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WHICH BANKS ARE (OVER) LEVERED? INSIGHTS FROM SHADOW BANKS AND UNINSURED LEVERAGE

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ABSTRACT

We examine why banks maintain such high financial leverage, with debt financing accounting for about 90% of banks' assets. To answer this question, we use uniquely assembled data on capital structure decisions of shadow banks that on the asset side conduct very similar business to banks. The shadow bank data provides us with a window into "free market" financing choices of financial intermediaries that unlike banks are lightly regulated and do not have access to insured deposit funding. We demonstrate that shadow banks employ twice the amount of equity capital compared to equivalent banks, with the most significant disparity observed between smaller and mid-size banks. Uninsured leverage, defined as uninsured debt funding to assets, increases with size for both banks and shadow banks while cost of debt declines with size. We rationalize these facts within a calibrated quantitative equilibrium model of intermediation. Our analysis reveals that the primary driver of high leverage among smaller and mid-size banks is their access to insured deposit funding. In the absence of deposit insurance, these banks would maintain a capitalization level at least 25% higher in relative terms than observed in the data. Conversely, deposit insurance plays a comparatively minor role in influencing the financial leverage of the largest banks, where the predominant factor is their capacity to generate money-like deposits. These results suggest a significant scope for the increase of capitalization of smaller and mid-size banks to align their capital structures with their private market counterparts. The aggregate consequences of such increase would be limited, because of reallocation of lending activity from smaller to large banks and to shadow banks.

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1. Introduction

The extensive overhaul of financial regulation in the U.S. and around the world was supposed to reduce the fragility of the banking system following the Great Financial Crisis. Less than 15 years later, the U.S. has experienced some of the largest bank failures in its history starting with the "run" Silicon Valley Bank and First Republic Bank, two large regional banks. The 2023 bank failures underscore the fundamental issue of banking vulnerability rooted in the high financial leverage employed by banks (Jiang et al. 2023). These failures have renewed interest in the regulation of banks' capital structure—capital regulation—and more broadly the role of safety nets such as deposit insurance.

The central idea of regulating bank leverage is that safety nets for debtholders cause banks to borrow excessively.[1] Because deposits are short-term and only partially insured, this further contributes to bank fragility (see Davilla and Goldstein, 2023). On the other hand, if banks take on leverage to provide intermediation services, then restricting banks' leverage likely results in fewer intermediary services. These services can be on the asset side, such as extending loans or other financial services to households or firms, and on the liability side though the creation of safe and liquid debt, or more broadly, through maturity and liquidity transformation.[2] Under this regulatory view, capital requirements aim to undo the effect of safety nets on bank leverage but not extend beyond that level. They should thus broadly replicate the capital structure that banks would have chosen if they had no access to safety nets provided by deposit funding.[3]

A notable feature of bank regulation is that it frequently imposes different capital requirements across the size distribution of banks. For example, the "Basel III endgame," regulatory proposal would increase capital requirements on the largest U.S. banks rather than on the much more numerous small banks, which have been historically more likely to default. In other words, apart from recognizing the potential systematic significance of large banks, the regulation implicitly suggests that larger banks, when deciding on leverage, either rely more extensively on safety nets or offer reduced intermediation services for equivalent leverage, particularly at the margin.

Motivated by this debate we investigate how much of banks' high financial leverage and the cost of their debt financing across the size distribution is driven by their access to deposit funding and the associated safety nets. We proceed in three steps. First, we assemble data on capital structure decisions of shadow banks, which conduct bank-like activities on the asset side. These financial intermediaries offer a representation of how banks would be financed if they lacked access to insured deposits and were not bound by capital requirements—essentially if their lenders internalized default risk. Through a comparative analysis of the capital structure decisions and the cost of debt funding of shadow banks, we uncover five primary facts that shed light on this issue.

In the second step, we provide a model of banks and shadow banks to quantify banks' provision of services on the liability and asset side across the size distribution. Prior literature of intermediary sector uses bank data or very aggregate data on shadow banks capital structure to discipline models. Instead, we use disaggregated data on shadow bank capital structure decisions and interest rates to do so. Observing choices of intermediaries and the cost of their liabilities in the absence of access to insured deposits allows us to

[1] See for instance, Dwyer (1981), Pyle (1984), Admati et al. (2013), Admati and Hellwig (2014), Calomiris and Jaremski (2016), Egan et al. (2017), Corbae and D'Erasmo (2019), and Davilla and Goldstein (2023).
[2] See for instance, Diamond and Rajan (2001), DeAngelo and Stulz (2015), Gorton and Pennacchi (1990), Deng et al. (2017) and Davilla and Goldstein (2023).
[3] If bank default generated large externalities, then such capital structure would provide a lower bound on capital requirements.

directly identify key driving forces in the model while sidestepping other indirect approaches such as taking a stance on correlation structure of shocks impacting intermediaries used in existing structural models.

Third, we use the calibrated model to ask how much leverage banks would choose if they were able to perform the same function on the asset and liability side, but its debtholders (depositors) would fully internalize default cost. This allows us to study the implications of insured deposit funding for aggregate provision of lending and money-like liabilities as well as distribution of these effects across the bank size.

Data: We start by empirically comparing shadow banks to banks. These financial intermediaries provide banking services but cannot fund themselves with insured deposits and are not subject to capital requirements. We construct, for the first time, shadow bank "call reports" from 2011 onwards using Freedom of Information Act (FOIA) requests from state regulators. We observe detailed balance sheet information on the structure of liabilities and asset, as well as interest rates paid on shadow bank debt funding. We also match the balance sheet information to the individual loans (mortgages) originated by shadow banks providing detailed insight into asset side activities. We cover more than four hundred largest shadow banks, accounting for about 80% of shadow bank loans originated during this period and originating over quarter of *all household debt* in the U.S. over almost a decade.

Shadow banks in our call reports are primarily in the mortgage origination business and sell most of the loans they originate. Our rich data allows us to find banks, which follow a very similar business model to shadow banks: they are primarily in the mortgage origination business and sell a similar share of their loans.[4] At the individual loan level, these banks specialize in originating and selling conforming residential loans that need to satisfy a tight set of guidelines issued by the Government Sponsored Enterprises (GSEs) and lend to customers of very similar creditworthiness.[5] In sum, this institutional feature allows us to achieve a tight comparisons between banks and shadow banks that follow a very similar business model, including the type of loans they originate. Even though we find an appropriate bank comparison group for shadow banks, our results barely change if we choose different comparison groups or use all banks as comparison. If anything, a better comparison group increases the differences between banks and shadow banks, suggesting that asset side differences between banks and shadow banks are not driving our results.

Using this shadow bank data and bank call reports we document the following five facts.

Fact 1: Shadow banks have substantially more equity capital—lower leverage—than banks (but substantially less than non-financial firms).

The average equity to asset ratio for banks is approximately 11% and is even lower at 10.5% for banks most comparable to shadow banks. Shadow banks' capitalization is more than twice as high at 25%, despite no capital requirement for shadow banks. These differences are very robust whether we adjust for differences in lending composition or assets, across bank control groups, and adjusting for risk weights. While shadow banks have substantially more capital than banks, their leverage is still substantially higher than that of non-financial firms, rejecting the idea that banks' capital structure choices would resemble that of non-financial firms in the absence of deposits. For comparison, the median shadow bank equity capitalization matches well with that of banks in the pre-deposit-insurance era suggesting that the capitalization models we observe are not specific to the narrow business model of modern shadow banks (e.g., Admati and Hellwig 2013, Hanson et al. 2015, Aldunate et al. 2019, Blickle et al. 2019).

[4] See Buchak et al. (2018) for the similarity in customers of banks and shadow banks in the mortgage market. For increase in propensity of banks to sell loans, see Buchak et al. (2018 and 2023) and Irani et al. (2021).

[5] The average FICO credit score difference between banks' and shadow banks' GSE backed loans is 4 points on the scale ranging from 300 to 850 and the average difference in interest rate is two basis points.

Fact 2: Leverage across shadow banks is substantially more dispersed than leverage across banks.

Banks leverage is extremely homogenous: the standard deviation in equity to asset ratio across banks is 3 percentage points (pp) across banks with substantially different business models and asset composition. Shadow banks' capitalizations, on the other hand, differ widely, with a standard deviation of 18pp. This fact is even more surprising because shadow banks' business models in our sample are substantially more homogenous than those of banks. Even if aggregated data on shadow banks were available, this vast heterogeneity in shadow bank leverage can only be measured using institution level data.

Fact 3: Shadow banks finance themselves primarily with short-term debt and originate long term loans, similar to banks. Shadow bank debt is much more concentrated than bank deposits.

Short term debt comprises 85% of bank debt funding and is largely provided by dispersed uninformed parties (depositors). Shadow banks' debt is almost exclusively (98%) short-term. Therefore, like banks, shadow banks engage in maturity transformation, originating long maturity mortgages using short-term debt funding. Thus, short-term debt funding is a robust feature of banking irrespective of deposit insurance.[6]

Fact 4: Shadow bank capitalization decreases substantially with size. Bank capitalization hardly changes with size. Uninsured leverage, defined as uninsured debt funding to assets, increases with size for both banks and shadow banks.

Large and small banks have similar equity to asset ratios. Large shadow banks have approximately 30pp less equity capital than small shadow banks. If intermediaries take on leverage to provide intermediation services, then one might expect the relationship between leverage and intermediary size to be at least qualitatively similar for banks and shadow banks. We reconcile this gap by showing that "uninsured leverage" substantially declines as intermediation size increases for both banks and shadow banks.

We define uninsured leverage as the ratio of uninsured debt to assets. Intuitively, banks' uninsured leverage comprises debt that is not subject to *direct* government guarantees. As we argue later, a substantial share of theories of intermediary capital structure require that debt-holders internalize some cost of default, at least off equilibrium. In other words, the theories are about uninsured leverage and have little to say about insured debt. Because both shadow banks' and banks' uninsured leverage increases with size it is likely that these institutions take on uninsured leverage to provide intermediation services in the same way.

One might be concerned that the similarity between banks and shadow bank use of uninsured leverage is spurious because we observe a specific type of banks and shadow banks—those which originate to distribute using GSEs—or that our sample is from the post-Dodd Frank era, or banks' too big to fail concerns etc. As external validity, we show that the positive uninsured leverage/size relationship also holds in pre-deposit-insurance banks both in the U.S. and Germany using data from Aldunate et al. (2019) and Blickle et al. (2019). Clearly these banks were subject to different regulations, had no deposit insurance, but also did not originate to distribute or invest much in residential mortgages. Yet, even in these vastly different circumstances, small banks used much less uninsured leverage than large banks. These banks were also much better capitalized on average than current banks. In other words, the relationship between uninsured leverage is not driven by the specifics of, too big to fail concerns, or the business model or asset composition of modern banks or shadow banks that we examine.

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[6] In contrast to banks, whose funding is provided by dispersed depositors, shadow bank debt takes the form of credit lines provided by, on average, 3 to 4 large banks.

Fact 5: Average interest rates on uninsured debt decline with size for banks and shadow banks. Shadow banks pay substantially higher rates than banks on debt across the size distribution.

We find that the average interest rate paid by shadow banks and banks on their uninsured debt *decreases* with size across the entire size distribution: the interest rates paid by largest intermediaries are about 1/3 lower than those of their smallest counterparts. While too big to fail concerns may explain the decline in debt costs in the extreme right tail of the size distribution, it is unlikely to explain why small, medium sized, or regional shadow banks pay higher rates on their uninsured debt than their banks counterparts. This evidence bolsters the idea that the same underlying forces drive uninsured leverage across the size distribution of banks and shadow banks. Banks face a substantially lower cost of uninsured debt funding than shadow banks. The shadow banks with the lowest funding costs pay similar interest rates to banks with the highest interest rates on uninsured deposits on average. This result implies that lenders perceive uninsured bank debt as safer than shadow bank debt despite banks' substantially higher overall leverage.

Model: In the second part of the paper, we present an equilibrium model in which banks and shadow banks choose capital structure and size by borrowing from households. The model explains the facts that we document qualitatively and quantitatively when we calibrate the model to the data. The calibration allows us to decompose the contribution of forces that drive intermediaries overall and uninsured leverage as well as their cost of debt across the size distribution. Even without the model, the empirical facts alone illustrate that lending can be accomplished with relatively high capitalization of over 25pp. The model allows us to also determine the extent to which intermediaries high leverage is necessary for the provision of money-like liabilities, while accounting for any remaining differences on the asset side.

The model has standard building blocks with one departure. The broad setting uses standard building blocks: heterogenous intermediaries raise equity and debt to facilitate lending, which is subject to declining returns to scale The representative household values bank and shadow bank debt because of their money-like properties. The money-like premia that arise as a result of these preferences are impounded into borrowing rates for shadow bank debt and bank debt (deposits) to clear the markets. In other words, intermediaries provide socially valuable lending on the asset side, and money-like debt on the liability side. Because debt issuance incorporates a money-premium, it allows intermediaries to extend more loans and choose a larger size, resulting in complementarities between lending and leverage. Productivity differences across intermediaries and the ability to issue money like claims shape the joint distribution of the intermediation sector. The market clears in aggregate. The more money-like debt claims intermediaries issue to the representative household, the smaller is the premium on intermediary debt. Because bank and shadow bank debt are imperfect substitutes, the model allows banks to issue more valuable liability claims (deposits) even in the absence of deposit insurance, capturing possible benefits of bank deposit franchise.[7]

We somewhat depart from the literature by assuming that insured depositors have an "equity like" property from the perspective of uninsured depositors: because they are insured, they do not run. This implies that, in addition to insured deposit funding being "cheap" because of safety nets, it also indirectly lowers the cost of *uninsured* funding. The allows the model to match Fact 5, that banks' interest rates on uninsured debt are lower than that of shadow banks, despite banks' higher overall leverage. Further, uninsured leverage plays a key role in determining deadweight cost of intermediary debt. Shadow banks differ from

[7] See, among others, Hannan and Berger (1991), Neumark and Sharpe (1992), Drechsler et al. (2017), Egan et al. (2017), Begenau and Stratford (2019), Xiao (2020), Egan et al. (2022), Wang et al. (2022) for evidence and analysis concerning the bank deposit franchise.

banks: they cannot access insured deposits. The extent to which insured deposits provide a safety net to equity and uninsured debtholders is determined in the data using calibration.

We calibrate the model to the data on shadow bank and bank capital structure, size, and interest rates paid on different types of intermediary debt. Shadow bank data is especially informative because it provides a direct window into financial intermediary capital structure costs and choices in the absence of insured deposits. Thus our estimation uses data whereas existing structural models of the intermediary sector use additional modeling assumptions. The calibrated model allows us to compute intermediary leverage, cost of debt, and size distribution as well as the aggregate intermediary debt premia in a new equilibrium in which banks debtholders fully internalize default. Because we hold the preferences of the representative household fixed and leave banks' ability to lend unchanged, this counterfactual isolates the contribution of insured deposit safety nets to bank leverage.

Without insured deposits, the average bank capitalization increases to 14% (about 25% in relative terms). The contribution of safety nets to leverage is largest for small banks, whose capitalization increases to 17%, or by over 50%. Conversely, removing large banks' ability to access insured deposits leaves their leverage largely unchanged from the data. In other words, large banks' leverage in the data (at their current capital requirement) is quite close to their counterfactual leverage choice if they had no access to deposit insurance but were also not constrained by capital requirements. The large bank counterfactual is a good place to better understand the role of insured deposits in the capital structure of banks. Even though their leverage does not change when we remove their access to insured deposits, their uninsured deposit rates rise by 300bp. The presence of insured deposits leads to substantially lower cost of uninsured debt, giving banks a substantial funding advantage over shadow banks.

The aggregate consequences of the absence of safety nets provided by insured deposits are limited. We find virtually no effect on aggregate lending volume but find important distributional effects. A sizable decline in lending by smaller banks is more than offset by a small increase in lending by the largest banks. Somewhat surprisingly, the aggregate provision of bank liabilities would increase by 0.6pp, despite the absence of insured deposits. The production of money-like liabilities is redistributed from the least productive small banks, which shrink and become better capitalized, to more productive large banks, which are more leveraged and choose a larger size. Despite limited substitutability, net changes are offset by the loan and liability provision of the shadow banking sector, resulting in negligible aggregate consequences.

Our baseline decomposition provides a lower bound on the effect of safety nets because we assume that the households' preferences for bank deposits remain unchanged when we remove deposit insurance. If, instead, households' preferences for bank debt increase with deposit insurance, safety nets are responsible for a much larger part of banks' leverage. If banks only offered shadow bank-like liabilities, their average capitalization would be 37%, a 26pp increase from their 11% capitalization in the data. Banks would still be substantially more leveraged than non-financial firms but would be better capitalized than shadow banks.

Overall, our counterfactuals conclude that the main contributor to leverage of large banks is their ability to produce money-like deposits, rather than the direct contribution of safety nets. The result is reversed for small banks. Despite their lower average productivity in lending, banks can command a large market share because they can offer substantially more valuable liabilities to households than shadow banks and because of safety nets of insured deposits.

One of the main policy relevant conclusions from our counterfactuals is that smaller and mid-size banks take more extensive advantage of safety nets than large banks and provide lower intermediation services for the same amount of leverage. In other words, our results suggest that absent externalities, capital requirements should be substantially *higher* for smaller banks than larger banks. For example, suppose, as the definition suggests, that global systemically important banking organization (GSIBs) are the only banks with important default externalities. Then these banks may need additional capital requirements above other large banks as is the case under current regulation. However, our findings suggest that for the rest of the banking sector, smaller banks should face higher capital requirements than larger non systemic banks. Similarly, small banks have historically faced smaller FDIC deposit insurance premia. These premia are supposed to reflect the cost of default to the Deposit Insurance Fund, and not externalities. Our model suggests that premia should instead be higher for the smallest banks. Overall, one of the main takeaways is that size-based regulation should potentially penalize smaller, rather than larger banks, at least in the part of the size distribution where externalities or market power do not play a large role.

Interpreted very broadly, our estimates could also imply that safety nets are partially responsible for the very large number of small banks in the U.S. Our model takes the number of banks and the productivity distribution as given. One could imagine, however, that large banks could acquire small banks and thus increase their productivity. Our model suggests that safety nets blunt such incentives, because they accrue disproportionally to smaller and subsidize unproductive banks. Acquisitions thus would raise productivity, but at the expense of rents from safety nets.

