

Controlling for technology The second leading explanation for the large increase in the shadow bank share is the technological advantage of shadow banks over traditional banks (Buchak et al., 2018). We rule out that our measure of exposure is indirectly capturing variation related to technological differences by performing two tests. In the first one, we control for variables that proxy for the receptiveness of a county to new technologies. Following Fuster et al. (2019), we include in our main specifications the population density of a county and its broadband access, both as of 2003. In the second test, we look specifically at the market share of *non-fintech* shadow banks. Fintech lenders are those that primarily originate mortgages online, and are most likely to rely on recent "big data" technology to screen borrowers. If our exposure variable is mostly picking up technological trends in online lending, the effects we find should be concentrated on fintech lenders.

Table 7 presents the results of adding the population density and broadband access measures as controls in the baseline specification (column (3) of Table 5) in its columns (1) through (3). Column (1) shows that the point estimate is practically unchanged if we control for the pop-

Table 7: Change in Shadow Bank Share 2003-2016

	Shadow Bank Share			Non-Fintech Shadow Bank Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure (e_{ct})	-11.425***	-24.758***	-24.910***	-9.079***	-8.597***	-10.838***
	(1.607)	(5.515)	(5.189)	(2.154)	(1.796)	(1.429)
	Covariates					
Pop. Density	Yes		Yes			
Broadband Access		Yes	Yes			
Initial SB share	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes		Yes	Yes
Economic Indicators	Yes	Yes	Yes			Yes
N	3,076	216	215	3,099	3,098	3,098
R-sq	0.284	0.549	0.599	0.024	0.143	0.259

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the county level, with weights equal to the population of each county, relating the change in shadow bank market share to the exposure measure e_{ct}. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results controlling for the population density of the county in 2003. Column (2) reports results controlling for the share of the population with access to broadband in 2003. Column (3) reports results controlling for both measures. Column (4) reports results on the non-fintech shadow bank share controlling only for the initial shadow bank share in 2003. Column (5) reports results on the non-fintech shadow bank share with the addition of 2003 demographic controls (population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelor's degree or more). Column (6) reports results on the non-fintech shadow bank share further controlling for economic indicators in 2003 (total lending in dollar amounts, employment, personal income, and population). The period considered is 2003-2016. Robust standard errors are below the coefficients in parentheses.

ulation density of the county. Column (2) shows that the coefficient increases in absolute value, but the sample size drops dramatically in these specifications because the broadband access data is unavailable for 90% of the counties. In this case, the estimated effect is more strongly negative and statistically significant. Finally, column (3) adds both controls simultaneously and the results are essentially the same as those in column (2).[14]

Columns (4) through (6) present the parallel results from Table 5 but now focusing exclusively on non-fintech shadow banks. As in Table 5, we start with a parsimonious specification in column (1) that only controls for the initial shadow bank share, and we progressively add the demographic and economic controls in columns (5) and (6). If we compare the three columns across the two tables, the coefficients are statistically indistinguishable from each other. There is the same strong negative relationship between the exposure to lower spreads and the rise in the market share of non-fintech shadow banks.

The takeaway is that our results are unchanged when controlling for common proxies of technological improvements or focusing on non-fintech lenders. We conclude that the effect of the exposure to lower spreads is unlikely to be driven by technological advances in online

[14] Where we note the sample size is still 10% of the whole sample because of the broadband access measure.

lending.

5.2 Shadow Bank Growth at the Intensive and Extensive Margins

We showed that counties with more exposed banks saw larger increases in the shadow bank market share of their mortgage market. In this section we unpack the rise in the market share into an intensive margin, i.e., the rise of incumbent traditional and shadow banks already present in the county in 2003, and an extensive margin, i.e., lenders entering the county after 2003. We show that incumbent banks decreased their volumes, while incumbent shadow banks increased theirs, resulting in an increase in the shadow bank share among incumbents. Moreover, highly exposed counties saw larger flows of entrants, with higher shares of shadow banks among their entrants. Thus, even though exposed counties saw larger inflows of shadow banks, less exposed traditional banks also increased their market share.

Intensive margin Table 8 presents the results for the incumbents, defined as the lenders already present in 2003. Column (1) through (3) look at the county-level growth rate of lending from incumbent banks, whereas columns (4) through (6) do the same for incumbent shadow banks. Columns (7) through (9) look at their combined volumes.[15] Columns (10) through (12) look at the change in the shadow banks share among incumbents.

Columns (1) through (3) show strongly positive and significant coefficients. These estimates confirm the notion that counties in which banks were more exposed to declining rates saw lower lending volumes growth. Columns (4) through (6), in turn, show strongly negative and significant coefficients, confirming that lending volumes by incumbent shadow banks increased strongly in those counties. Columns (7) through (9) show a decline for the combined volumes. The coefficient in column (9) at 6.098 is highly significant, and is below the point estimate in column (3), as expected. Columns (10) through (12) show a strong increase in the shadow bank share among incumbents, with a point estimate of -46.202, which is highly significant, in column (12). This is to be expected since, from previous columns, we know that traditional banks' lending volumes declined while shadow banks' volumes increased.

Hence, Table 8 shows that, if we restrict the analysis to incumbents, the market share of shadow banks increased markedly. This, in turn, is due to a strong decline in volumes by the affected (incumbent) banks, and a strong increase in volumes by (incumbent) shadow banks. Moreover, their combined volumes also show a clear decline, meaning the rise in volumes from (incumbent) shadow banks is not enough to substitute for the decline in affected (incumbent) banks.

[15] As in Section 4.2 we use origination counts to focus on quantities. Moreover, because these are growth rates, instead of changes in shares, we keep the 10 loan cutoff at the county-level. See footnote 12 for further details.

Table 8: Incumbent Bank and Shadow Bank Volumes 2003-2016

	Bank Loan Growth			Shadow Bank Loan Growth			Bank + Shadow Bank Loan Growth			Change in Shadow Bank Share (Incumbents)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exposure (e_{ct})	10.786***	8.920***	10.494***	-11.498***	-9.451***	-8.154***	4.192***	4.328***	6.098***	-57.295***	-41.885***	-46.202***
	(1.387)	(1.327)	(0.976)	(2.412)	(2.584)	(2.749)	(1.036)	(1.038)	(0.923)	(6.945)	(6.819)	(4.857)
Covariates												
Initial SB Share	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Economic Indicators			Yes			Yes			Yes			Yes
N	2,849	2,849	2,849	2,172	2,172	2,172	2,854	2,854	2,854	2,227	2,227	2,227
R-sq	0.086	0.116	0.186	0.022	0.051	0.083	0.020	0.040	0.081	0.117	0.203	0.297

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the county level, with weights equal to the population of each county, relating the growth in loan volume (in columns (1) through (9)) and the change in shadow bank share (among incumbents, in columns (10) through (12)) to the exposure measure e_{ct}. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Columns (1), (4), (7), and (10) report results controlling for the initial bank share coming from the sum of the weights in the exposure measure e_{ct}. Columns (2), (5), (8), and (11) report results with the addition of 2003 demographic controls (population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelor's degree or more). Columns (3), (6), (9), and (12) report results further controlling for economic indicators in 2003 (total lending in dollar amounts, employment, personal income, and population). The period considered is 2003-2016. Robust standard errors are below the coefficients in parentheses.

Extensive margin In Table 9 we look at the dynamics coming from entrants, i.e., traditional and shadow banks that were not present in 2003 but started lending in the county at some point between 2003 and 2016. Columns (1) through (3) look at the entrant share, i.e., the fraction of loans in 2016 that is coming from lenders that entered the county after 2003. In columns (4) through (6) we look at the shadow share of the entrants, i.e., the shadow bank share of the entrants to the county.