Related Literature: There is a vast literature and financial intermediation which we cannot hope to cover. We view the main contribution as twofold. First, we establish several novel facts on the capital structure of modern shadow banks and the cost of their debt financing across the size distribution. Second, we use these facts along with our quantitative model to study the extent to which banks' high leverage relative to shadow banks reflects the benefits intermediaries derive on the liability side of their balance sheet.

Below, we discuss a few recent papers that are most closely related to our work. First, an important aspect of our work is to emphasize the distinct role that uninsured deposits and uninsured in intermediary funding. In this regard, our paper is related to recent models that recognize differences between insured and uninsured deposit funding such as Davilla and Goldstein (2023) who focus on the question of optimal design of deposit insurance and the bank resolution process. We document that bank rates on uninsured debt are low relative to rates paid by shadow banks despite banks' higher leverage. Our modeling framework captures this fact by recognizing that that uninsured deposits are effectively senior with respect to the insured deposits because they run and insured deposits do not.

Second, our paper is related to quantitative models of intermediary capital regulation. Within this work we connect naturally to recent structural models of interaction between banks and shadow banks as well as work on preferences for deposit funding. There are three classes of models that are related to our work. First are structural models, which explicitly consider uninsured funding, such as Egan et al. (2017) and Albertazzi et al. (2022). Similar to our work, the latter incorporates micro-level data on the asset side to estimate the model. The second strand of models is those which consider mortgage lending, i.e., the asset side of banks, such as Buchak et al. (2018; 2023), Benetton (2021) and Benetton, Gavazza, and Surico (2021). The household side of our model builds on Begenau, and Landvoigt (2022) and is related to the Koijen and Yogo (2016) idea that securities' returns can deviate from their risk adjusted returns due to household preferences. Relative to these models, we simplify the run-behavior of uninsured depositors and the demand for bank lending. Instead, we focus on the intermediary size distribution, add a shadow banking sector and model their capital structure, and discipline the model with shadow bank data.

The closest paper to ours is Corbae and D'Erasmo (2021): similar to our model, they analyze regulation in a model of banks in which banks' asset and liability choices are endogenous. They also consider the size distribution, modeling large and small banks and competition from shadow banks—the latter are atomistic and *funded with equity*. Relative to their model, we simplify the model on the dimension of dynamics and thus cannot study business cycle dynamic or capital buffers. Instead, we focus on a richer size distribution of banks, add a non-degenerate size distribution of shadow banks and central to our contribution, study the capital structure for shadow banks and use shadow bank data to discipline our estimates.

Our paper is also related to the literature on the size distribution of banks. Two recent papers are particularly relevant. Huber (2021) finds that exogenous growth in bank size does not necessarily contribute to growth and can harm some borrowers. We consider the endogenous bank size distribution instead, and find that overall, more productive banks choose to be larger. Complementary to our work is d'Avernas et al. (2023) who study the size distribution of banks though the lens of small and large banks with a focus on heterogeneity in deposit demand, rather than the full equilibrium size and leverage distribution, which is the central interest of our paper.

Our paper is also connected to a vast literature emphasizing the importance of acknowledging value creation on the bank liability side. In our model investors value intermediary debt because of its money-like properties, with an endogenous money-like premiums arising for shadow bank debt and bank debt (deposits) that can also reflect the advantages of the deposit franchise.[8]

More broadly, our paper is related to work the literature, which has studied the design of deposit insurance and the resolution process (e.g., Granja et al. 2017 and Allen, Clark, Hickman and Richert 2023) and other policies in financial intermediation such as the role government guarantees play in banking and intermediation (e.g., Atkeson et al. 2019). We also connect with recent work that emphasizes the role of non-bank financial sector in intermediation and examines their funding.[9]

Our work also relates to models that investigate pass-through of macro-prudential, monetary, fiscal policies, and other shocks through financial intermediaries (He and Krishnamurthy 2013; Brunnermeier and Sannikov 2014; Greenwood et al. 2017; Elenev et al. 2021; Bianchi and Bigio 2022; DaVilla and Walther 2022; Buchak et al. 2023; Amador and Bianchi 2024). We add to this work using shadow bank call report data to discipline our calibration, and by emphasizing the role of funding choices of banks and shadow banks for the lending market equilibrium. Finally, we connect to literature that uses historical, pre-deposit insurance data and studies bank funding and lending choices in the absence of insured deposit funding (e.g., Calomiris and Jaremski 2016 and 2019; Aldunate et al. 2019, Blickle, Brunnermeier, and Luck 2019).

2. Institutional Background: Banks vs. Shadow Banks in the U.S. Mortgage Market

Loans are either originated by banks or by shadow banks. Banks are deposit taking corporations, and shadow banks are non-bank lenders. This definition is consistent with the Financial Stability Board, whose members comprise both national regulators of G20 countries, as well as international financial institutions, such as the International Monetary Fund, the World Bank, and the Bank of International Settlements, as well as international standard-setting and other bodies such as the Basel Committee on Banking Supervision (see Buchak et al. 2018). Deposit taking of banks exposes them to a substantially higher regulatory burden than shadow banks. For example, banks are subject to capital requirements, enhanced supervision from a

[8] For recent empirical and theoretical work highlighting the importance of the deposit franchise in banking activities see, among others, Drechsler et al. 2017, Egan et al. 2017, Xiao 2020, Egan et al. 2022, Wang et al. 2022.

[9] For recent work in this area see, among others, Gennaioli, Shleifer, and Vishny 2013; Moreira and Savov 2017; Buchak et al. 2018; Huang 2018; Ordonez 2018; Fuster et al. 2019; Xiao 2020; Irani et al. 2021; Gete and Rehrer 2021; Chernenko et al. 2022; Gopal and Schnabl 2022; Jiang 2023.

wide set of regulators, such as the FDIC, FED, OCC, and state regulators, as well as extensive compliance and rules. Shadow banks face limited supervision and regulation, primarily from state regulators.

Our main exercise is to compare the funding structure of shadow banks to banks. Ideally, we would like to compare banks and shadow banks that engage in similar activities on the asset side of the balance sheet. Our data covers all shadow banks, which originate mortgages; they also tend to sell the majority of the loans they originate. Banks, on the other hand, engage in a broader set of activities, for example, also providing loans to corporations. Here we compare the business models of shadow banks to those of banks on several key dimensions. We show that in the activities that do overlap, banks and shadow banks engage, on average, in similar activities. We also show that a significant subset of banks follows a business model similar to that of shadow banks on the asset side. When we compare shadow banks to banks in the rest of the paper, we narrow that comparison further by focusing on such banks.

Lending and Assets Composition

Lending is a major part of the business for both banks and shadow banks. Loans extended by both types of intermediaries are the largest item on their balance sheet accounting, on average, for a very similar portion of their assets. Using the call report data, which we discuss in the next section, we find that on average loans constitute about 67% of shadow bank assets, which is very close to 65% for banks (see Appendix A1). Because shadow banks specialize in mortgage lending, real estate loans constitute, on average, close to 100% of loans on their balance sheets. However, even for the average bank, about 80% of loans on the balance sheet are real estate loans. Moreover, residential mortgage loans are the most common category of real estate loans for both banks and shadow banks (for shadow banks, a vast majority are residential loans).

Propensity to Sell Loans and OTD Model

Shadow banks sell more than 90% of their loans, relying primarily on the originate-to-distribute (OTD) business model (Appendix A1, panel b). Despite a common perception that banks hold on to the loans they originate, banks also sell the majority of their loans (Buchak et al. 2023), including about 60% of the residential real estate loans (Appendix A1, panel b). Moreover, Buchak et al. (2023) find a substantial share of banks with a similar OTD business model to shadow banks. We find over 500 banks, which we later call OTD banks that sell about 90% of their loans. We later construct our comparison set using the OTD banks.

Borrower and Loan Characteristics

Shadow banks and banks compete head-to-head for the same borrowers in the same markets and offer similar contract terms over our sample period (see Buchak et al. 2018). Appendix A1 (panel b) compares the borrower characteristics for bank and shadow bank loans. Over the period 2011 to 2017, banks and shadow banks serve borrowers with similarly sized mortgages ($253K versus $225K on average) and broadly similar incomes ($129K versus $101K on average).

We further illustrate the similarity of loans and borrowers across banks and shadow banks using detailed data for the most common loan type during our sample period: loans sold to GSEs. These loans comprise more than half of all loan originations. Due to GSE data disclosure, we observe detailed borrower and contract level information. We present the results in Appendix A1 (panel c). Borrowers' creditworthiness is very similar, with average FICO score of 755 for shadow bank borrowers and 759 for bank borrowers.[10] These borrowers have very similar average LTV ratios (71.3 versus 71.9 pp), debt to income ratios (33.5 versus 32.9 pp), interest rates (4.01 versus 3.99 pp), and average loans amounts ($240K versus $231K).

[10] These borrowers also have very similar delinquency rates (Buchak et al. 2018).

Overall, this evidence confirms that in the main mortgage market shadow banks and banks serve very similar borrowers and offer very similar loan terms.

3. Constructing Shadow Bank Call Reports

3.A Constructing Shadow Bank Call Reports through FOIA

We construct a novel data set containing balance sheet information of shadow banks in the US residential mortgage origination market from 2011 to 2017. We use FOIA requests to collect data from shadow banks' quarterly call report filings to state regulators. Pursuant to the S.A.F.E. Mortgage Licensing Act of 2008, shadow banks that hold a state license or state registration to conduct mortgage origination are required to file a call report in each state in which they perform lending activities since 2011. We directed FOIA request to 50 states, and Massachusetts and Washington complied. As long as a shadow bank is registered or licensed in either of these states, we obtain information on all its operations across all U.S. states. Therefore, as we describe below, even sampling two states results in coverage of 80% of shadow bank mortgage originations. Each shadow bank has a unique ID in the National Mortgage License System (NMLS ID), which is used as an identifier in the call reports. The call report contains two components, Financial Condition (FC) and Residential Mortgage Loan Activity (RMLA). The FC collects data on the balance sheet and the income statement at the company level. The RMLA contains detailed information about individual debt facilities. For each debt item, we observe the provider (lender) name, the credit limit, and the amount of remaining limit that has not been drawn on each credit line. Together these components allow us to construct shadow bank "call reports" for our sample.

We combine our sample of shadow banks with loan level data from Home Mortgage Disclosure Act (HMDA), which has information on mortgage originations of virtually all lenders and the vast majority of mortgage applications in the United States. HMDA data includes loan type, purpose, amount, year of origination, and location information down to the applicant's census tract. It also contains demographic information on the applicant, including race and income. Important for our analysis, it includes the originator's identity, which we link manually across years. Finally, it documents if the originator sells the loan to a third party.[11]

We create a bridge between HMDA data and shadow bank call report data. Each shadow bank has a unique ID in the National Mortgage License System (NMLS ID), which we use as identifiers in the call reports. The NMLS ID is not publicly disclosed in the HMDA database. Instead, each financial intermediary has institution ID. To link the two data sets, we construct a crosswalk table by using the NMLS Consumer Access platform, where consumers can search for shadow bank registration information using company name and address.

Our data covers 429 shadow banks with complete call report and HMDA information. These shadow banks originated about $4 trillion of residential mortgages from 2011 to 2017. This accounts for about a third of all bank and shadow bank mortgage originations during this period. In our analysis we compare shadow banks with banks. The data on bank capital structure and interest expenses are obtained from bank regulatory call report filings, Form 031 and Form 041, publicly available on the *Federal Financial Institutions Examination Council (*FFIEC) website. Since the regulatory filing requirements changed several times post crisis, we check the historical 031 and 041 forms year by year to ensure the consistency.

[11] An important caveat with the sales data is that if the originator retains the loan through the end of the calendar year and sells it in the subsequent year, it is recorded in HMDA as a non-sale.

3.B Shadow Bank Call Reports: Coverage and Representativeness

To evaluate our coverage, we compare the origination volume by shadow banks in our sample with total shadow bank mortgage originations in HMDA data. After 2011, about 80% of total shadow bank mortgage origination in each year is covered by our sample (Figure 1, Panel a). Because call reports were not enforced in Massachusetts in 2011, our sample coverage is smaller but still covers more than 40% of the total shadow bank origination.

Panel (b) of Figure 1 compares the distribution of loan volume by shadow banks in our sample to the entire shadow bank population recorded by HMDA in 2017. Our data contains most shadow banks in the right tail of the entire shadow bank size distribution. Small local shadow banks in states other than Washington and Massachusetts are underrepresented. We cover 171 out of the 240 largest U.S. shadow banks identified in Buchak et al. (2018), and observe all shadow banks among the top 10 mortgage lenders in 2017. Our call reports miss 464 small shadow banks in in 2017, which comprise approximately 20% of mortgage origination, and originate on average $371 million.[12] As we will show, the overweighting of large shadow banks in our sample understates the average difference in the capital structure of banks and shadow banks.

3.C Summary Statistics: Assets, Liabilities, Income, Expenses, and Debt Facilities

Assets: Panel (a) of Table 1 displays the detailed composition of shadow bank assets. The largest asset categories are mortgage related: Mortgages held for sale comprise 64% of assets; Mortgages held for investment around 4%; Mortgage servicing rights comprise another 7.5% of assets. We also have information on other assets. The largest categories are Cash, which comprises 11.7% of assets, Receivables comprise 3.25% of assets, Buildings and properties another 2% and Derivatives' comprising 1.4%.

Liabilities: The liabilities side of the balance sheet contains detailed information on the financing structure of shadow banks. We explore the liabilities structure of shadow banks in substantial detail the body of the paper. In Panel (a) of Table 2, we provide some simple statistics. Equity capital accounts for about 25% of assets of shadow banks in our sample, averaged over the sample period. Almost half of this equity capital is from retained earnings and the rest is largely from common stock and paid-in capital. We also observe the composition of non-equity long-term and short-term liabilities, that together account for 75% of assets. Virtually all liabilities of shadow banks are short-term (about 90%), with short-term debt accounting for majority of this category. Since shadow banks have no deposits, all debt is uninsured.

Debt Facilities: For each debt facility we observe the provider (lender) name, the credit limit, and the amount of remaining limit that has not been drawn on each credit line. Panel (b) of Table 2 shows that this funding comes in the form of warehouse lines of credit provided, on average by around 4 lenders (median 3 lenders). These are credit lines which are secured with the mortgages originated by the lender, and generally have to be repaid in less than a year. Lenders to shadow banks fall into two categories, banks, such as Credit Suisse First Boston and JPMorgan Chase that provide about 93% of available credit line funding and non-bank financial institutions providing the rest.[13] Shadow banks draw only about half of the available credit lines (50.3%) over the sample period.

Income and Expenses: Panel (b) of Table 1 shows the composition of income and expense statement of shadow banks in our sample. Sales of mortgages in the secondary market and origination related income (e.g., fees) account for about 74% of shadow bank gross income, with secondary market sales accounting for about three fourths of it, reflecting the OTD business model of shadow banks. Mortgage servicing fees

[12] As we show later, capital structure of large shadow banks is more similar to that of banks.
[13] See Jiang (2023) for a more detailed analysis of credit lines to shadow banks

account for about 9% of gross income, in large part due to retaining servicing on significant portion of mortgages sold. On the expense side, personnel expenses account for about 56% of all expenses. Interest expenses are about 7% of total expenses of which a large part is interest payment on warehouse credit lines.

3.D Regulatory Capital for Shadow Banks

Shadow banks are not subject to capital requirements, and not required to report regulatory measures of capital or to use risk-weights when evaluating the amount of capital. Because our analysis focuses on comparing the capital structure of banks and shadow banks, including regulatory measures of capital, we need to construct regulatory capital equivalents for the Tier 1 capital for each shadow bank in our sample.

There are two components to constructing regulatory measures of capital for shadow banks: capital and risk weighted assets. Tier 1 capital is computed by summing common stock, paid-in capital, retained earnings, preferred stock, and noncontrolling interest. We do not observe the proportion of Category 1 and Category 2 residential mortgage loans to construct precise risk weighted assets. We therefore construct bounds on risk weighted assets using the range of weights. The lower bound assigns 20% to residential mortgages that are guaranteed or insured by the government (FHA, VA, or RHS), 50% to non-government insured mortgage loans, 250% to mortgage servicing rights, 0% to cash, securities, deferred tax assets, and goodwill and other intangible assets, and 100% to all other assets, such as receivables and property, equipment and other fixed assets. The upper bound is computed by assigning 100% weight to non-government insured mortgage loans while assigning the same weights as in the calculation of the lower bound on all other assets. We compute the upper (lower) bound of the asset risk weighted Tier 1 capital ratio by dividing the Tier 1 capital by the lower (upper) bound of the risk-weighted assets.

3.E Constructing Comparison Bank Samples

The central exercise in the paper is to compare the funding structure of shadow banks to banks. Ideally, such a comparison would use banks, who engage in identical activities as shadow banks on the asset side. As we discuss in Section 2, there are differences in the business model of the average bank and average shadow bank. On the other hand, there is a substantial number of banks, whose business model is very similar to shadow banks. They sell a similar share of loans they originate; they originate similar loans to a similar customer base. In addition, as Figure 2 (a) and (b) show, there is a substantial overlap in our sample of shadow banks and sample of all banks when we compare them on loan volume and on assets. We construct two main samples of banks, which engage in the same business model as banks. As we show in Sections 4 and 5, the choice of the comparison group of banks turns out to be irrelevant. Despite significant differences in the business model and asset holdings across banks, the capitalization differences across banks are tiny relative to the scope of our main facts. Nevertheless, it is useful to illustrate this fact.

Our two comparison sets focus on banks, which follow the OTD business model, just like shadow banks. Accordingly, we construct two sets of banks “OTD I” and “OTD II.” The OTD I sample focuses on banks’ mortgage lending. These banks are in the top five percent of all banks in the share of mortgages sold in a given year. We obtain this information from HMDA, which tracks loans sold within a year for every lender. Banks in aggregate sell approximately 60% of retail mortgages (Appendix A1). The average OTD I bank sells about 92.4%, which is very close to the percentage for shadow banks which is 94.4%. There are 549 banks in this subsample. The minimum percentage of loans sold for any OTD I banks is 85.5%.