Table 9: Entrants and their Composition 2003-2016

	Entrant Share 2003-2016			Shadow Bank Share of Entrants 2003-2016		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure (e_{ct})	-12.847***	-15.875***	-23.435***	-19.189***	-7.002*	-6.977***
	(2.195)	(2.224)	(2.130)	(5.059)	(4.064)	(2.236)
	Covariates					
Initial B Share	Yes	Yes	Yes	Yes	Yes	Yes
Demographics		Yes	Yes		Yes	Yes
Economic Indicators			Yes			Yes
N	2,870	2,870	2,870	2,870	2,870	2,870
R-sq	0.068	0.150	0.310	0.128	0.337	0.445

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the county level, with weights equal to the population of each county, relating the entrant share of loans in 2016 or the shadow bank share of entrant loans to the exposure measure e_{ct}. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Columns (1) and (4) report results controlling for the initial bank share coming from the sum of the weights in the exposure measure e_{ct}. Columns (2) and (5) report results with the addition of 2003 demographic controls (population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelor's degree or more). Columns (3) and (6) report results further controlling for economic indicators in 2003 (total lending in dollar amounts, employment, personal income, and population). The period considered is 2003-2016. Robust standard errors are below the coefficients in parentheses.

Columns (1) through (3) show a strong negative relationship between the exposure measure and the entrant shares. In the more demanding specification of column (3) the point estimate is -23.435 and highly significant. This means that counties in which banks suffered the most from the compression in spreads experienced aggressive entry by other lenders during the period. Interestingly, these entrants are comprised of both shadow banks and other, less exposed, traditional banks.

Columns (4) through (6) examine whether the share of shadow banks among the entrants is affected by the exposure measure. The point estimate in column (6) at -6.977 confirms the strong negative relationship between the exposure measure and the shadow share of entrants. Thus, even though competing traditional banks entered the affected counties alongside shadow banks, shadow banks still formed a larger share of the entrants.

Overall Table 9 shows that counties in which banks suffered the most from the decline in rates experienced more aggressive entry from outside competitors, and these competitors, in turn, had a larger share of shadow banks among them.

Table 10: Change in Shadow Bank Share 2003-2016

	Overall (1)	Non-GSE (2)	GSE (3)
Exposure (e_{ct})	-11.846***	-5.818***	-9.915***
	(1.653)	(1.841)	(1.911)
		Covariates	
Initial SB share	Yes	Yes	Yes
Demographics	Yes	Yes	Yes
Economic Indicators	Yes	Yes	Yes
N	3,099	3,098	3,098
R-sq	0.235	0.179	0.284

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the county level, with weights equal to the population of each county, relating the change in shadow bank market share to the exposure measure e_{ct}. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). All specifications include controls for the initial shadow bank share, demographics (population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelor's degree or more), and economic indicators in 2003 (total lending in dollar amounts, employment, personal income, and population). The period considered is 2003-2016. Robust standard errors are below the coefficients in parentheses.

5.3 Loan Types: GSE and Non-GSE Loans

In this section we look separately at GSE and non-GSE loans. In the GSE category we pool together loans sold to Fannie Mae, Freddie Mac, Ginnie Mae, and Farmer Mac as well as any FHA loan. The Non-GSE category includes the rest. We show that the results hold for *both* types of loans. Non-GSE loans form a much narrower category of loans that banks mostly keep on their balance sheets (including, e.g., "jumbo" loans above the conforming limit). GSE loans, on the one hand, are sold quickly to the GSEs by both traditional and shadow banks, hence these originations require less balance sheet space and may thus be less affected by the decline in interest rates. However, even GSE loans require a non-negligible holding period and therefore some balance sheet space, as studied by, e.g., Demyanyk and Loutskina (2016). Moreover, the easier securitization also makes it easier for shadow banks to originate GSE loans, which explains why their growth has been particularly strong in this segment (Buchak et al., 2022). We show that results similar to the non-GSE loans hold for the GSE segment.

Table 10 looks within the overall shadow bank share patterns of Table 5 and presents the results separately for the GSE and the non-GSE segments. For ease of comparison, column (1) retains the result for the overall share. If we compare with columns (2) and (3), we see the same strongly negative and highly significant relationship in both the non-GSE and GSE segments, with the non-GSE coefficient slightly lower in absolute value and the GSE coefficient practically indistinguishable from the overall share.

What explains the similarities across the two segments? As mentioned before, loans in the GSE segment also require balance sheet space on the part of banks, and shadow banks can more easily enter the GSE segment. However, in Section 6.2 we also show a third force that applies uniformly to both segments: banks that were most affected by the decline in rates also reduced their non-interest expenses relatively to their unexposed counterparts. In particular, we document a fall in premises, fixed assets, and salaries.[16] We interpret these findings as evidence that affected banks adapted to lower interest rates by reducing their expenses in key resources that affect the origination of both non-GSE and GSE loans, such as their personnel, building space and the general quality of their branch network.

5.4 Robustness

Section A.1 in the Internet Appendix contains the additional tables absent from the main text.

Bank market power In Table 15 we show that our main results are robust to the inclusion of controls for bank market power in local lending and deposit markets. Column (1) reproduces our baseline result from Table 5 for ease of reference. In column (2) we include the county deposit HHI, calculated as the sum of squared deposit shares of each bank in the county. Following Scharfstein and Sunderam (2016), in column (3) we include the market share of the top four lenders in the county (Top 4). Column (4) includes the deposit HHI and Top 4 measures simultaneously. In columns (5) we include the county-level expense beta, computed following equation (10) with the expense beta of each bank instead of the exposure measure.[17] Comparing the results in columns (2) through (5) with the result in column (1) we see that the coefficients are practically unchanged by the inclusion of these market power measures. The same negative and highly statistically significant relationship remains.

Weights In Table 16 we analyze whether our main results in Table 5 are sensitive to the weights employed. For reference, the first three columns correspond to our benchmark specification in

[16] These results hold separately for premises and fixed assets on the one hand, and salaries on the other.
[17] See Appendix A.5 for a detailed description of how we compute the expense beta.

Table 5. We then reestimate each column using, first, no weights, and then weighting by the county's total lending, first in dollar amounts and then in counts. As the table shows, there is practically no variation in the coefficients across the different weighted specifications. The unweighted specifications show slightly smaller effects when the controls are included, but overall all the specifications show the same strongly negative and highly significant relationship.

Pre-trends In order to rule out the possibility that our regional results are driven by trends that started before our period of analysis, in Table 17 we reestimate our main specifications in Table 5 controlling for the lags of the change in market share of shadow banks. In columns (1) and (2) we include columns (2) and (3) from Table 5 for ease of reference. In columns (3) and (4) we control for the change in the market share of shadow banks from 1990 to 2003, and in columns (5) and (6) we instead include the change from 1995 to 2003. As we compare across columns we see that the coefficients are practically unchanged.

Small and large banks We analyze whether the exposures of small and large banks play a different role. In Table 18 we re-estimate our main specifications from Table 5 splitting the exposure measure in two. We now include the exposure coming from the ten largest banks in 2003 in our sample, and we separately include the exposure coming from all other banks.[18] As the table shows, both exposure measures display the same strongly negative and highly statistically significant relationship. In particular, column (3) shows their coefficients are almost identically the same. Thus, we conclude that our results are coming from banks across the bank size distribution, with both large banks and small banks playing a relevant role.