OTD II banks are also selected based on selling of loans, but are not restricted to residential mortgages. We select banks whose share of loans held for sale (out of total loans) held on balance sheet is greater than 10%. Under reasonable assumptions on effective loan maturity, a 10% rate of loans held for sale is broadly consistent with the minimum 85.5% of mortgages sold out of total originations threshold that we had for banks in OTD I set.[14] Indeed, about 89% of mortgages originated by OTD II banks are sold (Appendix A1). There are 257 banks in this comparison set. Appendix A2 shows the relation between the measures used to construct the variants of "OTD" banks. It confirms that banks selling almost all their mortgage loans have on average loans held for sale to total loans ratio in excess of 10%.

For robustness, we also construct "synthetic mortgage banks" as another comparison group to mimic mortgage activities of shadow banks. Finally, we also compare key funding ratios of shadow banks to all the banks ("All Bank" or "Full Bank" sample), regardless of their exposure to activities done by shadow banks to understand how much tighter comparisons are useful in refining our inference.

Section 4: Shadow Bank and Traditional Bank Capitalization

4.A *Fact 1: Shadow Banks Have Substantially More Capital—Lower Leverage—than Banks*

We start by measuring capitalization—the central measure of bank leverage—of shadow banks and comparing it to banks. Shadow banks have a mean equity to asset ratio equal to 25%, relative to 11% for the average bank (Table 3, Panel (a)). Since capital regulation is frequently cast as a trade-off between lending and bank stability, it may also be informative to weigh institutions by the number of loans they originate. The average shadow bank mortgage is originated by a shadow bank with 21% equity to asset ratio, while the average bank mortgage is originated by a bank with a 11% equity to capital ratio. The average shadow bank in our sample thus funds itself with over twice as much equity as the average bank. In the rest of this sub-section, we show that this result is robust, and if anything, grows in magnitude as we improve the comparison between banks and shadow banks.

As we discuss in Section 2, on average banks are less likely to sell loans than shadow banks. If retaining loans is less capital intensive, this would justify the lower bank capitalization. Buchak et al. (2023) show the opposite is the case: banks, which sell more loans are on average *less* capitalized than other banks. We confirm this finding: OTD I banks' capital ratio of 10.2% and OTD II banks' capital ratio of 10.5% are lower than the average banks' capital ratio of 11%. Therefore, if we compare the capitalization of shadow banks to that of banks, which primarily engage in the same activity on the asset side, the differences between banks and shadow banks become *larger*.

These results also suggest that the choice of the bank comparison group does not matter: the differences in capitalization between different groups of banks are on the order of 1pp, whereas the difference in the capitalization of banks and shadow banks is around 14pp. Regardless of the comparison set, shadow banks have a substantially higher equity capital in their funding structure relative to banks. The magnitude of disparity becomes clear when one realizes that less than 0.5% of banks have equity capital large than shadow bank average of 25% (Figure 3). Figure 4 suggests that these differences are not driven by shadow banks' explosive growth or changes in composition during this period.

To formally account for differences in composition of banks and shadow banks that might drive their capitalization, we estimate the following specification:

[14] Suppose loans held to maturity have an effective maturity of 5 years (60 months) due to refinancing and prepayments, but loans held for sale are held on the balance sheet for about 1 month (consistent with Buchak et al. 2018). If the share of loans held for sale is 10%, then about 86.9% = 10%/[10% + (1 month/60 month)×90%] of originated loans are sold.

$$C_{i,t} = \alpha + \beta_1 ShadowBank_i + X'_{\mathrm{i,t}}\Gamma + \mu_t + \epsilon_{i,t}, \tag{1}$$

where $C_{i,t}$ (capitalization) is the equity to asset ratio of institution *i* at time *t*. The key variable of interest is the shadow bank indicator, $ShadowBank_i$, that takes the value of one if a lender is shadow bank and is zero otherwise. $X_{i,t}$ contains institution and local economic controls. These include the lender's growth (asset growth), the share of refinanced loans out of total loan origination portfolio, the share of government-insured loans out of total loan origination portfolio, the logarithm of annual mortgage volume in dollars, the logarithm of asset size in dollars and the logarithm of the weighted average of income per capita in states of operation of the institution, and a measure of geographic dispersion (diversification) of residential lending activity.[15] In addition, μ_t is the time fixed effect (year-quarter) which accounts for any time specific shocks that may impact capitalization ratios of all lenders. We estimate this specification across three different bank samples: the sample of all banks, OTD I, and OTD II.

Adjusting for differences in their lending and portfolios has an economically small impact on the difference in capital ratios between banks and shadow banks. In fact, adding controls increases the coefficient in every subsample. These coefficient estimates, which range between 10pp and 12pp confirm that shadow banks have about twice as much capital as corresponding banks. Adding controls changes estimates by at most 1.6pp, confirming our intuition that differences in characteristics between banks and shadow banks cannot explain differences in their capitalization. As we noted in Section 2, the mortgage market has undergone significant changes during our sample period, with the market share of shadow banks more than doubling (Buchak et al. 2018). Yet, the addition of time fixed effects barely changes the coefficient estimates, confirming the intuition from Figure 4 that the differences are not isolated to a specific period.

Regulatory Capital: Regulatory attention is frequently focused on risk-based capital ratios. In Section 2.D, we describe the construction of upper and lower bounds of tier 1 capital ratio for shadow banks. Shadow banks have a significantly higher tier 1 capital ratio relative to banks, even when we apply an extremely stringent lower bound (Figure 5). The lower bound shadow banks' average Tier 1 capital ratio is 29%, while the upper bound is 37%. Even the lower bound substantially exceeds the 16% average Tier 1 ratio of banks, and the 15% capital ratio of OTD I and OTD II banks. We re-estimate the regressions from Table 4 but using the upper and lower bound of Tier 1 capital ratios as dependent variable instead (Table 5). Overall, across all specifications, controls, subsamples, and different ways of measuring capital, we find a very robust pattern: shadow banks have, on average, significantly more equity in their capital and hence much lower leverage than deposit-taking banks.

4.B *Fact 2: Differences in Capitalization across Shadow Banks are Substantially Larger than those Across Banks*

Banks' capitalization is remarkably homogenous despite large differences in their business models, which differentiates them from non-financial firms (Hanson et al. 2015). In our sample, the standard deviation of bank capitalization is 2.9pp. Shadow banks in our sample are substantially more homogenous in their business model, with a focus on retail mortgage origination and OTD. If activities on asset side are driving the homogeneity of intermediaries' capitalization, we should observe an even higher degree of homogeneity in the capital structures across shadow banks in our sample. Instead, we that the dispersion in shadow bank capitalization exceeds that of banks by over 6 times, with the standard deviation of 18.3pp (Table 3, Panel

[15] The geographic dispersion of a lender is measured by the sum of squares of mortgage origination share in each county for that institution.

b). Thus, despite more homogenous business models, there is significantly more dispersion in capital ratio across shadow banks relative to banks.

To confirm that differences in dispersion are not the result of differences in asset composition, measurement error, or sample composition, we estimate differences across the capitalization of shadow banks and of banks using the following specification:

$$C_{i,t} = \alpha + X'_{\mathrm{i,t}}\Gamma + \mu_i + \mu_t + \epsilon_{i,t}, \tag{2}$$

where $C_{i,t}$ is the equity to asset ratio of institution i at time t. $X_{i,t}$ contains institution and local economic controls, μ_t contains time fixed effects, and μ_i contains institution fixed effects. We estimate this specification separately for banks and shadow banks.

The object of interest is the distribution of institution fixed effects. μ_i measures the time invariant difference in the capitalization of an institution relative to other institutions, controlling for differences in their characteristics (business models) and time. To account for potential measurement error in fixed effects, which could drive the dispersion across shadow banks, we estimate empirical Bayes fixed effects, and plot the distribution of fixed effects in Appendix A3. The standard deviation of the empirical Bayes fixed effects is 3.4 times as large as that of banks, confirming the results from the simple cuts of the data. This fact is striking because shadow banks' business models are substantially more homogenous than those of banks. Differences across shadow banks capitalization are reminiscent of large leverage differences across non-financial firms, even within narrowly defined industries (see Lemmon et al. 2008).

4.C *Fact 3: Shadow Bank Debt is Short Term, and Concentrated*

Bank debt has several distinctive features. It is primarily (85%) short-term, and the lenders (depositors) are dispersed; the majority (60%) is insured by the FDIC. [16] Short-term debt plays an even more important role in the debt structure of shadow banks, accounting for more than 98% of their debt (Figure 6).

The structure of shadow bank short-term debt differs significantly from that of bank debt on three dimensions: (i) Bank debt is partially insured, and shadow bank debt is uninsured is uninsured by definition: shadow banks cannot raise deposits, insured or otherwise. (ii) Bank debt is dispersed, and shadow bank is concentrated. Deposits—dispersed debt—represent about 95% of short-term debt funding of banks. Shadow banks could also finance themselves with dispersed short-term debt, for example, through commercial paper. Instead, they use credit lines provided by on average by 3.6 lenders (Table 2, panel b). Lender concentration is not an artifact of shadow banks being small: our sample is biased towards larger shadow banks, which on average originate about two billion dollars of loans per year. Appendix A4 shows the distribution of the number of lenders across shadow banks; even the 75th percentile bank has only 5 lenders, and very few have more than 10 lenders. (iii) The main provider of shadow bank short-term funding are large banks. Relative to dispersed depositors, concentrated bank lenders are likely more informed.

[16] Total debt excludes all trade-related liabilities, such as account payable and tax liabilities. Specifically, total debt includes debt facilities, commercial papers, mortgage debt, advanced federal home loans, and trusted preferred securities for shadow banks and it includes total deposits (for banks), repo, and an item called other borrowed money in the call report (such as FHLB advances or commercial papers).

Section 5: Intermediary Uninsured Leverage and Rates Across the Size Distribution

In this section we define a new bank capital structure concept of "uninsured leverage" and show a very robust pattern of increasing uninsured leverage across the size distribution for both shadow banks and banks. We also show that debt rates decline across the size distribution.

5.A Fact 4: Shadow Bank Capitalization Decreases Substantially with Size. Bank capitalization hardly changes with size. Uninsured leverage, defined as uninsured debt funding to assets, increases with size for both banks and shadow banks.

We begin by showing that shadow bank leverage increases substantially with size. As one would expect, this relationship is not present for banks, given small differences in bank leverage. In the second part of this section, we define a new bank capital structure concept of "uninsured leverage:" the uninsured part of their funding. We provide evidence that the size leverage relationship is not specific to shadow banks but is masked by insured deposit funding of banks. We find similar patterns for banks once we focus on uninsured leverage.

We start with showing simple cuts of raw data: we compute the average capitalization across size bins in Figure 7. Shadow bank capitalization declines substantially with leverage. The smallest shadow banks' capitalization ranges between approximately 46% and 58%. The largest shadow banks ranges between 15% and 20%. This result is robust across different measures of capitalization and size. Capitalization measured by Tier 1 capital also substantially declines with size (Appendix A5). Similar results are obtained for equity to asset ratio when use logarithm of assets as the size measure (see Appendix A7). This is not surprising since our two size measures, loan volume and assets, are highly correlated (see Appendix A6). In contrast to shadow banks and consistent with our finding that bank capitalization is remarkably homogenous, there is no relationship between bank leverage and size.

We more formally show that shadow bank capitalization declines with size, even if we benchmark it to banks, by estimating the following specification for the equity to asset ratio:

$$Ratio_{i,t} = \alpha + \beta_1 ShadowBank_i + \beta_2 ShadowBank_i \times Size_{i,t} + X'_{\mathrm{i,t}}\Gamma + \mu_t + \epsilon_{i,t} \qquad (3)$$

The key variables of interest are the shadow bank indicator, $ShadowBank_i$, and its interaction with size. $ShadowBank_i \times Size_{i,t}$. μ_t is the time fixed effect (year-quarter), which absorbs time series variation in equity to asset ratio. As before, $X_{i,t}$ contains controls. The estimated shadow bank dummy for capitalization is positive, while its interaction terms with size is negative across specifications and different bank comparison subsamples (Table 7). A two standard deviation change in size decreases shadow bank capitalization relative to corresponding banks by approximately 12-13pp across specifications. This result is robust across bank comparison groups (columns 2-4 of Table 7), and to different measures of capital and size (Appendix A9-A11).

We showed above that while shadow banks' leverage increases with size, banks' leverage does not. Now we show that banks' leverage increases in size for banks as well, if we measure their "uninsured leverage." We define "uninsured leverage" of a financial intermediary i as $L_i^u = \frac{D_i^u}{A_i}$, in which D_i^u represents the uninsured debt of intermediary i (uninsured deposits, foreign deposits, repos, other borrowed money, and subordinated debt). Uninsured leverage then measures the share of uninsured debt in the capital structure of a financial intermediary. Since shadow banks have no insured deposits, their uninsured leverage mechanically equals the share of their debt in the capital structure. For banks, the wedge between uninsured leverage and overall leverage is driven by insured deposits.

We focus on uninsured bank debt because a substantial share of theories of optimal capital structure require that debtholders internalize some cost of default, at least off equilibrium. For example, debt holders only have incentives to monitor if they suffer default costs in the absence of monitoring. Similarly, trade-off theories of capital structure require debtholders to internalize the cost of default. If shadow banks' leverage choices are determined by such considerations, then we might expect this to be true for banks as well, but only for the share of debt which is uninsured. Figure 9 illustrates how uninsured leverage evolves with size of banks and shadow banks. Uninsured shadow bank leverage increases from 54% to 80%, or about 26pp for shadow banks over the same size range. Uninsured leverage increases from 23% to 40%, or about 17pp, across the distribution of size in the sample of all banks. We also find a significant increase in uninsured bank leverage across other bank comparison samples (Panels b-d). Larger financial institutions, both banks and shadow banks, finance themselves with more uninsured leverage.

How does uninsured leverage of banks increase with size while overall leverage remains fairly stable? Since the overall amount of leverage stays fixed, it implies that the share of insured deposits to other debt funding (uninsured deposits) declines with bank size. Figure 8 confirms that intuition. Large banks rely much less on insured funding than small banks. This change in the composition of debt obscures the large increase in uninsured bank leverage with size.

Since banks' business models can differ significantly, one may be concerned that larger banks rely more on uninsured debt funding because they engage in fundamentally different activities than banks. A priori, this is not likely, since we observe the same pattern for shadow banks, which are much more homogenous. Nevertheless, we explore this alternative using the following regression specification:

$$L_{i,t}^{u} = \alpha + \beta Size_{i,t} + X_{i,t}'\Gamma + \mu_t + \epsilon_{i,t} \tag{4}$$

$L_{i,t}^{u}$ is the uninsured leverage of intermediary i in year t. $Size_{i,t}$ is our independent variable of interest. $X_{i,t}$ is a vector of institution and local economic controls, which we have used in our prior specifications. We include the year fixed effect in our regressions and estimate this specification separately for banks and shadow banks.

Confirming univariate results from Figure 9, uninsured leverage substantially increases with size for both banks and shadow banks (Table 8). A two standard deviation increase in size is correlated with an increase in uninsured leverage between 4.2–8.6pp for banks and about 13-20pp for shadow banks. Within the sample of all banks and shadow banks, this implies a relative increase by about 30% in the uninsured leverage (relative to their respective means). The results suggest that the (privately) optimal capital structure of financial intermediaries, both banks and shadow banks, tilts towards more (uninsured) debt as size of intermediaries increases. Again, this finding is robust to alternative definition of size (see Appendix A12).

5.B Fact 5: Intermediaries' Uninsured Debt Rates Decline with Size. Shadow banks pay substantially higher rates than banks on debt across the size distribution.

We next show that uninsured debt interest rates decline with size for banks and shadow banks. This evidence bolsters the idea that the same underlying forces drives the relationship between size and uninsured leverage changes for banks and shadow banks. Figure 10 shows that the average uninsured debt rates decline with size for both banks and shadow banks.[17] The decline is significant: the interest rates paid by the largest shadow banks are approximately 300bp lower than that of the smallest shadow banks; for banks, the difference is on the order of 100bp. In relative terms, interest rates decline by about 1/3 for both types of intermediaries across the size distribution.

Banks face a substantially lower cost of funding than shadow banks even on their uninsured debt. The average interest rate of shadow banks is 4.5%, while the average uninsured interest rate of banks is 2.3%. In other words, uninsured deposits are considered much safer or generate additional benefits to lenders relative to shadow bank debt despite higher bank leverage. The pricing of debt illustrates that deposit insurance and other benefits of deposits (e.g., their money like function) does not only lower interest rates on insured deposits, but also makes uninsured deposits safer.

One concern is that bank rates, especially on uninsured deposits, decline with size because larger banks provide more services, which are bundled with deposits. Depositors would pay for these services implicitly through lower deposit rates. Since we observe the same decline in rates for shadow banks this is less likely—it is unclear which services they would offer to the providers of debt. Nevertheless, we address this concern head-on in Figure 10 by examining rates on insured deposits, which should also capture service provision (Egan et al. 2017). We find no marked decline in insured rates; if anything, the cost of insured deposits is slightly increasing in size across a significant range. We probe this further and compute the within bank difference in uninsured and insured debt rates. The idea is that if a bank provides better services, which are priced in deposit rates, it does so for both insured and uninsured deposits. Figure 9 panel (c) plots how the difference in uninsured an insured debt rates change with size. Consistent with prior evidence, uninsured debt rates decline with bank size, even relative to insured deposit rates.

We also formally investigate the relationship between rates on uninsured debt and intermediary size using the following specification, which we estimate separately for banks and shadow banks:

$$Rate_{i,t}^{u} = \alpha + \beta Size_{i,t} + X_{i,t}'\Gamma + \mu_t + \epsilon_{i,t} \tag{5}$$

$Rate_{i,t}^{u}$ is the average interest rate an intermediary *i* pays on its uninsured debt in year *t*. $Size_{i,t}$ is our independent variable of interest, which is measured by the logarithm of mortgage origination volume. $X_{i,t}$ is a vector of institution and local economic control variables. We include the year fixed effect in our regressions and cluster the standard errors by shadow banks. For banks, we also estimate a separate specification, in which the dependent variable is instead the difference between insured and uninsured rates a bank pays $Rate_{i,t}^{u} - Rate_{i,t}^{i}$, where $Rate_{i,t}^{i}$ is the average interest rate an intermediary *i* pays on its insured debt in year *t*.