Excluding the housing boom and financial crisis Throughout the paper we use 2003-2016 as baseline period. Using a long time period is useful because the effects we are interested in, coming from the compression in spreads, are long-run effects and thus take time to materialize and become detectable in the data. However, a potential concern is that the 2003-2016 period includes two disruptive events in the mortgage market, the housing boom and the financial crisis. We thus re-estimate our results in the 2010-2016 period. The following results show that this shorter period is still sufficiently long to make the effects detectable.

Table 19 shows the results for the main specifications at the bank and county levels. Columns (1) through (6) show that the same results of Section 4 hold for the 2010-2016 period. The coefficients are of course different, reflecting, among other things, the shorter period. But the same relationships hold and results are highly statistically significant overall. For the county-level effects, columns (7) through (9) show the parallel results of Table 5 in Section 5 now for

[18] The top 10 banks as of 2003 are, in order of balance sheet size: JP Morgan Chase, Bank of America, Citibank, Wachovia, Wells Fargo, Bank One, FleetBoston Financial, U.S. Bank, SunTrust, and Bank of New York.

the 2010-2016 period. We observe the same strongly negative and statistically significant relationship. Moreover, as the comparison of Tables 5 and Table 19 reveals, the coefficients are practically identical.

In Tables 20 and 21 we repeat the exercises of Section 5, that is, controlling for tighter regulation or technological trends between 2010 and 2016.[19] Comparing Table 20 with Table 6 we see that the coefficients are practically identical, showing the same strongly negative and highly statistically significant relationship. Thus, the results in Table 20 reinforce the notion that the effects of exposure to declining rates are not due to the increased regulation burden faced by traditional banks after the financial crisis.

Table 21 presents the parallel results addressing concerns about technological trends, but for the 2010-2016 period. Comparing column (3) of Table 21 with column (9) of Table 19 we see that the effects are also essentially the same when we control for the population density and broadband access measures. The same strongly negative and highly statistically significant relationship remains. Columns (4) through (6) of Table 21 show that the same patterns are present for the market share of non-fintech shadow banks. Thus, these tests reject the notion that the exposure variable is indirectly capturing technological trends that disproportionally benefit shadow banks.

Loan originations: counts vs dollar amounts As mentioned before, given that the shadow bank market share is a ratio, any concern about the measurement of the loans in dollar amounts being influenced by home prices should be greatly attenuated. Regardless, here we repeat the main results using the number of loans instead. Table 22 shows the same specifications of Table 5 (in columns (1) through (3)) and Table 6 (in columns (4) through (7)). Table 23, in turn, presents the parallel results of Table 7. Comparing the results from Tables 22 and 23 with those of Tables 5, 6 and 7 we see that the same picture emerges. The coefficients are practically the same, and the same negative and highly statistically significant relationship holds.

6 Mechanisms: the Net Worth and Cost-Cutting Channels

In this section we inspect the mechanisms underlying our findings. We isolate two channels consistent with the model presented in Section 2. We first highlight the "bank net worth channel": a persistent fall in interest rates lowers bank profitability and equity growth, which in

[19] Because the dissolution of the OTS (which was completed in 2011) began in 2010 there is an artificially low OTS share in 2010; hence, we use 2008 as the start year for the OTS share control instead in Table 20. Furthermore, 2008 was the start year used by Buchak et al. (2022), so for consistency with this study and with the OTS measure, 2008 is used in place of 2010 for the T1RBC and MSR measures as well.

turns leads financially constrained banks to contract lending. In addition, exposure to low rates is particularly damaging for banks with a low initial capitalization, which suggests a complementarity between low rates and regulatory constraints. Second, we find that banks exposed to low rates respond by cutting costs, for instance by reducing their workforce and branch network. This "cost-cutting channel" can explain why our results hold for both GSE and non-GSE loans.

Table 11: Exposure and bank-level outcomes 2003-2016

	Cumulated Net Income (1)	Equity Growth (2)	Equity-Assets Ratio Growth (3)
Exposure (e_{bt})	0.801***	21.789***	0.002
	(0.183)	(8.368)	(0.183)
	Covariates		
Balance Sheet Controls	Yes	Yes	Yes
Expense Beta	Yes	Yes	Yes
N	3,399	3,404	3,279
R-sq	0.193	0.399	0.569

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the bank level, with weights equal to the loans in dollar amounts of each bank in 2003, relating the change in balance sheet item to the exposure measure e_{bt}. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results on the cumulated net income measure in equation (12). Column (2) reports results on equity growth. Column (3) reports results on the change in the equity to assets ratio. All specifications include controls for balance sheet measures (equity to assets ratio, log assets, and loan to assets ratio), and the expense beta. All outcome variables, as well as the exposure measure e_{bt}, were trimmed at the 5% level. The expense beta was trimmed at the 1% level. The period considered is 2003-2016. Bootstrap standard errors based on 1,000 simulations are below the coefficients in parentheses.

6.1 Net Worth Channel

We show that falling interest rates had a negative impact on exposed banks' profitability and equity growth. Moreover, we show that the impact on banks' capital is almost identical to the impact on the size of their balance sheet, which means their equity ratio did not change. In particular, we estimate equation (7):

$$\Delta y_{bt} = \alpha + \beta e_{bt} + controls_{bt_0} + u_{bt},$$

during the period 2003-2016, and in all regressions we maintain the controls from Section 4 (banks' equity ratio, log assets, loan-to-asset ratio, and the expense beta).

Table 11 presents the results. Column (1) looks at cumulative net income difference, defined as:

$$\int_{t_0}^{t} \left(\frac{\text{NetIncome}_{bs}}{\text{Assets}_{bs}} - \frac{\text{NetIncome}_{bt_0}}{\text{Assets}_{bt_0}} \right) ds. \tag{12}$$

The highly significant point estimate at 0.8 shows there is almost a one-to-one relationship between the exposure measure and the cumulated net income difference. Thus, as expected, banks that suffered the most in terms of spread compression, as captured by e_{bt}, also experienced larger cumulated declines in their earnings. In particular, this estimate means that the net income of a bank that suffered a 100 basis point cumulated decline in spreads over the period accumulated an 80 basis point net income decline compared to that of a bank that had zero exposure.

Column (2) looks at equity growth. The point estimate is positive and significant. This means that banks that were heavily exposed to the decline in spreads also experienced a lower equity growth during the period. The estimate, at 21.789, implies that the equity growth of a bank that suffered a 100 basis point cumulated decline in spreads over the period was about 22 percentage points lower than that of an unexposed bank. The transmission to equity shows that banks did not use earnings retention or equity issuance to offset their declining net interest income.

Column (3) shows the impact of the exposure variable in the equity ratio. If we compare the results for equity growth in column (2), with the results for asset growth in column (1) of Table 2, we see that the coefficients are almost identical. Remarkably, with a point estimate of 0.002, column (3) of Table 11 shows that the equity ratio did not change. This means that affected banks reacted to the impact they experienced in their equity funding by reducing their balance sheet accordingly, leaving their leverage ratio unchanged. This behavior is consistent, for instance, with a model in which banks already maximize their leverage subject to financial and regulatory constraints (Gertler and Kiyotaki, 2010).

Thus, banks that were more exposed to the decline in interest rates had lower earnings and lower equity growth rates during the period, which explains in part why they contracted lending. While we isolate declining interest rates as a novel factor behind the weakness in bank lending and the rise of shadow banks, this channel should be viewed as highly complementary to the regulatory view (Buchak et al., 2018; Irani et al., 2020). Indeed, at a theoretical level, leverage constraints that limit bank lending capacity are the key reason why the compression in profitability induced by low interest rates has an impact on lending. In the absence of financial constraints, lower interest rates could still hurt banks' earnings, but lending would be decoupled from past profitability.[20]

[20] For instance, Wang (2022) shows that the secular decline in interest rates *stimulates* traditional bank lending if the main constraint on lending stems from deposit market power instead (Drechsler et al., 2017). The reason is that low interest rates make cash more attractive as an alternative to deposits in the market for liquid savings instruments. As a result, banks lose market power at low rates and optimally

Empirically, we can examine directly the mediating role of regulation by studying the interaction between our measure of exposure to low interest rates and the tightness of regulatory constraints. Intuitively, the negative effect of declining rates on lending should be especially salient for banks that are heavily burdened by regulation. We test this hypothesis by comparing the lending responses of banks with high (i.e., above median) and low (i.e., below median) ratio of equity over assets by estimating the following equation:

$$\Delta y_{bt} = \alpha + \beta e_{bt} + \delta e_{bt} \times \text{Low Equity}_{bt_0} + controls_{bt_0} + u_{bt},$$

where the dummy variable Low Equity_{bt_0} equals 1 if bank b has a below-median 2003 equity ratio, and 0 otherwise (and is included in the controls). On average, banks with a low equity ratio should be closer to their capital requirement, and should thus contract lending relatively more in response to their exposure to low interest rates. We view equity ratio as a simple proxy for regulatory burden; as discussed in Greenwood et al. (2017), in practice bank regulation is increasingly complex, as banks face a multitude of constraints such as unweighted and risk-weighted capital requirements, stress tests, liquidity requirements, etc. and different constraints bind for different banks.

Table 12: Differential Effects for Highly Levered Banks 2003-2016

	Loans Growth (1)	Real Estate Loans Growth (2)	Commercial/Industrial Loans Growth (3)
Exposure (e_{bt})	31.682***	18.464***	52.961***
	(4.693)	(6.829)	(15.539)
Low Equity × Exposure	32.873***	53.418***	34.738***
	(8.003)	(9.555)	(17.711)
	Covariates		
Balance Sheet Controls	Yes	Yes	Yes
Expense Beta	Yes	Yes	Yes
N	3,414	3,404	3,408
R-sq	0.203	0.087	0.265

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the bank level, with weights equal to the loans in dollar amounts of each bank in 2003, relating the change in balance sheet item to the exposure measure e_{bt} and its interaction with the dummy variable Low Equity. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results on the bank-level loans growth. Column (2) reports results on the bank-level real estate loans growth. Column (3) reports results on the bank-level commercial and industrial loans growth. All specifications include controls for balance sheet measures (log assets, the dummy variable Low Equity, and the loan to assets ratio), and the expense beta. All outcome variables, as well as the exposure measure e_{bt}, were trimmed at the 5% level. The expense beta was trimmed at the 1% level. The period considered is 2003-2016. Bootstrap standard errors based on 1,000 simulations are below the coefficients in parentheses.

expand the supply of deposits, which reduces the reliance on costly wholesale funding and therefore also expands the supply of credit.

Table 12 presents the results for total loans, real estate loans, and C&I loans. In all cases we find a positive and highly significant estimate for δ: for a given exposure, banks with a low equity ratio contract lending by more. These results confirm that low interest rates are particularly damaging for constrained banks.

Table 13: Non-Interest Expense Channel 2003-2016

	Non-Interest Expense Measure		Change in GSE Shadow Bank Share
	(1)	(2)	(3)
Exposure	0.867***	1.566***	
	(0.157)	(0.365)	
Non-Interest Expense Measure			-6.332***
			(1.758)
	Covariates		
Bank Controls	Yes		
Initial SB share		Yes	Yes
Demographics		Yes	Yes
Economic Indicators		Yes	Yes
Level	Bank	County	County
Kleibergen-Paap F	-	-	18.4
N	3,419	3,098	3,098
R-sq	0.181	0.114	-

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the bank (column (1)) and county (columns (2) and (3)) levels, with weights equal to the loans in dollar amounts in 2003 of each bank in column (1), and to the population of each county in columns (2) and (3), relating the change in shadow bank market share or the non-interest expense measure to the exposure measure. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports bank-level results controlling for balance sheet measures (equity to assets ratio, log assets, and loan to assets ratio) and the expense beta. Column (3) instruments the non-interest expense measure with the exposure measure e_{ct}. Column (2) reports the first stage results from column (3). Column (3) reports results controlling for the initial shadow bank share, 2003 demographic controls (population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelor's degree or more), and economic indicators in 2003 (total lending in dollar amounts, employment, personal income, and population). The period considered is 2003-2016. A bootstrapped standard error based on 1,000 simulations is below the coefficient in parentheses in column (1) and robust standard errors are below the coefficients in parentheses in columns (2) and (3).

6.2 Cost-Cutting Channel

The similar responses of GSE and non-GSE loans described in Section 5.3 suggest that a common factor, unrelated to the ability to securitize loans, drives the decrease in originations by exposed banks. We now provide evidence that more exposed banks tried to counteract the decline in their interest income through a reduction in salaries and fixed assets, that ultimately reduced their origination capacity for all kinds of loans.

Table 13 presents the results. In column (1) we return to the bank-level specifications of Section 4 and estimate equation (7) using the cumulated decline in premises, fixed assets and salaries expenses. Specifically, we construct the cumulated non-interest expense as in equation (12), replacing net income by the sum of the non-interest expenses corresponding to premises, fixed assets, and salaries.[21] In column (2) we repeat the exercise at the county level. We compute the county-level non-interest expense measure in the same way we construct the county-level exposure measure in (10), and we estimate equation (9) using the same specification of Table 5 column (3). Finally, in column (3) we run an IV regression of the change in GSE shadow bank market share on the cumulated non-interest expense measure, instrumented with the exposure during the period, e_{c2016}.

Column (1) shows a strong positive relationship between the compression in spreads and the non-interest expense measure. The 0.867 coefficient is only slightly lower than one. This means that for each additional 100 basis points compression in spreads banks ended up with an 87 basis points lower non-interest expense measure. Column (2) is the first stage of column (3) and shows that the same relationship of column (1) holds at the county level, with a highly significant point estimate of 1.566. Thus, counties in which banks were more exposed to the compression in spreads also saw the county-level non-interest expense measure decline.

Column (3) shows the IV estimate that results from instrumenting the county-level non-interest expense measure with the county-level exposure. We see a very strong and negative relationship, and the (robust) first stage F statistic is well above the 10 threshold. Thus, counties in which banks reduced their cumulated non-interest expenses by more saw larger increases in the shadow bank market share along the GSE segment. This pattern supports the idea that even if GSE lending is less demanding for banks' balance sheets, the responses triggered by the lower rates are still able to affect banks' GSE lending, resulting in an increase in the shadow bank market share in that segment as well.

7 Conclusion

The residential mortgage market has seen a sharp increase in the market share of shadow banks at the expense of commercial banks. Recent studies relate this shift to the tighter regulation faced by traditional banks after the financial crisis and technological advantages that benefited shadow banks. In this paper we propose a new channel. We argue that the persistent decline in interest rates has hurt banks by compressing the spreads they earn, and this in turn has led

[21] Even though this measure exclusively focuses on non-interest expenses coming from premises, fixed assets and salaries, we will refer to it as "non-interest expense" for convenience.

them to contract lending, opening space for shadow banks to expand. We provide extensive evidence that this pattern is unrelated to the shifts in regulation after the financial crisis and to the technological edge of shadow banks.