The results in Table 9 confirm that the average rate on uninsured debt declines significantly with size for both banks and shadow banks. A two standard deviation increase in size is correlated with a 200bp decline in uninsured debt rate for shadow banks and about 46bp decline for banks. Moreover, the within-bank difference between uninsured debt and insured deposit rates declines by about 60bp, suggesting that the majority of the effect is driven by the decline in rates on uninsured debt. To recap, larger financial intermediaries have higher uninsured leverage, and pay lower average rates on their uninsured debt. This is true both for banks, and for shadow banks.

5.C Robustness

[17] The cost of uninsured debt is calculated using an intermediary's total interest expense on uninsured debt in year t divided by its total uninsured debt outstanding in year *t*.

We conduct several tests in Appendix. In Appendix C, we provide asset-side subsample robustness. We form subsamples of OTD banks to match on balance sheet composition and mortgage portfolio characteristics with shadow banks. Table C1 presents the summary statistics of the matched OTD bank samples and the shadow bank sample. Figure C4 replicates the size and capital ratio relationship using the matched samples, non-MSR sample, which contains institutions that do not hold mortgage servicing rights, and non-FinTech sample, respectively.

In Figures C5 and C6, we compare shadow banks, banks, other financial companies, and non-financial companies in Compustat database. Figure C5 shows the dispersion of capital ratios and short-term funding ratios. Figure C6 plots the capital ratios against size. In each of these analyses we reach similar conclusions.

Lastly in Tables C2 and C3, we report the correlation between size and geographic concentration, cash flow volatility, and growth. Size is measured by loan volume in Table C2 and is measured by asset in Table C3. The results suggest that larger banks and shadow banks tend to be less geographic concentrated, and more so for banks. Growth is negatively correlated with size for banks but is positively correlated with size for shadow banks. Cash flow volatility is more negatively correlated with size for shadow banks.

In Appendix D, we provide liability-side robustness checks. In Table D1, we present bank deposit breakdowns: brokered deposits, non-transaction account deposits, including time deposits and savings deposits. We then show the size-leverage relationships with leverage measured by each subcategory in Figure D2-D5. In Figure D6-D8, we construct Non-Transaction Bank samples, in which we keep banks whose non-transaction account deposits make up at least 75% of their total deposits. In other words, these banks' deposits provide little liquidity services. Finally, Figure D9 shows the size-capital ratio relationship using non-transaction bank samples. Again, in each of these analyses, we reach similar conclusions.

5.D External Validity: Pre-deposit-insurance banks in U.S and Germany

We now show that the capital structure of shadow banks in the post 2011 U.S. resembles that of pre-deposit-insurance banks in the U.S. and Germany: they are better capitalized than modern banks, with substantial heterogeneity in leverage across institutions, funded predominantly with short term debt, and leverage increases substantially with size. Our analysis so far is based on the idea that shadow banks and banks engage in similar activities, and that the first order difference in the capital structure between these institutions is banks' ability to obtain insured deposits, and the regulatory framework aimed at banks. However, our sample is limited to the post 2011 period and shadow banks in the U.S. One concern is that the differences we observe between shadow banks and banks may be limited to the regulatory and economic environment in this period. We now provide further evidence that the capital structure of our shadow banks mimics that of banks without deposit insurance. Since there are no modern U.S. banks without deposit insurance, we look into the pre-deposit insurance period both in the U.S. and Germany.

Aldunate et al. (2019) collect data on more than 6,000 U.S. banks in in 1928, prior to the establishment of the FDIC. Using their data, we plot the leverage of these banks as a function of bank size in Appendix B1.[18] Three facts stand out. First, these banks are substantially better capitalized than modern banks, with average equity to assets of about 18pp, which is close to the capitalization of shadow banks in our sample. Second, there are substantial differences in capitalization across banks before deposit insurance. Last, the leverage of pre-FDIC banks strongly increased with bank size. In other words, the pre-FDIC banks display the same (uninsured) leverage and size relationship we document in modern U.S. shadow banks. Given that the funding structure of pre-deposit insurance banks is similar to modern shadow banks, it is unlikely that

[18] We thank Aldunate et al. (2019) for generously sharing their data.

shadow banks' capital structure arose as a response to post-financial-crisis circumstances. We observe the same patterns in the data from German banks in 1931 collected by Blickle et al. (2019), which we present in Appendix B2.[19]

To summarize, the capital structure of modern shadow banks in the U.S. resembles that of pre-deposit-insurance banks in the U.S. and Germany. The resemblance to pre-deposit insurance banks suggests our results are unlikely due to factors which are specific to shadow banks' business model such as originating mortgages—residential mortgages were not the primary activity of the pre-FDIC banks. It also rejects the alternative that our results are specific to the post-crisis period or the specifics of the modern U.S. financial system in which they operate.

6. Model

We present a model of banks' and shadow banks' capital structure. The model has two objectives. First, we show that the simple model with mostly standard building blocks can generate the facts that we document in the previous section: i) Banks have higher overall leverage than shadow banks, but lower uninsured leverage. ii) Banks leverage is homogenous, and shadow banks' leverage is dispersed. iii) Uninsured leverage increases in intermediary size, and interest rates decrease in intermediary size. iv) Despite their higher leverage, banks pay lower rates on their uninsured debt. While simple, the model lends itself to calibration, and can also quantitatively match the patterns in the data. Second, we use the model to clarify that that insured depositors have an "equity like" property from the perspective of uninsured depositors: because they are insured, they do not run and thus do not contribute to the deadweight cost of debt funding. Thereby, they lower the cost of uninsured debt for banks. Last, we use the calibrated model to ask how much leverage banks would choose if they were able to perform the same function on the asset and liability side, but its debtholders (depositors) would fully internalize default cost. This allows us to investigate the implications of insured deposit funding for aggregate provision of lending and money-like liabilities as well as distribution of these effects across the intermediary size.

The model has standard building blocks: intermediaries raise external funding to facilitate lending, which is subject to declining returns to scale. Investors value intermediary debt because of its money-like properties, with an endogenous money-like premiums arising for shadow bank debt and bank debt (deposits) that can also reflect the advantages of the deposit franchise. When *uninsured* debt is impaired, it can lead to inefficient liquidation due to a run on the debt. This feature captures the fact that insured depositors are sleepy, and are not concerned with bank liquidation, and uninsured depositors see other uninsured depositors as the main competing claim on banks' assets.[20] The main difference between banks and shadow banks is access to financing and regulation: banks can access insured deposits which comes at the cost of capital requirements. As we document, all debt is short-term. We therefore do not model the term structure of bank debt and present a simple two-period model.

6.A Setting

6.A.1 Investment

Intermediaries choose how much to lend, and how to finance their lending. Lending is defined broadly and represents any activity an intermediary might take that requires capital: it can involve extending loans to borrowers, purchasing debt securities, and loan securitization. There are two types of intermediaries:

[19] We thank Marcus Brunnermeier, our discussant at NBER Corporate Finance Meeting, for providing these facts.
[20] For example, the run of uninsured depositors in the case of Silicon Valley Bank (see Jiang et al. 2023).

shadow banks and banks indexed $j \epsilon \{s, b\}$ respectively. Intermediaries differ in their ability to facilitate lending, which we parameterize with λ; $0 \leq \underline{\lambda} < \lambda < \overline{\lambda} < 1$. An intermediary with a higher λ has a better lending technology. $F^j(\lambda)$ designate the distribution of technology across intermediaries of type j. Intuitively, banks and shadow banks can differ in the distribution of lending technology; there are individual banks that are better at lending than shadow banks and vice versa. These differences can be purely technological but can also have regulatory origins, if, for example, bank supervision makes it more difficult for banks to lend.

An intermediary i, with a lending technology λ_i chooses how much to lend, a_i. Let $\mathbf{A} = (a_1, \dots, a_i, \dots)$ designate the lending by all intermediaries in the market. Lending is risky and exhibits declining returns to scale from the perspective of an individual intermediary and possibly in the aggregate. There are two states of the world. The good state arises with probability p. In the good state, the gross return on lending is $f \quad (a_i, \mathbf{A})$, with decreasing returns to scale, $f_a \quad (a_i, \mathbf{A}) > 0$, $f_{aa}(a_i, \mathbf{A}) < 0$. Intuitively, intermediaries first deploy the assets towards the most profitable uses. Declining returns can arise either because demand for loans is somewhat elastic, or because the costs of screening and monitoring loans increase with loan origination. The returns to lending by intermediary i are also a function of lending by other intermediaries, $\mathbf{A}$, because intermediaries, banks and shadow banks, compete for borrowers, either directly (Buchak et al. 2018, 2023) or indirectly through multi-market linkages. Because all intermediaries are small, they do not internalize the impact of their own lending decisions on the aggregate amount of lending, $f_{Aa}(a_i, \mathbf{A}) = 0$. For simplicity of exposition, we omit the dependence of profits on the aggregate amount of lending, unless it is explicitly necessary, and write $f(a_i)$ unless required.

In the bad state, with probability (1-p), loans generate $\lambda_i f(a_i)$. The idea is that differences in ability materialize in bad times. For example, a better intermediary, with a higher λ_i is able to intervene faster when borrowers' performance declines and is therefore able to recover a higher fraction of assets or can do so more cheaply. The technology can also represent screening, with $1 - \lambda_i$ representing the rate of false positives: borrowers who were ex ante not creditworthy but were nevertheless approved for a loan. Finally, λ_i can also reflect exposure of a lender to regulatory burden outside of those implied by bank capital requirements, which increases the expected cost of being in financial distress.

6.A.2 Financing

To finance amount a_i, an intermediary i can access three types of financing: equity E_i, uninsured debt D_i^U, and insured deposits D_i^I; only banks can access insured debt. We now discuss the supply and demand of financing before discussing the equilibrium.

Supply of Funds: Funding is provided by representative investors with an opportunity cost of capital normalized to 1. They are risk-neutral in terms of the expected asset payoffs with an additively separable utility of consumption. In addition, from evaluating investments from the perspective of expected cash flows, these investors value financial intermediary debt beyond its returns, for example, because of its money-like properties or services bundled into debt (deposits). Therefore, they are willing to potentially provide intermediary funding below the opportunity cost of capital, giving rise to a money-like premium of intermediary debt (Nagel, 2016; Begenau and Landvoigt, 2022; Krishnamurthy and Li, 2022).

The representative investor's net utility from holding intermediary debt in the excess of utility from debt repayments is the following:

$$U(D_b, D_s) = \underbrace{\xi_d (D_b^{\epsilon} + \eta D_s^{\epsilon})^{\frac{1}{\epsilon}}}_{Money-like\ benefit} \quad \underbrace{-\gamma^b D_b - \gamma^s D_s}_{Excess\ cost\ of\ intermediary\ debt} \tag{M1}$$

where $D_b = \sum_{i \in B} D_i$ and $D_s = \sum_{i \in S} D_i$ designate the total expected value of debt issued by banks and shadow banks, respectively. $\xi_d (D_b^{\epsilon} + \eta D_s^{\epsilon})^{\frac{1}{\epsilon}}$ designates the utility benefit the representative investor derives from intermediary debt in dollar terms. A higher ξ_d captures the average benefit of intermediary debt, for example, that it can be used as collateral in other transactions or that deposits are used for services, such as payments. η is the preference that investors place on bank versus shadow bank debt. For example, if deposits are more useful than shadow bank debt, then $\eta < 1$. Moreover, households imperfectly substitute between the liabilities of banks and shadow banks, where ϵ governs the elasticity of substitution.

γ^b and γ^s are the endogenous equilibrium money like premia of intermediary debt, which are implied in the interest rates paid on bank and shadow bank debt, which we define below. They measure the decline in expected return (accounting for potential default risk) relative to the opportunity cost of capital of 1, that investors realize from purchasing bank debt and shadow bank debt, respectively. Investors take interest rates on intermediary debt and credit risk and thus the money like premiums (γ^b and γ^s) as given.

We choose a parsimonious specification for the benefits to intermediary debt. We could instead assume that household preferences differ across intermediaries, so that D_b^{ϵ} and D_s^{ϵ} would be aggregates of debt provided by individual intermediaries. Critically, one could imagine that households' preferences could differ across the size distribution. Figure 10, Panel B shows that interest rates paid on insured deposits of banks only slightly differ across the size distribution (if anything, larger banks pay higher interest rates on average). This suggests that households' valuation of money-like part of debt does not differ much across the size distribution of banks, once risk is accounted for. We therefore opt for a parsimonious version of the model rather than directly incorporating these quantitatively small differences.

Demand for Funds: We now discuss demand for equity and debt for different types of intermediaries.

Equity: To focus on the trade-off between costs and benefits of debt, we assume that equity funding is frictionless. This is akin to assuming all equity funding is provided by deep pocketed insiders.[21]

Debt: All intermediaries can raise non-contingent uninsured debt D_i^U, with a corresponding interest rate r_i^U. Banks differ from shadow banks because they can also raise insured deposits, D_i^I, at a rate r_i^I. In the baseline model we ignore the fact that shadow bank debt is intermediated by banks. In Section 6.F we extend the model to consider the idea that constraints in bank lending may spill over to shadow bank costs of funding.

As we discussed above, the benefit of financial intermediary debt (relative to regular corporate debt) is that it is valued by investors beyond its returns at equilibrium premiums of γ^b and γ^s. Debt funding is not frictionless due to a deadweight cost resulting from uninsured debt runs. Even if runs do not result in bank failure, they cause the intermediary to inefficiently liquidate some projects, or render it unable to pursue further profitable projects resulting in a deadweight cost. Specifically, if an intermediary bank suffers a shortfall, i.e., its cashflows are lower than its outstanding uninsured debt, $f(a_i)\lambda_i < D_i^U(1 + r_i^U)$, uninsured debtholders run. This expression tries to capture the idea that insured depositors are "sleepy", so they allow uninsured depositors *de facto priority* on the assets of the bank. In other words, uninsured depositors run when the bank is in distress, potentially causing default, or alternatively, exacerbating

[21] See Bolton and Scharfstein (1990), Leland (1994), and DeMarzo and Fishman (2007), Egan et al (2017), and Begenau and Landvoigt (2022) within the context of financial firms.

distress for the bank.[22] The deadweight per dollar cost is $\delta\left(\frac{D_i^U}{a_i}-\lambda_i\right)^2$ is a simple function of the shortfall rate in the bad state and the outstanding balance of uninsured debt relative to the assets a_i, its uninsured leverage, with the parameter δ capturing the extent of these costs, which we calibrate to the data.[23] The convenient functional form captures the idea that runs become proportionally more expensive as they increase in magnitude, since intermediaries first liquidate or abandon the lowest cost projects.

Insured deposits differ from other debt in two important ways. First, because they are insured, depositors do not internalize the cost of shortfalls as they are always repaid and they do not run. Second, insured deposits have an acquisition cost of Δ, which arises because banks operate branches, advertise, and incur other costs that are typically associated with these typically small accounts (Egan et al 2017; Egan and Sunderam 2020). In addition, Δ also reflects an administrative insurance premium charged on deposits by the insuring agency (FDIC). In the absence of such costs, banks would never use any other source of financing. Last, banks are also subject to capital requirements, which limit leverage of bank *i* as $\frac{D_i^U+D_i^I}{a_i}\leq\bar{l}$.

6.B Intermediary Choice of Capital Structure and Size

6.B.1 Shadow Banks

An intermediary chooses its financing and size to maximize dividends to its shareholders. Shadow bank *i* chooses how much external equity E_i to raise, and how much (uninsured) debt D_i^U to issue, resulting in total assets of a_i. In choosing its capital structure, the shadow bank accounts for the fact that its choice will affect the pricing of uninsured debt. Equity holders are protected by limited liability, and maximize the expected value of equity, v_i^{SB}:

$$v_i^s=\max_{E_i,D_i^U}\; p\,\underbrace{max\left(f(a_i)-D_i^U\left(1+r_i^U\right),0\right)}_{Good\ state}+(1-p)\underbrace{max\left(\lambda_i f(a_i)-D_i^U\left(1+r_i^U\right),0\right)}_{Bad\ state}-E_i \quad \text{(M2)}$$

In equilibrium, cost of debt accounts for potential distress and money-like premium when setting interest rates. As we prove in Appendix E1, the intermediary chooses enough uninsured debt such that shadow bank debt is risky in equilibrium, $D_i^U\left(1+r_i^U\right)>f(a_i)\lambda_i$, which is consistent with the data. Then, accounting for equilibrium debt pricing and risk, we can re-write the optimization problem for equity holders of shadow banks as choosing (uninsured) leverage $l_i^U\equiv\frac{D_i^U}{a_i}$ and asset size a_i, which maximizes the total value of claims on the intermediary:

$$v_i^{j=s}=\max_{a_i,l_i^U}\underbrace{f(a_i)(p+(1-p)\lambda_i)-a_i}_{Profits\ from\ lending}+\underbrace{a_i l_i^U\gamma^j}_{Money-like\ benefit}-\underbrace{(1-p)a_i\delta\left(l_i^U-\lambda_i\right)^2}_{Run\ cost} \quad \text{(M3)}$$

In choosing its size and capital structure, the shadow bank trades off profits from lending, the money-like benefit from issuing debt, and the run cost of uninsured debt. Debtholders are willing to provide funding below the opportunity cost of capital due to the money-like "liquidity" properties of intermediary debt that provide them additional utility.

6.B.2 Banks

[22] Egan et al. (2017) micro-found the mechanism. Martin, Puri, and Ufier (2018) find evidence for uninsured deposit outflows prior to bank failure. The mechanism mirrors the run on regional banks in March and April of 2023, which resulted in some of the largest failures in the US banking history (Jiang et al. 2023).

[23] Granja et al. (2017) estimate that the FDIC loses 28% of assets from selling failed banks.