Our cross-sectional empirical strategy seeks to credibly identify the impact of declining rates, but requires us to difference out aggregate effects. A natural but challenging next step, that we leave for future work, is to quantify how much of the aggregate rise of shadow banks can be explained by the secular decline in interest rates. In order to overcome the "missing intercept" problem, this exercise would require either a structural framework building on the model in Section 2 (as in, e.g., Buchak et al. 2018, Begenau and Landvoigt 2021), or the use of semi-structural methods as in Sarto (2022) or Wolf (2022).

The rise of non-bank lenders is a broad phenomenon, and has also been documented in the context of commercial real estate, small business lending (Gopal and Schnabl, 2022), and syndicated loans (Irani et al., 2020). We focused on the residential mortgage market, which has received most of the attention in the literature on the emergence of shadow banking, in part due to the availability of rich county-level data. But the mechanisms we describe should apply more broadly, as confirmed by our bank-level analysis showing that exposed banks contract several components of their balance sheets, including both real estate loans and corporate loans. An important next step is to extend our analysis to understand how the secular decline in interest rates affects the rise of shadow banks in other credit markets.

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Internet Appendix

For Online Publication

A Additional Results and Material

A.1 Additional Tables

Table 14: Largest Lending Institutions

Panel A: Top 10 Banks				
Rank	Type of Lender	Lender Name	Volume (Bn)	Market Share (%)
1	Bank	Wells Fargo	138.43	6.64
2	Bank	JPMorgan Chase	90.38	4.33
3	Bank	Bank of America	58.63	2.81
4	Bank	Freedom Mortgage Corporation	32.16	1.72
5	Bank	US Bank	29.32	1.41
6	Bank	Flagstar Bank	26.58	1.27
7	Bank	Citibank	25.39	1.21
8	Bank	USAA Federal Savings	14.87	0.71
9	Bank	Suntrust	14.54	0.70
10	Bank	PNC Bank	14.46	0.69

Panel B: Top 10 Nonbanks				
Rank	Type of Lender	Lender Name	Volume (Bn)	Market Share (%)
1	Fintech	Quicken Loans	90.55	4.34
2	Fintech	Loandepot.com	35.77	1.72
3	Nonbank	Caliber Home Loans	27.78	1.33
4	Nonbank	United Shore	22.90	1.10
5	Fintech	Guaranteed Rate	18.49	0.89
6	Nonbank	Finance of America	17.72	0.85
7	Nonbank	Fairway Independent	15.90	0.76
8	Nonbank	Guild Mortgage	15.20	0.73
9	Nonbank	Stearns Lending	14.84	0.71
10	Nonbank	Nationstar Mortgage	13.36	0.64

Table 15: Change in Shadow Bank Share 2003-2016, Bank Market Power

	Shadow Bank Share				
	(1)	(2)	(3)	(4)	(5)
Exposure (e_{ct})	-11.846***	-12.158***	-11.893***	-12.293***	-11.660***
	(1.653)	(1.653)	(1.635)	(1.629)	(1.949)
	Covariates				
Initial SB share	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes
Economic Indicators	Yes	Yes	Yes	Yes	Yes
Deposit HHI		Yes		Yes	
Top 4 Share			Yes	Yes	
Expense Beta					Yes
N	3,098	3,077	3,098	3,077	3,098
R-sq	0.235	0.238	0.255	0.260	0.235

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the county level, with weights equal to the population of each county, relating the change in shadow bank market share to the exposure measure e_{ct}. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results controlling only for the initial shadow bank share in 2003, 2003 demographic controls (population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelor's degree or more), and economic indicators in 2003 (total lending in dollar amounts, employment, personal income, and population). Column (2) reports results controlling for the deposit HHI in the county in 2003. Column (3) reports results controlling for the share of lending accounted for by the four largest lenders in the county. Column (4) reports results controlling for both of these measures. Column (5) reports results controlling for the expense beta. The period considered is 2003-2016. Robust standard errors are below the coefficients in parentheses.

Table 16: Effects of Different Weighting Schemes on Change in Shadow Bank Share 2003-2016

	Population			No weights			Lending by dollar amounts			Lending by loan counts		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exposure (e_{ct})	-10.890***	-9.557***	-11.846***	-8.540***	-5.984***	-6.912***	-10.466***	-10.425***	-14.126***	-9.876***	-9.663***	-12.586***
	(2.553)	(2.192)	(1.653)	(1.502)	(1.366)	(1.416)	(2.768)	(2.627)	(2.318)	(2.084)	(2.192)	(1.842)
	Covariates											
Initial SB Share	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Economic Indicators			Yes			Yes			Yes			Yes
N	3,099	3,098	3,098	3,099	3,098	3,098	3,099	3,098	3,098	3,099	3,098	3,098
R-sq	0.034	0.151	0.235	0.048	0.171	0.194	0.090	0.207	0.288	0.071	0.171	0.238

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the bank level, with weights equal to the population in 2003 for columns (1)-(3), unweighted in columns (4)-(6), the total lending in the county by dollar amounts in 2003 for columns (7)-(9), and the total lending in the county by number of loans for columns (10)-(12), relating the change in shadow bank share to the exposure measure e_{ct}. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Columns (1), (4), (7), and (10) report results controlling only for the initial shadow bank share in 2003. Columns (2), (5), (8), and (11) report results with the addition of 2003 demographics controls (population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelor's degree or more). Columns (3), (6), (9), and (12) report results further controlling for economic indicators in 2003 (total lending in dollar amounts, employment, personal income, and population). The period considered is 2003-2016. Robust standard errors are below the coefficients in parentheses.

Table 17: Change in Shadow Bank Share 2003-2016, Pre-trend Analysis

	Shadow Bank Share					
	Baseline		1990-2003 Controls		1995-2003 Controls	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure (e_{ct})	-9.557***	-11.846***	-9.786***	-12.147***	-9.802***	-11.901***
	(2.192)	(1.653)	(2.234)	(1.680)	(2.251)	(1.652)
Δ Shadow Bank Share (1990-2003)			0.001	-0.011		
			(0.013)	(0.013)		
Δ Shadow Bank Share (1995-2003)					0.022	-0.014
					(0.021)	(0.020)
	Covariates					
Initial SB share	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Economic Indicators		Yes		Yes		Yes
N	3,098	3,098	2,912	2,912	3,084	3,084
R-sq	0.151	0.235	0.154	0.238	0.152	0.236

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the county level, with weights equal to the population of each county, relating the change in shadow bank market share to the exposure measure e_{ct}. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Columns (1), (3), and (5) report results controlling for the initial shadow bank share in 2003 and 2003 demographic controls (population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelor's degree or more). Columns (2), (4), and (6) report results further controlling for economic indicators in 2003 (total lending in dollar amounts, employment, personal income, and population). Columns (1) and (2) report baseline results without the inclusion of any additional controls. Columns (3) and (4) report results controlling for the change in shadow bank share during the period 1990-2003. Columns (5) and (6) report results controlling for the change in shadow bank share during the period 1995-2003. The period considered is 2003-2016. Robust standard errors are below the coefficients in parentheses.

Table 18: Change in Shadow Bank Share 2003-2016

	Shadow Bank Share		
	(1)	(2)	(3)
Exposure - Top 10 (e_{ct})	-8.122**	-7.587**	-12.172***
	(3.855)	(3.010)	(2.390)
Exposure - Non Top 10 (e_{ct})	-12.115***	-10.504***	-11.698***
	(2.835)	(2.488)	(1.973)
	Covariates		
Initial SB share	Yes	Yes	Yes
Demographics		Yes	Yes
Economic Indicators			Yes
N	3,099	3,098	3,098
R-sq	0.037	0.152	0.235

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the county level, with weights equal to the population of each county, relating the change in shadow bank market share to the exposure measure e_{ct}, split between the top 10 national institutions (by size of assets) and the rest. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results controlling only for the initial shadow bank share in 2003. Column (2) reports results with the addition of 2003 demographic controls (population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelor's degree or more). Column (3) reports results further controlling for economic indicators in 2003 (total lending in dollar amounts, employment, personal income, and population). The period considered is 2003-2016. Robust standard errors are below the coefficients in parentheses.

Table 19: Effects of Compression in Spreads and Change in Shadow Bank Share 2010-2016

	Bank-Level						County-Level		
	Equity Growth	Assets Growth	Loans Growth	Securities Growth	Other Assets Growth	Real Estate Loans Growth	Change in Shadow Bank Share		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Exposure (e_{bt}, e_{ct})	10.743***	11.677***	9.946***	15.779***	10.144**	19.332***	-7.946*	-10.965***	-13.115***
	(1.503)	(1.688)	(1.179)	(4.280)	(4.075)	(1.858)	(4.554)	(3.181)	(2.400)
	Covariates								
Balance Sheet Controls	Yes	Yes	Yes	Yes	Yes	Yes			
Expense Beta	Yes	Yes	Yes	Yes	Yes	Yes			
Initial SB Share							Yes	Yes	Yes
Demographics								Yes	Yes
Economic Indicators									Yes
N	2,916	2,917	2,916	2,919	2,917	2,918	3,099	3,098	3,098
R-sq	0.288	0.250	0.113	0.347	0.250	0.350	0.011	0.151	0.223

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the bank level, with weights equal to the loans in dollar amounts of each bank in 2010 for columns (1)-(6) and equal to the population of the county in 2010 for columns (7)-(9), relating the change in balance sheet item (columns (1)-(6)) or shadow bank share (columns (7)-(9)) to the exposure measure e_{bt} (or e_{ct}) . The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results on the bank-level equity growth. Column (2) reports results on the bank-level assets growth. Column (3) reports results on the bank-level loans growth. Column (4) reports results on the bank-level securities growth. Column (5) reports results on the bank-level other assets growth. Column (6) reports results on the bank-level real estate loans growth. All specifications in columns (1)-(6) include controls for balance sheet measures (equity to assets ratio, log assets, and loan to assets ratio), and the expense beta. Column (7) reports results on the change in shadow bank share controlling only for the initial shadow bank share in 2010. Column (8) reports results with the addition of 2010 demographics controls (population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelor's degree or more). Column (9) reports results further controlling for economic indicators in 2010 (total lending in dollar amounts, employment, personal income, and population). In the bank-level specifications, outcome variables, along with the expense beta, were trimmed at the 1% level, and the exposure measure, e_{bt}, was trimmed at the 5% level. The period considered is 2010-2016. Bootstrap standard errors based on 1,000 simulations are below the coefficients in parentheses in columns (1)-(6). Robust standard errors are below the coefficients in parentheses in columns (7)-(9).

Table 20: Change in Shadow Bank Share 2010-2016

	Shadow Bank Share			
	(1)	(2)	(3)	(4)
Exposure (e_{ct})	-12.942***	-13.029***	-13.341***	-13.208***
	(2.436)	(2.400)	(2.476)	(2.482)
	Covariates			
OTS	Yes			Yes
T1RBC		Yes		Yes
MSR			Yes	Yes
N	3,098	3,098	3,098	3,098
R-sq	0.224	0.225	0.225	0.227

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the county level, with weights equal to the population of each county, relating the change in shadow bank market share to the exposure measure e_{ct}. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2010 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results controlling for the share of originated loans regulated by the Office of Thrift Supervision (OTS) in 2008. Column (2) reports results controlling for the change in the county-level tier 1 risk-based capital ratio (T1RBC) between 2008 and 2016. Column (3) reports results controlling for the county-level mortgage servicing rights (MSR) as a percentage of tier 1 capital in 2008. Column (4) reports results controlling for all three measures. All specifications include controls for the initial shadow bank share, demographics, and economic indicators. The period considered is 2010-2016. Robust standard errors are below the coefficients in parentheses.

Table 21: Change in Shadow Bank Share 2010-2016

	Shadow Bank Share			Non-Fintech Shadow Bank Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure (e_{ct})	-15.623***	-6.662	-13.856***	-6.652*	-8.703***	-10.707***
	(1.818)	(4.985)	(4.216)	(3.662)	(2.706)	(2.032)
	Covariates					
Pop. Density	Yes		Yes			
Broadband Access		Yes	Yes			
Initial SB share	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes		Yes	Yes
Economic Indicators	Yes	Yes	Yes			Yes
N	3,076	326	325	3,099	3,098	3,098
R-sq	0.266	0.416	0.470	0.011	0.117	0.193

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the county level, with weights equal to the population of each county, relating the change in shadow bank market share to the exposure measure e_{ct}. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2010 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results controlling for the population density of the county in 2010. Column (2) reports results controlling for the share of the population with access to broadband in 2010. Column (3) reports results controlling for both measures. Column (4) reports results on the non-fintech shadow bank share controlling only for the initial shadow bank share in 2010. Column (5) reports results on the non-fintech shadow bank share with the addition of 2010 demographic controls (population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelor's degree or more). Column (6) reports results on the non-fintech shadow bank share further controlling for economic indicators in 2010 (total lending in dollar amounts, employment, personal income, and population). The period considered is 2010-2016. Robust standard errors are below the coefficients in parentheses.

Table 22: Change in Shadow Bank Share 2003-2016, Loan Counts

	Shadow Bank Share						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure (e_{ct})	-7.138***	-7.344***	-11.509***	-12.948***	-12.373***	-10.622***	-12.640***
	(1.940)	(2.009)	(1.399)	(1.554)	(1.481)	(1.477)	(1.680)
	Covariates						
Initial SB share	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics		Yes	Yes	Yes	Yes	Yes	Yes
Economic Indicators			Yes	Yes	Yes	Yes	Yes
OTS				Yes			Yes
T1RBC					Yes		Yes
MSR						Yes	Yes
N	3,099	3,098	3,098	3,098	3,098	3,098	3,098
R-sq	0.051	0.152	0.284	0.286	0.288	0.287	0.293

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the county level, with weights equal to the population of each county, relating the change in shadow bank market share to the exposure measure e_{ct}. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results controlling only for the initial shadow bank share in 2003. Column (2) reports results with the addition of 2003 demographic controls (population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelor's degree or more). Column (3) reports results further controlling for economic indicators in 2003 (total lending in dollar amounts, employment, personal income, and population). Columns (4)-(7) include controls for all three measures. Column (4) reports results controlling for the share of originated loans regulated by the Office of Thrift Supervision (OTS) in 2003. Column (5) reports results controlling for the change in the county-level tier 1 risk-based capital ratio (T1RBC) between 2003 and 2016. Column (6) reports results controlling for the county-level mortgage servicing rights (MSR) as a percentage of tier 1 capital in 2003. Column (7) reports results controlling for all three measures. The period considered is 2003-2016. Robust standard errors are below the coefficients in parentheses.