Banks also choose capital structure and size. They differ from shadow banks because they can also access insured deposits but are constrained by capital requirements. For brevity, we do not write down the bank problem in its entirety. In Appendix E2 we show that, similar to banks in the data, as long as insured deposits acquisition costs are not too high, bank i will issue a strictly positive amount of insured deposits, $D_i^I > 0$, and enough uninsured debt, such that it is risky and default happens in the bad state $D_i^U\left(1 + r_i^U\right) > f(a_i)\lambda_i$. Then, accounting for the equilibrium pricing of insured deposits and uninsured debt, the banks' problem boils down to choosing its asset size a_i, its uninsured leverage l_i^U, and insured leverage, $l_i^I \equiv \frac{D_i^I}{a_i}$, which maximize the total value of claims subject to the capital requirements. We write below the constrained maximization problem of the bank, with the Lagrange multiplier on the capital requirement constraint capturing the shadow cost of capital requirements from the perspective of the banks' equity holders. For clarity, we bold and blue the terms, in which banks' problem differs from that solved by shadow banks:

$$\begin{aligned} v_i^{j=b} = \max_{a_i, l_i^I, l_i^U} & \underbrace{f(a_i)(p + (1-p)\lambda_i) - a_i}_{Profits\ from\ lending} + \underbrace{\boldsymbol{a_i}(\boldsymbol{l_i^I} + l_i^U)\gamma^j}_{Money-like\ benefit} \\ & - \underbrace{(1-p)a_i\delta\left(l_i^U - \lambda_i\right)^2}_{Run\ cost} \quad \underbrace{\boldsymbol{-a_i l_i^I \Delta}}_{Insured\ deposit\ acquistion\ cost} \\ & + \quad \underbrace{\boldsymbol{a_i l_i^I (1-p)}}_{Deposit\ insurance\ benefit} \quad + \quad \underbrace{\boldsymbol{\Lambda_i(\bar{l} - l_i^I - l_i^U)}}_{Shadow\ cost\ of\ capital\ requirements} \end{aligned} \tag{M4}$$

In addition to the tradeoff faced by shadow banks, banks face additional costs and benefits associated with insured deposits. They trade the acquisition cost with money-like benefit of insured debt and the benefit of deposit insurance. The latter arises because the banks will default in the bad state (uninsured debt is risky in equilibrium), but insured depositors do not account for that in setting their interest rate. There is also an associated shadow cost of capital requirements when capital requirements bind. When banks overall leverage is at the capital requirement $\bar{l}$, the only remaining bank choices are how much of this leverage is funded by uninsured debt versus insured deposits (uninsured leverage) and size.

6.B.3 Equilibrium

The competitive equilibrium is an allocation of financing to financial intermediaries and interest rates on intermediary debt, such that

i) Intermediaries maximize the expected value of equity (eqn. M3 and M4 hold for all *i*).
ii) Households maximize utility (eqn. M1 holds).
iii) Debt markets clear:

$$D_b = \sum_{i \in B} (l_b^I + l_b^U) a_i \,; \quad D_s = \sum_{i \in S} l_b^U a_i$$

6.C Discussion: Determinants of Intermediary Size and Uninsured Leverage

We solve for the optimal choice of size and uninsured leverage in Appendix E. Here, we instead discuss some of the first order forces that allow our model to replicate the patterns in the data. To simplify the discussion, we focus on the situation in which capital requirements bind, which is what we observe in the data.[24] Banks and shadow banks optimize on two margins: they equalize the marginal benefit (MB) and marginal cost (MC) of capital when choosing size, and they choose uninsured leverage by equalizing the marginal money-premium benefit and with the MC of runs. Because the MC of capital depends on the leverage choice itself, size and capital structure are codetermined. While intermediaries take the money-premium as given, it is determined in equilibrium by clearing the demand for money-like assets from households, and the supply of different types of intermediary debt. In other words, if intermediaries issue more debt in aggregate, the money premium implied in interest rates declines. We now dig into some more intuition around these tradeoffs to see how they rationalize the basic shadow bank patterns we observe in the data.

6.C.1 Uninsured Leverage

For ease of comparison, we write the tradeoffs for banks, which reduce to those of shadow banks by setting insured deposit and capital requirement terms to zero (in blue and bold). Uninsured leverage is determined by equalizing the equilibrium marginal money-premium benefit with the MC of runs:

$$\underbrace{\gamma^j}_{M.\ money\ premium\ Benefit\ of\ uninsured\ leverage} \quad \underbrace{-\boldsymbol{\Lambda_i}/\boldsymbol{a_i}}_{shadow\ cost\ of\ CR} = \underbrace{(1-p)2\delta\left(l_i^U - \lambda_i\right)}_{MC\ of\ runs} \tag{M5}$$

This expression illustrates why banks can have higher overall leverage but lower uninsured leverage than shadow banks (Figure 9); why there is dispersion in uninsured leverage of intermediaries uninsured leverage (Figure 8), even if there is no dispersion in bank leverage (Figure 7).

Shadow banks choose their leverage unconstrained (as if $\Lambda_i = 0$). Higher money-like benefits of debt (γ^j) increase leverage, and higher run costs decrease leverage. Because more productive shadow banks (i.e., higher λ_i), have smaller marginal cost of runs for a given amount of leverage, they choose higher leverage. Banks face the same tradeoff as shadow banks, but every additional unit of uninsured leverage has a shadow cost $\boldsymbol{\Lambda_i}$, since it effectively displaces a unit of insured deposits. Intuitively, the banks will borrow uninsured until the point where the expected deadweight cost of uninsured debt due to runs equal the insured debt acquisition costs. Past that point banks will fill the remaining debt capacity with insured deposits until they reach the regulatory capital constraint. This also explains why banks will always finance themselves with some uninsured debt as long as the insured deposits have a positive acquisition cost.

The shadow cost of capital requirements also implies that for a given level of productivity λ_i, a bank has a lower *uninsured leverage* than a shadow bank, even if its total leverage is higher, which is consistent with the distribution of uninsured leverage in Figure 8.

Mirroring the data, there is dispersion in leverage within banks and shadow banks. More productive intermediaries, those with higher λ_i, have smaller marginal cost of runs for a given amount of leverage and choose higher leverage. Therefore, even though overall bank leverage is fixed at $\bar{l}$, there is dispersion in uninsured leverage within banks and shadow banks, driven by λ_i.

6.C.2 Intermediary Size

Intermediaries choose size by equalizing the marginal benefit (MB) and marginal cost (MC) of capital:

[24] As long as long as the acquisition cost of insured deposits is sufficiently cheap, the bank capital constraint will always bind. In dynamic model, the capital constraint does not need to bind all the time even if insured deposits are sufficiently attractively priced due to the buffer stock dynamics as in Corbae and D'Erasmo (2019).

$$\underbrace{f_a'(a_i)(p+(1-p)\lambda_i)}_{MB\ of\ capital}$$
$$= \underbrace{1 \quad \underbrace{-\gamma^j\left(l_i^U+\boldsymbol{l_i^I}\right)}_{Money-like\ benefit} \quad \underbrace{+(1-p)\delta\left(l_i^U-\lambda_i\right)^2}_{Run\ cost\ of\ uninsured\ debt} \quad \underbrace{-\boldsymbol{l_i^I(1-p)}}_{\boldsymbol{Deposit\ insurance\ benefit}} \quad \underbrace{+\boldsymbol{l_i^I\Delta}}_{\boldsymbol{Cost\ of\ i.\ deposits}}.}_{MC\ of\ capital} \tag{M6}$$

More productive intermediaries (i.e., higher λ_i) choose a larger size. Because they have a higher ability to facilitate loans, they have a higher MB of capital and a lower MC of capital at a given size.

This expression illustrates why insured deposits can incentivize bank to choose a larger size, i.e., to facilitate more lending and provide more money-like debt, even if they are not subsidized. Consider a bank and shadow bank with the same ability to facilitate loans (i.e., same λ) and who choose the same overall leverage. Such banks and shadow banks have the same MB of capital. The difference comes from banks' access to insured deposits, which can allow them to lower their MC of capital. This does not need to rely on deposit funding being subsidized as insured deposits also lower the deadweight costs of runs. A bank can always replicate the capital structure of a shadow bank if capital requirements do not bind. By choosing to fund itself with some insured deposits it reveals that it benefits from having a different capital structure.

The cost of capital tradeoff also illustrates how capital requirements decrease the provision of lending and other securities in the economy. A common explanation of how capital requirements affect the size of banks assumes that banks cannot raise equity. Then capital requirements limit the amount of debt funding and mechanically lower the amount of lending a bank can facilitate. This force is absent from our model because banks can fund themselves with equity as well as debt. The effect of capital requirements is therefore indirect: capital requirements increase the marginal cost of capital by limiting banks' choices (RHS of M6).

6.C.3 Intermediary Size and Uninsured Leverage

As eqn. M6 shows, size is determined by the MC of capital, which depends on the leverage choice itself. At the equilibrium level of capital structure debtholders are willing to provide funding below the opportunity cost of capital due to the money-like properties of intermediary debt and deposit insurance for banks, which lowers the MC of capital. Thus, size and capital structure are codetermined.

The two trade-offs in eqn. M5 and M6 rationalize the basic patterns we observe in the data. First, it is the heterogeneity on the asset side of the balance sheet, which drives heterogeneity in capital structure choices, resulting in dispersion of uninsured leverage. This dispersion in leverage would arise even if intermediaries' sizes were exogenously determined. Second, uninsured leverage increases with size because the intermediaries which choose higher leverage are also more productive (i.e., higher λ) and end up with a larger size. The increase in size is partially due to higher productivity, and partially due to the lower equilibrium cost of capital given the chosen leverage.

6. D Calibration

We now calibrate the model to qualitatively and quantitatively match the four facts that we document in the first part of the paper: (i) Banks have higher overall leverage than shadow banks, but lower uninsured leverage; (ii) Banks leverage is homogenous, and shadow banks' leverage dispersed; (iii) Uninsured leverage increases in intermediary size; (iv) interest rates on uninsured debt decline with size for banks and shadow banks and (v) Despite their higher leverage, banks pay lower rates on their uninsured debt. Replicating these facts quantitatively suggests that the model is able to capture the first order forces driving the capital structure decisions across banks and shadow banks. Shadow bank call report data provide important discipline for the model. They incorporate capital structure choices and market interest rates on uninsured debt of intermediaries in the absence of insured deposits. Without these data, financing choices of intermediaries without deposits would have to be inferred from the structure of the model and just bank data.

We use the sample of banks which are most comparable to shadow banks on the asset side to calibrate the model (“OTD” bank sample). We discretize the intermediary size distribution in 25 size bins of banks and shadow banks. We then match moments related to financing and asset side of financial intermediation within each bin.

Financing: We use shadow bank call reports, bank call reports, and HMDA data to calibrate the liability side of the model. To match moments related to financing we use shadow bank and bank call report data from 2012 to 2017. Within each size bin, we match 7 moments related to bank financing: (1) average bank size; (2) average shadow bank size; (3) average shadow bank leverage, (4) average bank uninsured leverage, (5) shadow bank cost of debt, (6) bank cost of uninsured debt, and (7) difference between banks’ and shadow banks’ costs of debt.

Assets: The asset side of the model is characterized by two important elements, the production function $f(a_i)$ and the lending technology λ_i. We calibrate the asset side in two steps. In the first step, we parameterize intermediaries’ production function as below and estimate it using shadow bank call reports:

$$f(a_i, \boldsymbol{A}) = \frac{\xi_a}{\sum_{i\in S} a_i^{\beta} + \sum_{i\in B} a_i^{\beta}} a_i^{\beta}. \tag{M7}$$

β governs the returns to scale at intermediary level. $\frac{\xi_a}{\sum_{i\in S} a_i^{\beta}+\sum_{i\in B} a_i^{\beta}}$ measures how quickly an intermediary’s profit declines with the aggregate amount of intermediation. The denominator, $\sum_{i\in S} a_i^{\beta} + \sum_{i\in B} a_i^{\beta}$, captures the idea that profits decline with total supply of lending. To obtain the value of β in the production function, we take log of (M7) and estimate the following specification using shadow bank call reports from 2012 to 2017:

$$log(f_{it}) \ = \ \beta \ log(a_{it}) + \mu_t + \varepsilon_{it} \tag{M8}$$

where f_{it} is intermediary *i*'s total output (i.e., total interest income plus the value of loans) in year t, a_{it} is lender i's input (i.e., total value of originated loans) in year t, μ_t is year fixed effects that control for aggregate demand shocks, and ε_{it} is intermediary i's idiosyncratic productivity shocks in year t. In the second step, with the estimated β, we calibrate ξ_a and the distribution of lending ability of banks, $F_b(\lambda)$, and shadow banks, $F_{sb}(\lambda)$, non-parametrically, by jointly matching the 7 moments previously discussion across the 25 size bins.

The calibrated parameters are presented in Table 10. We simulate the model using these parameters and compare the resulting distribution of uninsured leverage and interest rates across the size distribution with the actual data (Figure 11). Our simulated data can replicate the main facts we presented above qualitatively and quantitatively. We next discuss how the model parameters are identified, and the quantitative implications of our calibrated parameters.

6.D.1 Liabilities: Costs and Benefits of Intermediary Debt Financing

Two key takeaways emerge from our calibration of the costs and benefits of debt financing of intermediaries. First, banks’ deposits provide higher money-like services than shadow bank debt, resulting in a 50bp equilibrium deposit premium over shadow bank debt. Second, insured deposits benefit from deposit insurance but are costly to acquire.

We quantify the money-like premium from the data by exploiting three direct consequences of a higher premium. First, for a fixed amount of leverage, interest rates on uninsured debt decline with the premium. Second, intermediaries increase their leverage all else equal. And third, intermediaries choose a larger size because of lower cost of capital. Rates alone are not sufficient to pin down the premium, because banks pay lower interest rates on uninsured debt partially as compensation for lower risk of uninsured debt due to lower uninsured leverage. Therefore, the preference for bank and shadow bank debt is broadly identified by intermediaries' choice of uninsured leverage, by the rates that intermediaries pay on their uninsured debt, and by the size distribution of intermediaries.

We find that in equilibrium, households pay a 50bp premium for bank deposits over shadow bank debt, $\gamma_B = 140bp > \gamma_S = 90bp$.[25] The extent of the premium for bank debt is also broadly consistent with the literature (e.g., Hanson et al. (2015), Nagel (2016), Sunderam (2015)). The premium implies that intermediaries borrowing rates are lower than they would be given the riskiness of uninsured debt—in other words, intermediaries interest rate over and above the risk free rate is lower than the full compensation for risk. This premium arises because households value bank deposits above and beyond other intermediary debt because of the services that banks bundle with their deposit offerings (Egan et al 2017). Specifically, we calibrate $\eta = 0.67$, so households value the money-like flow from shadow bank debt at about 70% of the utility obtained from deposits.

The second important determinant of bank leverage is the profitability of insured deposits. We find that insured deposits benefit from deposit insurance but are costly to acquire. The cost of insured deposits, Δ, captures the deposit insurance premium, but also additional costs of acquiring deposits, such as marketing and the cost of branches and labor that are bundled in deposit services. We calibrate the cost of raising additional insured deposits is approximately 6.75%. This estimate is close to 5.5% in Egan et al. (2017), despite using very different data and a different source of variation in the data. Importantly, our calibration finds that these costs approximately offset the benefit of deposit insurance. This result rationalizes two seemingly opposing views: that deposit insurance is subsidized, but insured deposits are only marginally profitable or even unprofitable because of high costs of acquisition. This is consistent with the claims of the industry that banks expend substantial resources on managing and attracting insured deposits.

Overall, our calibration suggests that banks' higher leverage may at least partially be rationalized by their additional provision of money-like claims. Banks have access to insured deposits which provide them with a funding advantage. At worst, they could replicate the capital structure of shadow banks but are able to optimize their cost of capital further by partly funding themselves with insured deposits. The uninsured deposit funding exposes banks to solvency runs by uninsured depositors in the "bad state" as recently illustrated in practice by failure of the Silicon Valley Bank (see Jiang et al. 2023).

6.D.2 Assets

Intermediaries use the funding they obtain to facilitate activities we broadly call lending. We find no differences in the profitability of banks and shadow banks in the good state of the world: $A_s = A_b$. Shadow banks have on average a superior ability to obtain repayment in the bad state of the world, with a substantially higher mean of the distribution of $F(\lambda_i)$. The distributions of bank and shadow bank λ do overlap: there are banks which are better at lending than some shadow banks and vice versa. This result is primarily identified from the size distribution of banks and shadow banks that is implied by the intermediary cost of capital. Intuitively, banks' cost of capital is lower than that of shadow banks with the same ability

[25] $\eta = 0.67$ is close to the liquidity preference parameter in Begenau and Landvoigt (2022). We obtain ϵ and ξ_d from the household maximization problem, taking calibrated γ_B and γ_S as given (see on-line Appendix).

(λ). The lower cost of capital implies that the banks should be the primary lenders in this market. Instead, shadow banks are larger, suggesting that they have a superior ability to extend loans.[26] The lower distribution of bank productivity is consistent with the idea that obtaining a bank charter is significantly more costly than incorporating as a shadow bank, but conditional on entry, allows accessing capital at a lower cost.[27]

6.E Decomposition: Why is Bank Leverage High Across the Size Distribution?

In this section we ask how much of banks' high leverage is due to the provision of lending and the production of money-like liabilities and how much is due to deposit insurance and other safety net incentives for leverage? In other words, for which banks along the size distribution do the current capital requirements constrain the provision of intermediary services, and for which do they curb excess leverage due to safety nets.

6.E.1 Role of Insured Deposit Funding (Safety Nets) in Bank Leverage

We first ask how much leverage banks would choose if their debtholders would fully internalize default costs—i.e., in the absence of deposit insurance or other safety nets embedded in insured deposits. Formally, we recompute the equilibrium outcomes in an economy, in which banks cannot issue insured deposits We keep other primitives, including investors' preferences for bank debt fixed as defined in eq. (M1). We therefore recompute the extent of lending for each intermediary, its issuance of debt and equity, as well as interest rates on debt and the implied money-like premium, which clear the demand from households and aggregate intermediary debt issuance. The strong assumption in this counterfactual (for now) is that investors' preferences for bank debt are separable from deposit insurance, i.e., the absence of deposit insurance does not change the usefulness of deposits from the perspective of households.