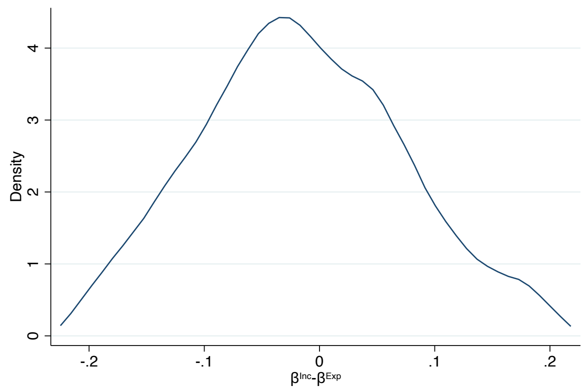
Table 23: Change in Shadow Bank Share 2003-2016, Loan Counts

	Shadow Bank Share			Non-Fintech Shadow Bank Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure (e_{ct})	-11.274***	-20.156***	-20.555***	-5.180***	-6.318***	-10.227***
	(1.402)	(5.051)	(4.992)	(1.845)	(1.716)	(1.292)
	Covariates					
Pop. Density	Yes		Yes			
Broadband Access		Yes	Yes			
Initial SB share	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes		Yes	Yes
Economic Indicators	Yes	Yes	Yes			Yes
N	3,076	216	215	3,099	3,098	3,098
R-sq	0.306	0.540	0.553	0.018	0.139	0.285

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the county level, with weights equal to the population of each county, relating the change in shadow bank market share to the exposure measure e_{ct}. The county-level exposure e_{ct} is a weighted average of the bank-level exposure e_{bt}, where the weights are the banks' shares of total mortgage lending in county c as of 2003 from HMDA. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results controlling for the population density of the county in 2003. Column (2) reports results controlling for the share of the population with access to broadband in 2003. Column (3) reports results controlling for both measures. Column (4) reports results on the non-fintech shadow bank share controlling only for the initial shadow bank share in 2003. Column (5) reports results on the non-fintech shadow bank share with the addition of 2003 demographic controls (population shares of Hispanics, Native Americans, Blacks, Asians, males, those below age 35, those above age 65, those with only a high school diploma, those with some college, and those with a bachelor's degree or more). Column (6) reports results on the non-fintech shadow bank share further controlling for economic indicators in 2003 (total lending in dollar amounts, employment, personal income, and population). The period considered is 2003-2016. Robust standard errors are below the coefficients in parentheses.

A.2 Additional Figures



Note: The figure shows the kernel density estimate of the NIM beta, $\beta_b^{\text{Inc}} - \beta_b^{\text{Exp}}$.

Figure 5: Distribution of the NIM beta.

A.3 Proofs

Proof of Lemma 1. The bank profitability condition states that banks' long-run excess return on equity ρ must be sustained through a combination of deposit spreads and loan spreads net of lending costs:

$$\rho = \phi s_d + (1+\phi)\left[s_\ell - \gamma^B\right].$$

The leverage constraint $D^B \leq \phi E^B$ is binding in any equilibrium hence the deposit market clearing condition

$$\mathcal{D}(s_d, r) = \phi E^B$$

yields an equilibrium deposit spread $s_d(E^B, r)$ that increases with r and decreases with ϕE^B.

For banks to be willing to lend the loan spread must at least cover their costs hence $s_\ell \geq \gamma^B$. Suppose first that $s_\ell = \gamma^B$ in equilibrium. Then the bank profitability condition writes

$$\rho = \phi s_d(\phi E^B, r)$$

which determines E^B as an increasing function of r. This is indeed an equilibrium if

$$\mathcal{L}(\gamma^B) - L^{SB}(\gamma^B - \gamma^{SB}) \leq (1+\phi)E^B(r)$$

or $r \geq \bar{r}$ where $\bar{r}$ solves

$$\mathcal{L}(\gamma^B) - L^{SB}(\gamma^B - \gamma^{SB}) = (1+\phi)E^B(\bar{r}).$$

From the deposit market clearing condition this can be rewritten as

$$\mathcal{L}(\gamma^B) - L^{SB}(\gamma^B - \gamma^{SB}) = (1+\phi)\mathcal{D}\left(\frac{\rho}{\phi}, \bar{r}\right).$$

Proof of Proposition 1. Focusing on the regime $r < \bar{r}$ the equilibrium conditions are

$$\mathcal{L}(s_\ell) - L^{SB}(s_\ell - \gamma^{SB}) = (1+\phi)E^B \tag{13}$$

$$\mathcal{D}(s_d, r) = \phi E^B \tag{14}$$

$$\rho = \phi s_d + (1+\phi)(s_\ell - \gamma^B) \tag{15}$$

Define $\hat{\mathcal{L}}(s_\ell;\gamma^{SB}) = \mathcal{L}(s_\ell) - L^{SB}(s_\ell - \gamma^{SB})$. We can combine (13)-(15) to get a single equation in s_ℓ:

$$\hat{\mathcal{L}}(s_\ell;\gamma^{SB}) = (\psi+1)\mathcal{D}(\rho\psi - (\psi+1)(s_\ell - \gamma^B), r) \tag{16}$$

where $\psi = 1/\phi$. Equation (16) states that the residual demand for bank loans $\hat{\mathcal{L}}(s_\ell;\gamma^{SB})$ (total demand net of shadow bank supply) equals the supply of bank loans. The right-hand side is decreasing in s_ℓ and the left-hand side is increasing in s_ℓ hence there is a unique solution s_ℓ.

1. A decrease in ϕ corresponds to an increase in ψ. Partially differentiating the right-hand side with respect to ψ, we have

$$\begin{aligned}\frac{\partial}{\partial\psi}\Big[(\psi+1)\mathcal{D}(\rho\psi - (\psi+1)(s_\ell-\gamma^B), r)\Big] &= \mathcal{D}(x,r) + (\psi+1)(\rho - (s_\ell - \gamma^B))\mathcal{D}_{s_d}(x,r) \\ &= \mathcal{D}(x,r) + (\rho + s_d)\mathcal{D}_{s_d}(x,r) \\ &= \mathcal{D}(x,r)\left\{1 - (\frac{\rho}{s_d}+1)\epsilon_{\mathcal{D}}(x,r)\right\}\end{aligned}$$

   where $s_d = \rho\psi - (\psi+1)(s_\ell - \gamma^B)$ and $\epsilon_{\mathcal{D}}$ is the deposit demand elasticity with respect to the deposit spread. Since $\epsilon_{\mathcal{D}}\phi \geq 1$ and

$$\rho/s_d + 1 = \phi + (1+\phi)\frac{s_\ell - \gamma^B}{s_d} \geq \phi,$$

   the bracket is negative therefore the equilibrium loan spread s_ℓ and bank lending $\hat{\mathcal{L}}(s_\ell;\gamma^{SB})$ increases as ϕ decreases, whereas shadow bank lending $L^{SB}(s_\ell - \gamma^{SB})$ increases.

2. A decrease in γ^{SB} shifts the residual demand for bank loans $\hat{\mathcal{L}}$ down hence s_ℓ and bank lending both fall. Since s_ℓ falls, total lending (combining banks and shadow banks) increases hence shadow bank lending increases.

3. A decrease in r shifts the right-hand side of (16) down due to increase competition between deposits and cash, hence bank lending falls and s_ℓ increases. Total lending $\mathcal{L}$ falls and shadow bank lending L^{SB} increases.