Bank capital and capital requirements: Our calibration implies that current leverage is partially driven by safety nets and partially by the provision of valuable financial intermediation. When bank debtholders fully internalize default, average bank capitalization increases to 14pp, or by over 25% in relative terms (Table 11A). On the other hand, even if banks fully internalize default costs, their leverage is still above that of shadow banks in the data. This result implies that high leverage is to a large degree a result of the provision of productive financial intermediation on the asset and liability dimensions.

The effect of safety nets is largest for small banks and smallest for large banks. Small banks face the largest increase in capitalization in the counterfactual (Table 11B and in Figure 12). The average capitalization of banks in the smallest quartile increases to 17pp, or over 50% in relative terms and highlights their reliance on safety nets of insured deposits. Medium size banks also experience a significant 2pp increase in bank capitalization, or by about 20% in relative terms. Small banks have the largest share of insured deposit funding, which all else equal, increases the recovery on uninsured debt. This result is consistent with small banks paying a higher interest rate on their uninsured debt despite having lower uninsured leverage and the same total leverage as large banks. It is also broadly consistent with a higher failure probability of small banks (Granja et al. 2017).

The results are very different for large banks. The capitalization of the average bank in the largest size quartile remains unchanged at 11pp. If the money-like premium of deposits is fully separable from deposit insurance, then these banks' capitalization is similar than it would be without safety nets. The capitalization

[26] Better lending technology of shadow banks can reflect purely technological factors or differences in regulatory burdens (outside of capital requirements) faced by banks (see Buchak et al. 2018, 2023 for evidence).

[27] Consistent with the higher bank entry cost is their lower turnover relative to shadow banks (Buchak et al. 2023).

of the largest banks (top 1%) in the counterfactual (9pp) is actually somewhat lower than under the current capital requirements.

Thus, if lenders to banks fully internalized the cost of default, then capital requirements would only bind for the largest banks. All other banks would voluntarily choose to fund themselves with more capital than demanded by current capital requirements. Even though insured deposits are not very profitable on the margin, internalizing default would still lead to a substantial increase in the capitalization for most banks. As we discuss below, uninsured depositors indirectly benefit from deposit insurance because it makes insured depositors "sleepy."

Role of sleepy insured deposits: The increase in the interest rate bank pay on their uninsured deposits highlights the role played by "sleepy insured depositors." When depositors internalize default, interest rates are almost 300bp higher than currently paid by banks, (Table 12A). An increase in interest rates may seem surprising because banks in the counterfactual are better capitalized, so losses are absorbed by a *larger* equity slice. And, as we show below, the change in aggregate amount of intermediary debt is small, leading to a small change in the intermediary debt money premium, which does not explain this change. Instead, the result is driven by the absence of sleepy insured depositors. Because insured depositors are sleepy, they allow uninsured depositors to front run and extract more assets in distressed banks than they would if insured depositors would also run. From the perspective of uninsured depositors, insured depositors are equity-like in the bad state of the world. This explains why banks pay such low interest rates on their uninsured debt despite their high leverage in the presence of insured deposits.

Distributional implications: We can also assess the distributional effects by plotting capital ratios when there is no bank safety net, i.e., no capital requirement and depositors internalize bank default. The plots emphasize the distributional effect of safety nets across small and large banks. As shown in Figure 13 panel A, when there is no safety net, the capital ratios of small and mid-sized banks increase significantly, consistent with our finding that small banks benefit the most from deposit insurance. In other words, in absence of deposit insurance, the capital requirement is not binding for small and mid-sized banks. On the other hand, capital ratios of the largest banks would decrease. Thus, the capital requirement would still be binding for the largest banks even if there was no deposit insurance.

The plots also emphasize that policies affect the size distribution of banks. In response to the removal of safety nets, banks respond to changes in the cost of capital by adjusting their size in addition to their leverage. As shown in Figure 13 Panel B, the removal of safety nets widens the size distribution of banks. Small and mid-sized banks shrink without deposit insurance, while large banks grow.

One might expect that large changes in bank safety nets would also spill over to the shadow banks' capital structure. Intuitively, shadow bank leverage and size would increase when bank funding is less subsidized. In Figure 13 Panel C and D, we find that the impact of the bank safety net is mainly within the banking sector. Removal of bank safety net would only slightly increase shadow banks' leverage ratio, as we describe next.

Aggregate implications: Despite large changes in some banks' leverage, the aggregate consequences of bank depositors internalizing default are limited, especially from the perspective of lending (Table 12, Panel C). Our calibration suggests that aggregate lending would be virtually unchanged (a slight increase by 0.1pp), and aggregate provision of bank liabilities would increase by 0.6pp. The aggregate impact is partially limited because of the redistribution from small to very large banks, and the adjustment of the shadow banking sector. Small and mid-sized (and less productive) banks would choose to be more capitalized and would shrink a bit because of a slightly higher cost of capital but would also issue fewer deposits. On the other hand, the largest (and most productive) banks would be somewhat less capitalized than they currently are. They would lend a bit more because of a small decrease in their overall cost of capital due to their ability to borrow more, and issue more deposits. Overall, the banking sector would issue 1.7% more loans, and provide 2.3% more liabilities. These increases would be offset by a shrinking of loan and liability provision of the shadow banking sector, resulting in negligible aggregate consequences.

6.E.2 Decomposition: Safety Nets vs. Money-Like Liabilities

In the previous counterfactual, we explore the effect of safety nets on bank leverage. Our baseline counterfactual provides a *lower bound* on the effect of safety nets on bank leverage. We have assumed that households separately value deposit insurance and the money-like properties of bank deposits. In other words, the loss of deposit insurance does not diminish the value of the services depositors obtain from the bank. Next, we relax this assumption. We show that if households' preferences for money-like properties of bank deposits diminished with no deposit insurance, safety nets would then explain a substantially larger part of banks' leverage. We do it by presenting several counterfactuals in which we vary banks' abilities to issue valuable, money-like liabilities (see Table 11 and 12). Combining the two types of counterfactuals allows us to decompose the contributions of safety nets and money-like liabilities to bank leverage.

In the most extreme counterfactual, we study the capital structure choice of banks if their funding opportunities equal those of shadow banks, i.e., we take away the safety net advantage and money-creation advantage of banks. Formally, we equalize households' preferences over bank debt and shadow bank debt and remove the safety-net aspect of deposit funding. All intermediary debt still carries a premium, but banks do not provide special liabilities relative to shadow banks. This baseline counterfactual suggests that if banks did not have access to safety nets and could only offer shadow bank-like liabilities, their average capitalization would be 37pp (32pp value weighted), a 26pp increase from their 11pp capitalization in the data (Table 11). While this increase is largest for smaller banks, even the largest banks see substantial increase in their capitalization (by 23pp). While banks would still be substantially more leveraged than non-financial firms, they would be better capitalized than shadow banks. In this extreme counterfactual, safety nets are responsible for a large part of bank leverage. This is not surprising, since our calibration reveals that shadow banks are better at lending than banks and can accomplish the lending with relatively low leverage. With no advantage in debt funding, banks would have lower leverage than shadow banks.

In the middle-of-the-road counterfactual we set households' preferences such that the equilibrium premium depositors pay for bank debt over shadow bank debt declines by half. In that case the average banks capitalization increases to 31pp (see Table 11). While the increase is larger for small banks, whose capitalization increases to 35pp, the capitalization of big banks also increase substantially (to 28pp).

Comparing the counterfactuals allows us to decompose the effects of safety nets and money-like liabilities on banks' capital structure. Removing both safety nets and an advantage in issuing money like securities increases average bank capitalization by 26pp. Using our counterfactual analysis from prior section, we recall that removing only safety nets increases bank capitalization by 3pp. Hence, the 26pp capitalization "gap" of banks relative to shadow banks is accounted for by the contribution of safety nets of insured deposits (3pp) and the household preference for bank debt (23pp). Therefore, banks' ability to issue debt, which is valued by households, substantially exceeds the *direct* contribution of safety nets such as deposit insurance to bank leverage.

Finally, we note that removing in addition the money-creation advantage of banks would have limited aggregate consequences for lending (see Table 12C). In our baseline scenario when we remove only banks' safety nets, this effect was partly driven by the reallocation of lending from smaller to largest banks.

Removing in addition the money-creation advantage of banks, would result in significant decline in aggregate bank lending of about 15%. However, this decline is partly compensated by a significant increase in lending by shadow banks. Consequently, the aggregate lending remains largely unchanged (a decrease by about 0.2%).

Why is Lending Associated with Relatively Low Intermediary Leverage?

Our data reveal that shadow banks can lend with relatively low leverage—high capital. Our model highlights the broad economic intuition for the low leverage associated with lending intermediation. Both equity and debt financing can be used to fund lending activities. In our model, optimal leverage from the bank's perspective lowers the cost of capital and allows for more lending. Imagine, however, that lending is very valuable, but debt funding becomes expensive because safety nets for deposits are removed. Then an intermediary can increase its lending through issuing equity. This is the intuition that is frequently used to argue that capital requirements are not costly. Our model shows that this intuition is partially correct. If leverage becomes relatively costlier, equity funding can be used to expand lending, but replicating financing of non-financial firms or even 100% equity financing is far from efficient for intermediaries as well, as we can see from shadow bank choices.

Even if lending can be achieved with relatively low leverage, intermediaries cannot provide more money-like claims without issuing debt. Because our calibration finds a large demand for money-like securities offered by banks, it drives banks choice of low capitalization. In the middle-of-the-road counterfactual above (see Table 12 Panel C), banks offer much less money-like debt, and the aggregate lending by banks drops by 12.2%. The reduction in bank lending is partially offset by an increase in shadow bank lending (6.3%). As a result, the total credit supply declines by -0.16%. But the aggregate provision of money like securities declines by approximately 7%, due to a limited substitution between bank and shadow bank debt.

Overall, the message from across our counterfactuals is that small banks leverage is much more dependent on safety nets, while large banks leverage is to a large degree driven by the provision of valuable money-like deposits. The aggregate consequences of the absence of safety nets provided by insured deposits are limited, because of reallocation from smaller banks to large banks and to shadow banks that can accomplish a lot of lending with substantially smaller leverage.

6.F Extension: Bank-Shadow Bank Funding Relationship

In the baseline calibration we ignore the idea that banks intermediate household debt to shadow banks. In panel (a) of Appendix F.1, we show that over 99.5% of shadow bank debt is intermediated by big banks, defined as banks with total assets in the top quartile among all banks. To account for this effect, we model an intermediation wedge in shadow bank debt. Intuitively, a part of money-like benefit that shadow bank debt provides to households, γ^s, is lost due to deadweight cost of intermediation, resulting in a lower effective money-like premium obtained by shadow banks, $\tilde{\gamma}^s$. Because our counterfactuals have the most impact on small bank lending, and if anything, expand lending by the largest banks, we should expect a small equilibrium impact of this channel. Nevertheless, we quantitively evaluate this channel.

We specify the bank intermediation wedge discussed above as follows: $\tilde{\gamma}^s = \gamma^s(1 - \omega\left(\sum_{i \in B_{big}} a_i\right))$. Intuitively, if large banks lend more in our model *all else equal*, they are also more likely to lend more to shadow banks, i.e., the intermediation wedge declines. Because the total amount of large bank assets, $\sum_{i \in B_{big}} a_i$, depends on the money premia itself, $\tilde{\gamma}^s, \gamma^s, and\ a_i$ are jointly determined in equilibrium.

In panel (b) of Appendix F.1, we estimate that shadow bank cost of debt increases by about 4bps when the funding from banks declines by 1%, and thus we parameterize $\omega\left(\sum_{i\in B_{big}} a_i\right) = 4bps\left(\ln\left(\sum_{i\in B_{big}} a_i\right) - \tau\right)$. Because we cannot pin down the absolute level of the wedge in the data, we set τ such that the wedge is 0 at the observed equilibrium $\omega\left(\sum_{i\in B_{big}} a_{i|data}\right) = 0$.

To estimate the effect of this channel we compute the equilibrium of no-safety nets under the extended model that incorporates large bank lending to shadow banks. We then compare the equilibrium to one of the baseline models. In Appendix F.2, we plot the capital ratios and total investments of banks and shadow banks when we explicitly account for the bank intermediation wedge. Doing so barely affects our estimates about the effects of safety nets on intermediaries' capital ratios and total investment. For example, the average capitalization (E/A ratio) of banks and shadow banks respectively change by 0.01pp. The extent of lending also remains unchanged. The small differences should not be surprising given our finding above that removing safety nets has little effect on the capitalization or lending of the largest banks. Of course, policies that would directly target large banks, such as the Basel III endgame, would exacerbate the wedge.

7. Discussion: Capital Structure of Intermediaries, and Implications for Policy

The main contribution of our paper is to establish several novel facts on the capital structure of shadow banks and use them along with our quantitative model to study the extent to which banks' high leverage relative to shadow banks reflects the benefits intermediaries derive on the liability side of their balance sheet. The higher capitalization of shadow banks that we document shows that the provision of lending can be achieved with substantially more limited leverage than that of existing banks: the average shadow bank loan is issued by a shadow bank with 25% capitalization. Our quantitative model confirms this empirical observation and determines, if anything, that the current level of bank lending could be accomplished with much higher capitalization. In other words, if the only function of intermediaries is to facilitate lending, then regulating leverage at current levels of capital requirements would come with little cost, at least for the type of lending activities we focus on.

We find evidence that the high leverage of banks is quantitatively determined on the liability side, both through the effect of safety nets and though the provision of money-like securities (e.g., see Diamond and Dybvig 1983; Allen and Gale 1998; DeAngelo and Stulz 2015). Across different specifications, our model suggests that safety nets contribute substantially to the leverage of small and mid-sized banks. Safety nets also provide incentives for the leverage of large banks. However, the extent to which their leverage is "excessive", depends on how the money-like premium reflecting household preferences for bank debt moves with deposit insurance. Under full separability, large bank leverage is below the level of provision of money-like securities in the absence of insured deposit funding, even if the aggregate effect is negligible.

These results also have regulatory implications. The US banking sector has experienced several bank failures in 2023 following a decline in the value of bank assets that triggered uninsured depositors – central element in our framework -- induced solvency runs (see Jiang et al. 2023). These failures have renewed the interest in the role of banks' capital structure and the role of safety nets provided by deposit insurance. One highly debated regulatory response to it is to impose stricter capital requirements on banks. At its core, regulating bank capital structure trades-off bank stability with ability to finance intermediary activities. Our baseline estimates suggest that current capital requirements do not constrain the aggregate provision of lending and money-like securities beyond the level chosen by intermediaries without access to deposit subsidies. This observation is also consistent with relatively modest effects of higher capital requirements on aggregate lending volume (Buchak et al. 2023). Because our model does not account for negative externalities arising from bank failures, even substantially higher capital requirements could be justified.

Second, bank regulations are often dependent on size. Capital requirements, FDIC assessment rates, as well as other forms of regulation are frequently stricter for large banks. We find that the contribution of safety nets to leverage is largest for small and mid-size banks. Because FDIC assessment rates are supposed to undo the issue of excess leverage due to deposit insurance, our model suggests these fees should decrease with size, which is the opposite of current policy. In terms of regulations designed to prevent spillovers from bank failures, such as capital or liquidity requirements, they may be more stringent for large banks, particularly those deemed systemically important. However, our analysis indicates that for the remainder of the banking sector, smaller and mid-size banks should encounter higher capital requirements compared to larger non-systemic banks, especially if these regulations and implicit taxes aim to counterbalance deposit subsidies. Interpreted broadly, our estimates also suggest that safety nets embedded in the insured deposit funding play a role in the proliferation of small banks in the U.S.

More broadly, our empirical results speak to the question of whether financial intermediaries are "special" from the perspective of funding. On the one hand, intermediary capital structure differs substantially from non-financial firms. Shadow banks' capital structure shows that the financial intermediaries are funded with substantially more debt than non-financials and rely almost exclusively on short term debt funding. Our findings point to predominance of short-term debt funding structure among financial intermediaries irrespective of their access to deposit funding. First, the short-term financing could serve as a disciplining device for financial intermediaries (e.g., Calomiris and Kahn 1991; Diamond and Rajan 2001). Since shadow bank debt is highly concentrated and provided by potentially informed lenders (large banks), the broad message of monitoring resonates. However, to the extent the short-term debt indeed plays such role, our findings point out that the fragility induced by highly dispersed (and potentially uninformed) debtholders is not an essential component of such monitoring function.

On the other hand, the structure of shadow bank debt suggests that intermediary funding is also similar to non-financial firms. The homogeneity and dispersion of bank leverage, which distinguishes bank capital structure from that of non-financial firms, is not present in shadow banks. Moreover, we show large heterogeneity in banks' uninsured leverage. Because uninsured leverage robustly increases in size, as our model suggests, asset side determinants are an important factor in financial intermediary leverage. The substantial residual heterogeneity across capital structures of financial intermediaries of similar size is also consistent with models where leverage is dependent on the history of the firm's realized cashflows (e.g., DeMarzo and Sannikov 2006; DeMarzo and Fishman 2007; Bias et al. 2007; Bolton et al. 2011; He and Krishnamurthy 2011; Brunnermeier and Sannikov 2014; DeMarzo and He 2016; Admati et al. 2018).

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Table 1: Shadow Bank Call Reports – Asset and Income Composition

This table reports the mean asset composition (panel a) and income statement (panel b) of shadow banks active in the US mortgage market in our sample ranging from 2011 Q1 to 2017 Q4. We restrict attention to mortgage companies that are required to file HMDA reports and originate mortgage loans. This restriction leaves us with 429 shadow banks that have a license in the two states that provided us data. *Data Sources:* Shadow banks' quarterly call report filings to state regulators.