A.4 Extension with non-interest expenses

This extension of the model follows Drechsler et al. (2023). Suppose that following standard q-theory logic banks invest in non-interest expenses c according to a function

$$c = c(s_d)$$

that increases with the deposit spread s_d that the bank expects to earn with $0 \leq c' \leq 1$. For simplicity expenses are only a function of deposit spreads and not loan spreads; the result is unchanged if c is an increasing function of both s_d and s_ℓ. Equivalently effective bank loan supply is an increasing function of spreads:

$$\alpha(c(\sigma(s_\ell - \gamma^B)))(1+\phi)E^B$$

In this extended model the equilibrium conditions become

$$\hat{\mathcal{L}}(s_\ell; \gamma^B) = \alpha(c(s_d))(1+\phi)E^B \tag{17}$$

$$\mathcal{D}(s_d, r) = \phi E^B \tag{18}$$

$$\rho = \phi(s_d - c(s_d)) + (1+\phi)(s_\ell - \gamma^B) \tag{19}$$

Inverting equation (19) as a function of s_d we obtain

$$s_d = \sigma(s_\ell - \gamma^B)$$

where σ is a decreasing function (that also depends on ρ and ϕ). Plugging back into (17)-(18) we get

$$\hat{\mathcal{L}}(s_\ell; \gamma^B) = \alpha(c(\sigma(s_\ell - \gamma^B)))(1+\psi)\mathcal{D}(\sigma(s_\ell - \gamma^B), r)$$

which determines the equilibrium loan spread s_ℓ. As in Proposition 1 a negative shock to r shifts the right-hand side down which increases s_ℓ. Relative to Proposition 1 which assumes a fixed $\alpha = 1$, the effect is amplified by the function $\alpha(c(\sigma(s_\ell - \gamma^B)))$ that increases with s_ℓ.

A.5 Exposure and Bank Betas

Our exposure measure e_{bt} captures the compression in spreads experienced by a bank that has a fixed balance sheet composition and is faced with the national average interest rates on both sides of its balance sheet. A higher exposure can arise from holding assets whose yields are more sensitive to the general decline in interest rates and/or issuing liabilities whose yields are less sensitive to falling rates.

At first glance the fact that banks are exposed seems inconsistent with recent results in Drechsler et al. (2021) showing that banks tend to match the interest-rate sensitivities of their assets and liabilities, thereby insulating their income from short-run interest rate fluctuations. However, the aggregate evidence in the introduction shows that hedging might be harder to achieve over long periods, especially once rates approach the zero lower bound, as depicted by the declining aggregate NIM, which ultimately drives our exposure variable.

Table 24: Exposure and betas 2003-2016

	Exposure (e_{bt}) (1)	Exposure (e_{bt}) (2)	NIM beta ($\beta^{\text{Inc}} - \beta^{\text{Exp}}$) (3)
NIM beta ($\beta^{\text{Inc}} - \beta^{\text{Exp}}$)	3.188***	3.278***	
	(0.540)	(0.567)	
Expense beta (β^{Exp})		–0.458	0.353
		(0.913)	(0.247)
	Covariates		
Balance Sheet Controls	Yes	Yes	Yes
N	3,303	3,303	3,594
R-sq	0.517	0.518	0.303

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports coefficient estimates of weighted least square regressions at the bank level, with weights equal to the loans in dollar amounts of each bank in 2003, relating the exposure measure e_{bt} to the NIM beta and the expense beta. The bank level exposure e_{bt} is derived from Call Report data following equation (6). Column (1) reports results on the exposure measure e_{bt} with the NIM beta. Column (2) further controls for the expense beta. Column (3) reports results on the NIM beta with the expense beta. All specifications include controls for balance sheet measures (equity to assets ratio, log assets, and loan to assets ratio). The expense beta, NIM beta, and exposure measure e_{bt} were trimmed at the 5% level. The period considered is 2003-2016. Bootstrap standard errors based on 1,000 simulations are below the coefficients in parentheses.

To understand better the link between our exposure and other measures of short-run interest-rate sensitivity, we construct "betas", for both assets and liabilities, following Drechsler et al. (2021); we sketch the approach here and refer to their paper for more details. For each bank b, we run a time-series regression of the change in the average interest expense rate r_{bt}^{Exp} on four lags of the change in the Fed funds rate, using quarterly data between 1984Q4 and 2002Q4. The expense beta β_b^{Exp} is defined as the sum of the regression coefficients, hence a lower expense beta means that the average rate paid on the bank's liabilities is less responsive to changes in interest rates.[22] The income beta β_b^{Inc} is constructed in the same way, using interest income r_{bt}^{Inc} as dependent variable instead of interest expense r_{bt}^{Exp}. Finally, we define the NIM beta as the difference $\beta_b^{\text{Inc}} - \beta_b^{\text{Exp}}$.

If banks were able to perfectly match their betas, setting $\beta_b^{\text{Inc}} - \beta_b^{\text{Exp}} = 0$, the decline in interest rates would have little effect on their profits. Even though the mean NIM beta in our sample is indeed close to zero, -0.015, the 0.09 standard deviation shows substantial variation across banks.[23]

Table 24 shows the relationship between the exposure measure and the NIM beta. As in Section 4, in all the specifications we control for banks' equity ratio (equity divided by assets), bank size (log assets), and the ratio of loans to assets. Moreover, to capture the same coefficient regardless of whether interest rates are rising or declining, we use $\left(\beta_b^{\text{Inc}} - \beta_b^{\text{Exp}}\right) \Delta r_t$ instead of the spread itself.

Column (1) shows a strongly positive and statistically significant relationship between the NIM beta and the exposure measure, with a coefficient of 3.188. Thus, banks whose cost of funds adjusted less than the income rate suffered the most in terms of the exposure measure e_{bt}. Column (2) adds the expense beta to the specification in column (1).[24] The idea behind this specification is to check whether banks' market power over their deposits (Drechsler et al., 2017) plays a role in explaining the variation in our exposure measure. As expected, column (2) shows the coefficient on β_b^{Exp} is negative, but it is not statistically significant. The coefficient on the NIM beta essentially remains unchanged and highly significant. Finally, column (3) shows there is a positive coefficient when running the NIM beta against the expense beta. That is, banks that have less market power on their funding side (i.e., a higher expense beta) tend to have larger positive imbalances between their income and expense betas. However, the coefficient it not statistically significant.

Thus, we conclude that the exposure e_{bt} is related to banks' inability to perfectly match their income and their expense betas, but is unrelated to the absolute values of these sensitivities; in particular, e_{bt} is not just a measure of deposit market power. Moreover, e_{bt} is less affected by unobserved bank-specific shocks than the NIM beta. The NIM beta captures differences in

[22] The regression equation is $\Delta r_{bt}^{\text{Exp}} = \alpha_b + \sum_{\tau=0}^{3} \beta_{b,\tau}^{\text{Exp}} \Delta r_{t-\tau} + \epsilon_{bt}$ where r is the Fed funds rate, and $\beta_b^{\text{Exp}} = \sum_{\tau=0}^{3} \beta_{b,\tau}^{\text{Exp}}$.

[23] Appendix Figure 5 shows the entire distribution of the NIM beta. A significant fraction of the sample features NIM betas above 0.1 and below -0.1.

[24] As before, to capture the same coefficient regardless of whether rates are increasing or decreasing, we include $\beta_b^{\text{Exp}} \Delta ffr_t$.

balance sheet composition but also differences in the bank-specific pricing of each balance sheet item. Our exposure measure removes the second source of variation, by using national rates in (6) instead of bank-specific rates.