Panel A: Asset composition as percentage of total assets

	Mean
Cash	11.66%
Receivable	3.24%
Securities	0.34%
Mortgages Held for Sale	63.61%
Mortgages Held for Investment	3.55%
Mortgage Servicing Rights	7.56%
Real Estate Owned	0.28%
Building and Properties	2.00%
Good will and Intangible Assets	0.33%
Derivatives	1.43%
Technology Capital	0.40%
No. of Institutions	429

Panel B: Income and expense composition as percentage of total income and expenses

Gross Income	Mean	**Total Expenses**	Mean
Total Interest Income	8.48%	Total Interest Expenses	7.13%
Mortgages Held for Sale	5.16%	Warehouse Interest Expense	5.48%
Mortgages Held for Investment	1.90%	MBS Prepayment Interest Shortfall	0.10%
Securities	0.10%	MSR Assets	0.15%
Other Interest Income	0.69%	Debt Issuance	0.48%
Total Origination-Related Income	17.89%	Other Interest Expense	0.91%
Origination Fees	11.25%	Total Personnel Expenses	55.64%
Fees Received from Correspondents	2.15%	Total Origination Compensation	40.31%
Other Origination-Related Income	3.22%	Total Servicing Compensation	1.95%
Total Secondary Market Gains on Sale	55.79%	Other Personnel	6.77%
Mortgages Sold with Servicing Retained	18.50%	Total Other Non-Interest Expenses	27.36%
Capitalized Servicing Rights	7.19%	Equipment Depreciation	4.30%
Mortgages Sold with Servicing Released	27.09%	Technology-Related Expenses	1.65%
Other Gains from Loan Sale	-2.25%	Consulting/Legal Fees	2.04%
Total Servicing-Related Non-Interest Income	7.62%		
Servicing Fees	9.22%		
Subservicing Fees	1.22%		
Late Fees	0.70%		
Change in MSR Value	-1.65%		
MSR Sale	0.05%		
No. of Institutions	429		429

Table 2: Shadow Bank Call Reports – Liability and Equity Composition

This table reports the liability and equity composition of shadow banks active in the US mortgage market in our sample ranging from 2011 Q1 to 2017 Q4. We restrict attention to mortgage companies that are required to file HMDA reports and originate mortgage loans. This restriction leaves us with 429 shadow banks that have a license in the two states that provided us data. The table shows the average liability and equity shares and 25th, median and 75th percentiles for liability and asset shares. Panel (b) presents statistics on the providers of the short-term warehouse line of credit to shadow banks. These lines of credit account for most of the shadow banks' debt. Panel (b) reports the number of creditors, the percentage of credit used (drawn) relative to the overall credit limit, and the dollar-weighted composition of creditors among credit lines provided and the credit lines used grouped by banks, government sponsored enterprises (GSEs), non-bank financial institutions, and other category. *Data Sources:* Shadow banks' quarterly call report filings.

Panel A: Shadow banks' liability and equity composition

	Mean	25th	Median	75th
Total Liabilities	74.98	69.59	80.89	87.18
Short-term Liabilities	66.18	56.91	75.45	83.78
Debt Facilities	59.42	48.28	69.45	78.8
Commercial Papers	0	0	0	0
Other Account Payables	1.98	0	0.02	1.23
Accrued Expenses	2.91	1.13	2.3	3.77
Other Short-term Liabilities	1.37	0	0.25	1.46
Long-term Liabilities	8.17	0.55	1.91	5.44
Mortgage Debt	1.65	0	0	0
Trust Preferred Securities	0	0	0	0
Other Long-term Liabilities	3.27	0	0	0.8
Servicing Liabilities	0.47	0	0	0
Derivative Liabilities	0.28	0	0	0.24
Repurchase Reserves	0.97	0	0.34	1.17
Subordinated Debt	0.07	0	0	0
Total Equity	24.9	12.68	19	30.32
Preferred Stock	0.24	0	0	0
Common Stock (Partner's Capital)	6.29	0	0.1	8.78
Paid-in Capital	6.75	0	0.71	5.18
Non-control Interest	0.01	0	0	0
Other Comprehensive Income	0.07	0	0	0
Retained Earnings	11.33	0	8.74	17.85
Treasury Stocks	-0.1	0	0	0
No. of Institutions	429			

Panel B: Providers of short-term warehouse lines of credit to shadow banks

	Mean	25th	Median	75th
Number of Creditors	3.62	2	3	5
Credit Lines Used/ Credit Limit	50.29%	35.02%	51.13%	67.07%
Credit Lines Limit: Lender Composition				
Banks	93.11%	100%	100%	100%
GSE	0.70%	0%	0%	0%
Non-Bank Financial Institution	5.78%	0%	0%	0%
Other	0.42%	0%	0%	0%
Credit Lines Used: Lender Composition				
Banks	94.58%	100%	100%	100%
GSE	0.40%	0%	0%	0%
Non-Bank Financial Institution	4.59%	0%	0%	0%
Other	0.43%	0%	0%	0%
No. of Institutions	413			

Table 3: Summary Statistics – Shadow Bank versus Bank Funding Composition

Panel (a) of this table compares average funding composition of shadow banks and banks during our sample period ranging from 2011 Q1 to 2017 Q4. We restrict attention to mortgage companies that are required to file HMDA reports and originate mortgage loans. Removing companies that do not show up in HMDA database, this restriction leaves us with 429 shadow banks that have a license in the two states that provide us data. Column (1) shows the statistics for the shadow bank sample. Column (2) for the full bank sample. Column (3) for originate-to-distribute (OTD) banks version I defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA is in the top five percent among all banks. The average percentage of mortgages sold of OTD banks is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. Column (4) shows these statistics for version II OTD banks defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with about 85.5% minimum threshold of mortgages sold out of total originated for OTD banks of version 1 (see Section 2E). Column (5) shows the statistics for the synthetic mortgage bank sample created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. Panel (b) shows the distribution of equity to asset ratio for shadow banks and the above bank comparison groups. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filing, and HMDA.

Panel A: Funding composition of shadow banks and banks

	(1)	(2)	(3)	(4)	(5)
	Shadow Bank Sample	Bank Full Sample	OTD Bank I	OTD Bank II	Synthetic Mortgage Bank
Total Liabilities	75.0	89.1	89.3	89.6	88.1
Short-term Liabilities	66.2	76.5	76.0	76.9	60.7
Debt Facilities	59.4	73.1	71.4	69.7	54.6
Insured	0.0	49.6	48.5	45.4	50.4
Uninsured	59.4	23.4	22.8	24.4	4.3
Long-term Liabilities	8.2	12.6	13.3	12.5	27.2
Equity	24.9	10.9	10.7	10.4	11.9
Preferred Stock	0.2	0.1	0.1	0.1	0.0
Common Stock	6.3	1.0	1.0	1.0	-1.2
Paid-in Capital	6.7	5.0	5.0	6.0	0.8
Retained Earnings	11.3	4.8	4.4	3.0	12.5
No. of Institutions	429	4,822	549	257	4,822

Panel B: Distribution of equity to asset ratio for shadow banks and banks

	Asset-Weighted Mean	Volume-Weighted Mean	Mean	S.D.	10th	25th	50th	75th	90th
Shadow Bank	17.0	20.7	24.9	18.3	9.2	12.7	19.0	30.3	50.3
Bank Full Sample	11.5	11.2	10.9	2.9	8.2	9.2	10.4	12.1	14.3
OTD Bank I	10.2	10.5	10.7	2.8	7.9	9.1	10.2	11.8	13.9
OTD Bank II	10.5	10.6	10.4	2.9	7.4	8.8	10.1	11.6	13.3
Synthetic Mortgage Bank	11.6	11.4	11.9	2.8	9.1	10.2	11.5	13.1	15.2

Table 4: Equity to Asset Ratio – Shadow Banks versus Banks

This table reports results of OLS regression of equity to asset ratio on shadow bank indicator. The sample consists of shadow banks and all banks (Column 1 and 2), shadow banks and (originate-to-distribute) OTD banks of version I (Column 3 and 4), shadow banks and OTD banks of version II (Column 5 and 6), shadow banks and synthetic mortgage banks (Column 7 and 8). The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. In column (3) and (4) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. The year-quarter time fixed effects (*Date FE*) are included in all specifications. *Institution controls* include the asset growth, the share of refinanced mortgages out of total mortgage origination volume, the share of government-insured mortgages out of total mortgage origination volume, the logarithm of annual mortgage origination volume in dollars, the logarithm of asset size in dollars, the geographic loan dispersion, and the logarithm of the weighted average of income per capita in states of operation, where each state income per capita is weighted by the share of institution *i*'s loan origination in this state out of total loan origination of institution *i*, as reported in HMDA. Standard errors in the parentheses are clustered by institution. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.

	Shadow Bank vs All Bank		Shadow Bank vs OTD Bank I		Shadow Bank vs OTD Bank II		Shadow Bank vs Synthetic Mortgage Bank	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shadow Bank	10.92	11.26	10.93	12.30	11.06	11.85	9.97	10.12
	(0.67)	(0.85)	(0.69)	(1.17)	(0.70)	(1.22)	(0.67)	(0.85)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institution Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	115,167	109,411	11,724	10,947	8,992	8,401	115,167	109,411
R^2	0.253	0.258	0.230	0.292	0.157	0.242	0.223	0.230
Y-Variable Mean	11.56	11.56	16.71	16.73	19.02	18.99	12.46	12.47
Shadow Banks	21.91	21.97	21.93	22.02	21.91	21.97	21.91	21.97
Banks	10.92	10.94	10.64	10.68	10.33	10.37	11.88	11.89

Table 5: Tier 1 Capital Ratio – Shadow Banks versus Banks

This table reports results of OLS regressions of risk-based tier 1 capital ratio on shadow bank indicator. The sample consists of shadow banks and all banks (Column 1 and 2), shadow banks and OTD banks of version I (Column 3 and 4), shadow banks and OTD banks of version II (Column 5 and 6), shadow banks and synthetic mortgage banks which (Column 7 and 8). Since shadow banks do not report risk-based tier 1 capital ratios, we compute this ratio by applying the Basel III risk-based tier 1 capital ratio formula. Since we do not observe the detailed risk profiles for each type of assets held on the shadow banks' balance sheet, we use the upper bound and lower bound of shadow banks' tier 1 capital ratios in panel (a) and (b), respectively. These bounds are computed as described in Section 2.D. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. In column (3) and (4) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. The year-quarter time fixed effects (*Date FE*) are included in all specifications. *Institution controls* include asset growth, the share of refinanced mortgages out of total mortgage origination volume, the share of government-insured mortgages out of total mortgage origination volume, the logarithm of annual mortgage origination volume in dollars, the logarithm of asset size in dollars, the geographic loan dispersion, and the logarithm of the weighted average of income per capita in states of operation, where each state income per capita is weighted by the share of institution *i*'s loan origination in this state out of total loan origination of institution *i*, as reported in HMDA. Standard errors in the parentheses are clustered by institution. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.

Panel A: Tier 1 capital ratio (upper bound)

	Shadow Bank vs All Bank		Shadow Bank vs OTD Bank I		Shadow Bank vs OTD Bank II		Shadow Bank vs Synthetic Mortgage Bank	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shadow Bank	20.84	21.05	21.54	21.47	21.30	19.39	15.48	14.57
	(0.83)	(1.08)	(0.92)	(1.41)	(0.94)	(1.61)	(0.82)	(1.06)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institution Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	115,167	109,411	11,724	10,947	8,992	8,401	115,167	109,411
R^2	0.255	0.289	0.357	0.410	0.245	0.311	0.202	0.234
Y-Variable Mean	17.35	17.33	27.19	27.18	31.65	31.59	22.36	22.37
Shadow Banks	37.06	37.20	37.24	37.37	37.06	37.20	37.06	37.20
Banks	16.12	16.13	15.50	15.53	15.41	15.40	21.45	21.47

Panel B: Tier 1 capital ratio (lower bound)

	Shadow Bank vs All Bank		Shadow Bank vs OTD Bank I		Shadow Bank vs OTD Bank II		Shadow Bank vs Synthetic Mortgage Bank	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shadow Bank	10.98	11.01	11.52	11.32	11.37	9.68	5.62	4.53
	(0.72)	(0.94)	(0.83)	(1.28)	(0.85)	(1.47)	(0.71)	(0.91)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institution Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	115,167	109,411	11,724	10,947	8,992	8,401	115,167	109,411
R^2	0.098	0.138	0.189	0.251	0.128	0.204	0.042	0.077
Y-Variable Mean	16.77	16.77	21.85	21.85	24.26	24.20	21.79	21.80
Shadow Banks	27.20	27.25	27.32	27.37	27.20	27.25	27.20	27.25
Banks	16.12	16.13	15.50	15.53	15.41	15.40	21.45	21.47

Table 6: Short-Term Debt to Total Debt – Shadow Banks vs Banks

This table reports results of OLS regressions of short-term debt to total debt on shadow bank indicator. Short-term debt is defined as funding with less than 1-year time to maturity or repricing. For shadow banks we treat all debt items that are classified as "short-term liabilities" in the call reports as short-term debt. When computing short-term debt for banks, we add short-term deposits (time deposits with more than 1-year maturity are excluded), repo, short-term borrowings and trading liabilities. The sample consists of shadow banks and all banks (Column 1 and 2), shadow banks and OTD banks of version I (Column 3 and 4), shadow banks and OTD banks of version II (Column 5 and 6), shadow banks and synthetic mortgage banks which (Column 7 and 8). The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. In column (3) and (4) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. The year-quarter time fixed effects (*Date FE*) are included in all specifications. *Institution controls* include the asset growth, the share of refinanced mortgages out of total mortgage origination volume, the share of government-insured mortgages out of total mortgage origination volume, the logarithm of annual mortgage origination volume in dollars, the logarithm of asset size in dollars, the geographic loan dispersion, and the logarithm of the weighted average of income per capita in states of operation, where each state income per capita is weighted by the share of institution *i*'s loan origination in this state out of total loan origination of institution *i*, as reported in HMDA. Standard errors in the parentheses are clustered by institution. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.

	Shadow Bank vs All Bank		Shadow Bank vs OTD Bank I		Shadow Bank vs OTD Bank II		Shadow Bank vs Synthetic Mortgage Bank	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shadow Bank	11.97	16.44	12.57	10.11	12.07	9.34	28.84	28.04
	(0.52)	(1.03)	(0.75)	(1.76)	(0.86)	(1.73)	(0.52)	(0.94)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institution Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	114,780	109,067	11,445	10,696	8,605	8,057	114,780	109,067
R^2	0.094	0.111	0.286	0.316	0.209	0.263	0.381	0.397
Y-Variable Mean	86.48	86.55	91.90	91.90	94.87	94.80	70.44	70.49
Shadow Banks	98.09	98.06	98.10	98.08	98.09	98.06	98.09	98.06
Banks	85.80	85.89	85.01	85.13	85.78	85.90	68.82	68.92

Table 7: Equity to Asset Ratio and Size – Shadow Banks vs Banks

This table reports results of OLS regression of equity to asset ratio on shadow bank indicator, and its interaction with size. The size is measured by the logarithm of annual mortgage origination volume in dollars (*Loan Volume*). The sample consists of shadow banks and all banks (Column 1), shadow banks and OTD banks of version I (Column 2), shadow banks and OTD banks of version II (Column 3), shadow banks and synthetic mortgage banks which are constructed by replacing all bank assets with residential mortgages (Column 4). The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. In column (2) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. The year-quarter time fixed effects (*Date FE*) are included in all specifications. *Institution controls* include the asset growth, the share of refinanced mortgages out of total mortgage origination volume, the share of government-insured mortgages out of total mortgage origination volume, the logarithm of annual mortgage origination volume in dollars, the geographic loan dispersion, and the logarithm of the weighted average of income per capita in states of operation, where each state income per capita is weighted by the share of institution *i*'s loan origination in this state out of total loan origination of institution *i*, as reported in HMDA. The estimated coefficient of the interaction term of shadow bank indicator with loan volume is scaled by one standard deviation of loan volume. Standard errors in the parentheses are clustered by institution. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.

	Shadow Bank vs All Bank	Shadow Bank vs OTD Bank I	Shadow Bank vs OTD Bank II	Shadow Bank vs Synthetic Mortgage Bank
	(1)	(2)	(3)	(4)
Shadow Bank	82.40	77.81	82.71	80.78
	(11.05)	(11.99)	(11.06)	(11.06)
Shadow Bank × Loan Volume	-6.70	-6.24	-6.73	-6.63
	(1.03)	(1.12)	(1.03)	(1.03)
Date FE	Yes	Yes	Yes	Yes
Institution Controls	Yes	Yes	Yes	Yes
Observations	109,411	10,947	8,401	109,411
R^2	0.304	0.320	0.268	0.277
Y-Variable Mean	11.56	16.73	18.99	12.47
Shadow Banks	21.97	22.02	21.97	21.97
Banks	10.94	10.68	10.37	11.89

Table 8: Uninsured Leverage and Size – Shadow Banks vs Banks

This table reports results of OLS regression of uninsured leverage defined as the uninsured debt to asset ratio on size for shadow banks (panel a) and banks (panel b). The size is measured by the logarithm of annual mortgage origination volume in dollars (*Loan Volume*). For shadow banks all debt items as uninsured. For banks uninsured debt is defined as total debt less insured deposits. In panel (b) the sample consists of all banks (Column 1 and 2), OTD banks I (Column 3 and 4), OTD banks II (Column 5 and 6), and synthetic mortgage banks (Column 7 and 8). The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. The year-quarter time fixed effects (*Date FE*) are included in all specifications. *Institution controls* include the asset growth, the share of refinanced mortgages out of total mortgage origination volume, the share of government-insured mortgages out of total mortgage origination volume, the geographic loan dispersion, and the logarithm of the weighted average of income per capita in states of operation, where each state income per capita is weighted by the share of institution *i*'s loan origination in this state out of total loan origination of institution *i*, as reported in HMDA. The estimated coefficient of loan volume is scaled by one standard deviation of loan volume. Standard errors in the parentheses are clustered by institution. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.

Panel A: Debt to asset ratio for shadow banks

	Shadow Bank	
	(1)	(2)
Loan Volume	6.61	10.75
	(0.49)	(1.62)
Date FE	Yes	Yes
Institution Controls	No	Yes
Observations	6,744	6,241
R^2	0.897	0.907
Y-Variable Mean	64.30	64.16

Panel B: Uninsured debt to asset ratio for banks

	All Bank		OTD Bank I		OTD Bank II		Synthetic Mortgage Bank	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Loan Volume	3.36	4.33	3.07	4.39	2.13	2.29	3.36	4.33
	(0.05)	(0.23)	(0.15)	(0.81)	(0.38)	(0.95)	(0.05)	(0.23)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institution Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	108,423	103,170	5,422	5,107	2,248	2,160	108,423	103,170
R^2	0.858	0.868	0.855	0.863	0.850	0.871	0.858	0.868
Y-Variable Mean	29.48	29.63	29.99	30.22	33.68	33.82	29.48	29.63

Table 9: Uninsured Debt Cost and Size – Shadow Banks vs Banks

This table reports regression results of average annual interest rate on shadow bank debt (Column 1 and 2), annual uninsured bank debt (Column 3 and 4), and an annual uninsured-insured debt interest rate spread for banks (Column 5 and 6), all in percentage points, on size measured by the logarithm of annual mortgage origination volume in dollars (*Loan Volume*). We note that all shadow bank debt is uninsured. The uninsured-insured interest rate spread is defined as within bank difference between interest rate on uninsured and insured debt. The year fixed effects (*Date FE*) are included in all specifications. *Institution controls* include annual asset growth, the share of refinanced mortgages out of total mortgage origination volume, the share of government-insured mortgages out of total mortgage origination volume, the geographic loan dispersion, and the logarithm of the weighted average of income per capita in states of operation, where each state income per capita is weighted by the share of institution *i*'s loan origination in this state out of total loan origination of institution *i*, as reported in HMDA. The estimated coefficient of loan volume is scaled by one standard deviation of loan volume. Standard errors in the parentheses are clustered by institution. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.

	Shadow Bank Sample Interest Rate		Full Bank Sample Interest Rate		Full Bank Sample Uninsured-Insured Spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Loan Volume	-1.10	-0.98	-0.21	-0.23	-0.28	-0.30
	(0.12)	(0.12)	(0.01)	(0.01)	(0.01)	(0.01)
Institution Controls	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,015	1,823	27,270	27,137	27,270	27,137
R^2	0.080	0.081	0.320	0.344	0.268	0.299
Y-Variable Mean	4.42	3.97	2.33	2.33	1.25	1.25

Table 10: Calibrated Parameters

Parameter values. The distributions $F^j(\lambda)$ are calibrated non-parametrically. The table presents the mean and standard deviation for ease of comparison.

Parameter	Description	Value
Asset Side Parameters		
$\mu(\lambda_s)$	Mean of shadow bank recovery rate	0.25
$\sigma(\lambda_s)$	Standard deviation of shadow bank recovery rate	0.08
$\mu(\lambda_b)$	Mean of bank recovery rate	0.11
$\sigma(\lambda_b)$	Standard deviation of bank recovery rate	0.03
P	Probability of bad state (%)	6.50
β	Intermediary economies of scale	0.97
ζ_a	Aggregate asset-side economies of scale	10.9
Financing Parameters (Intermediaries)		
γ_s	Shadow bank equilibrium liquidity premium	89bps
γ_b	Bank liquidity equilibrium premium	139bps
δ	Per-dollar run cost	14pp
τ	Insured deposit acquisition cost	6.75pp
Financing Parameters (Household Preferences)		
ξ_d	Household money-like preference weight	0.01
ϵ	Elasticity of substitution between bank and shadow bank debt	0.92
η	Money-like service of shadow bank debt relative to bank debt	0.67

Table 11: Counterfactual Bank Capital Ratios

This table compares the bank capital ratios in the data and the counterfactual bank capital ratios. Panel A presents the mean and standard deviation. Panel B presents the average capital ratios by size bin. The first row in each panel presents bank capital ratio in the data. The *No Safety Nets* counterfactual presents the bank capital ratios in the absence of capital requirement and when depositors internalize default. The *No Safety Nets & Money-Like Advantage Reduced by Half* counterfactual presents the bank capital ratios when in addition we reduce the bank debt's money like advantage relative to shadow bank debt by half. The *No Safety Nets & No Money-Like Advantage* counterfactual presents the bank capital ratios in the absence of capital requirement and when depositors internalize default and banks' debt has no money like advantage relative to shadow banks' debt.

Panel A: Bank Capital Ratios

	Mean		Stdev
	Equal-Weighted	Value-Weighted	
Bank Capital Ratio (Data)	0.11	0.11	0.03
Counterfactual Capital Ratios			
No Safety Nets	0.14	0.10	0.09
No Safety Nets & Money-Like Advantage Reduced by Half	0.31	0.26	0.12
No Safety Nets & No Money-Like Advantage	0.37	0.32	0.12

Panel B: Bank Capital Ratios by Bank Size

	Size bin			
	1	2	3	4
Bank Capital Ratio	0.11	0.11	0.10	0.11
Counterfactual Capital Ratios				
No Safety Nets	0.17	0.14	0.13	0.11
No Safety Nets & Money-Like Advantage Reduced by Half	0.35	0.32	0.30	0.28
No Safety Nets & No Money-Like Advantage	0.41	0.38	0.35	0.34

Table 12: Counterfactual Cost of Uninsured Bank Debt and Aggregate Implications

This table presents counterfactual results. Panel A and B compare the cost of uninsured debt in the data and in the counterfactuals. Panel A presents the mean and standard deviation. Panel B presents the cost by size bin. The first row in each panel presents the cost in the data. The *No Safety Nets* counterfactual presents interest rates on uninsured bank debt in the absence of capital requirement and when depositors internalize default. The *No Safety Nets & Money-Like Advantage Reduced by Half* counterfactual presents interest rates on uninsured bank debt when in addition we reduce the bank debt's money like advantage relative to shadow bank debt by half. The *No Safety Nets & No Money-Like Advantage* counterfactual presents interest rates on uninsured bank debt in the absence of capital requirement and when depositors internalize default and banks' debt has no money like advantage relative to shadow banks' debt. Panel C shows the percentage change in the aggregate lending and money-like provision (debt level) in the *No Safety Nets* counterfactual, *No Safety Nets & Money-Like Advantage Reduced by Half* counterfactual, and *No Safety Nets & No Money-Like Advantage* counterfactual relative to the baseline, respectively.

Panel A: Cost of Uninsured Debt

	Mean		Stdev
	Equal-Weighted	Value-Weighted	
Interest Rates on Uninsured Bank Debt	2.39%	2.15%	2.07%
Counterfactual Interest Rates on Uninsured Bank Debt			
No Safety Nets	5.34%	4.96%	0.93%
No Safety Nets & Money-Like Advantage Reduced by Half	5.34%	4.92%	1.14%
No Safety Nets & No Money-Like Advantage	5.32%	4.88%	1.22%

Panel B: Cost of Uninsured Debt by Bank Size

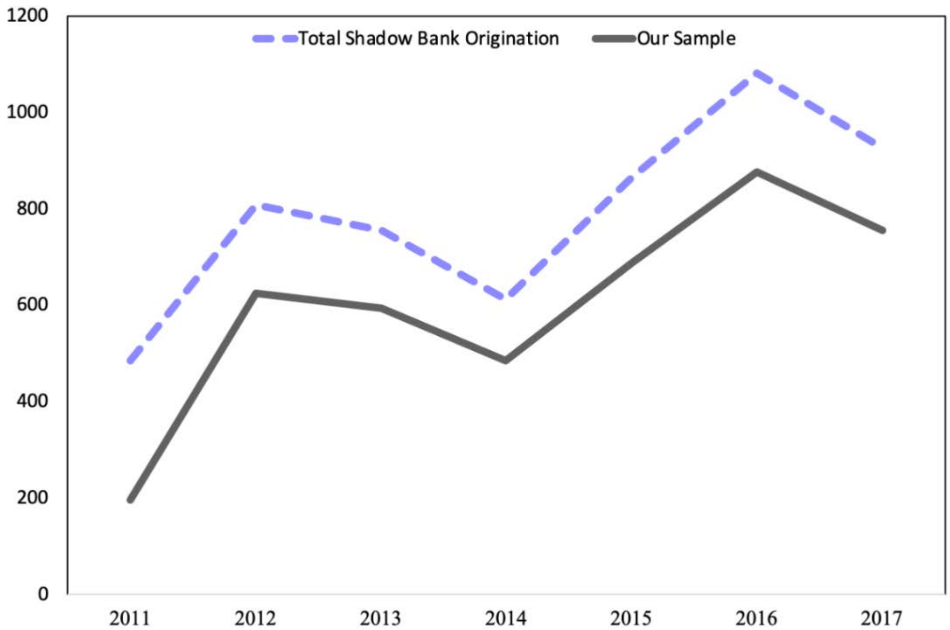
	Size bin			
	1	2	3	4
Interest Rates on Uninsured Bank Debt	2.86%	2.44%	2.36%	1.90%
Counterfactual Interest Rates on Uninsured Bank Debt				
No Safety Nets	5.65%	5.38%	5.23%	5.10%
No Safety Nets & Money-Like Advantage Reduced by Half	5.72%	5.38%	5.20%	5.04%
No Safety Nets & No Money-Like Advantage	5.73%	5.37%	5.17%	5.00%

Panel C: Counterfactual Aggregate Lending and Money-like Provision

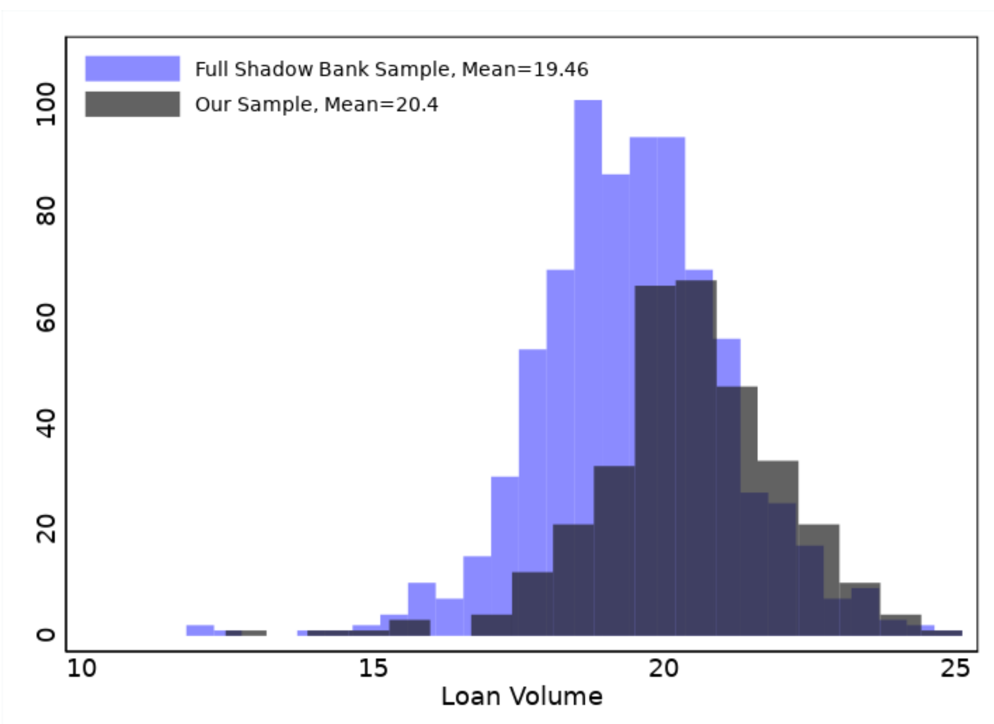
	Bank	Shadow Bank	Total
No Safety Nets:			
Counterfactual lending relative to actual	1.65%	-0.75%	0.09%
Counterfactual money-like provision (debt level) relative to actual	2.34%	-0.48%	0.57%
No Safety Nets & Money-Like Advantage Reduced by Half:			
Counterfactual lending relative to actual	-12.2%	6.3%	-0.16%
Counterfactual money-like provision (debt level) relative to actual	-27.7%	4.9%	-7.2%
No Safety Nets & No Money-Like Advantage			
Counterfactual lending relative to actual	-15.3%	8.0%	-0.2%
Counterfactual money-like provision (debt level) relative to actual	-35.9%	6.1%	-9.5%

Figure 1: Sample Coverage

This figure compares our sample coverage to the shadow bank loan origination coverage recorded in the HMDA data. Panel (a) plots the total shadow bank loan origination (in $bn) with the loan origination from our sample coverage, by year. Panel (b) plots the histograms (frequency) of the logarithm of loan origination size for shadow banks in our sample as well as shadow banks in the HMDA data in 2017.



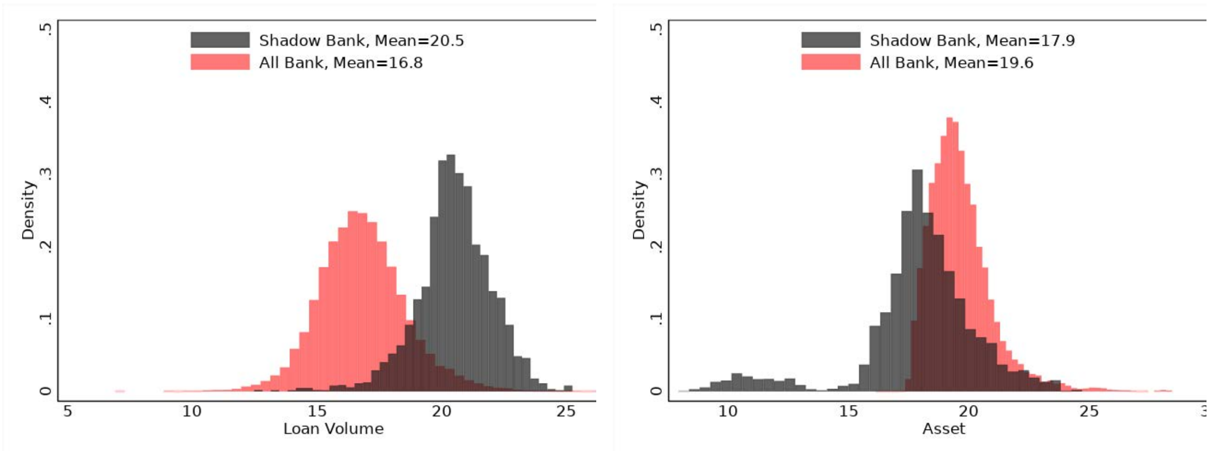
(a) Sample Coverage by Year



(b) 2017 Sample Size Distribution

Figure 2: Histograms for Shadow Bank and All Bank

This figure plots the histograms (density) of the logarithm of annual loan origination volume in dollars (panel a) and the logarithm of assets in dollars (panel b) for shadow banks and banks in our sample. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.

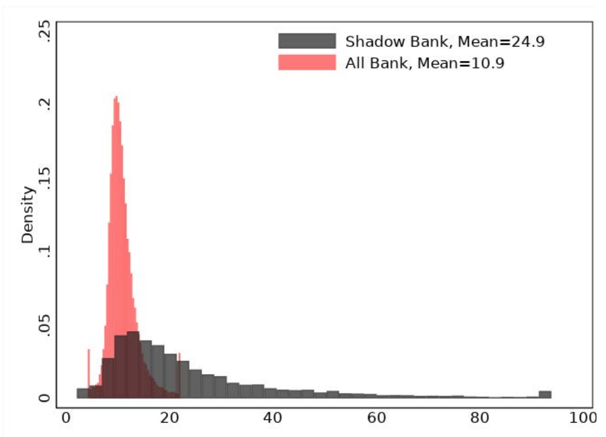


(a) Loan Volume Distribution

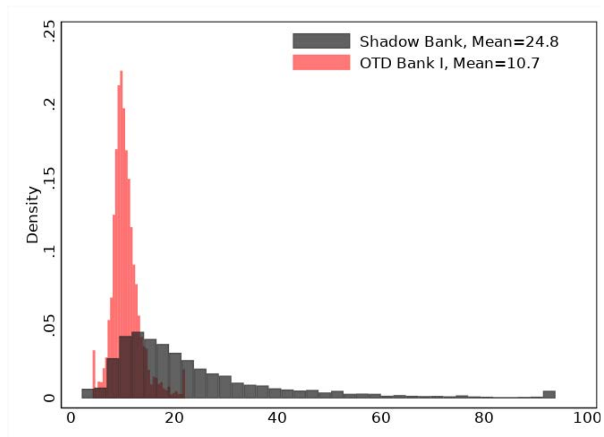
(b) Asset Distribution

Figure 3: Equity to Asset Ratio – Shadow Banks vs Banks

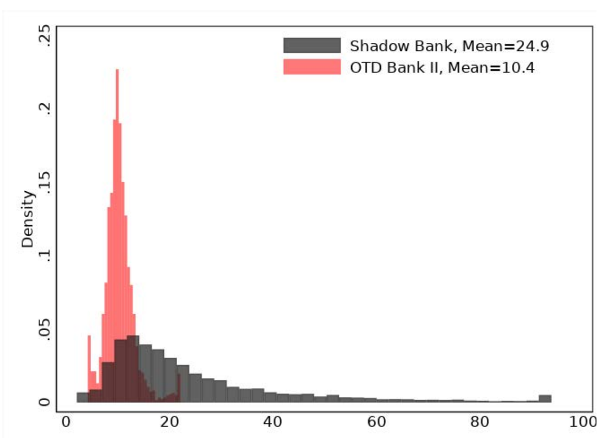
This figure plots the histograms (density) of equity to asset ratio for shadow banks and banks. Panel (a) compares shadow banks to all banks, panel (b) shadow banks to OTD banks of version I, panel (c) shadow banks to OTD banks of version II, panel (d) shadow banks to synthetic mortgage banks. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA is in the top decile among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold among shadow banks is 94.4%. In panel (b) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with about 86% threshold of mortgages sold out of total originated that we use to define OTD banks I (see Section 2.E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. *Data Sources:* Shadow banks' quarterly call report filings to state regulators and bank regulatory call report filings.



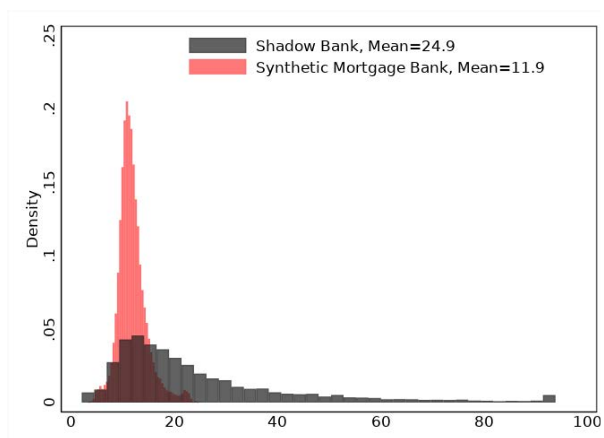
(a) Shadow Bank vs All Bank



(b) Shadow Bank vs OTD Bank I



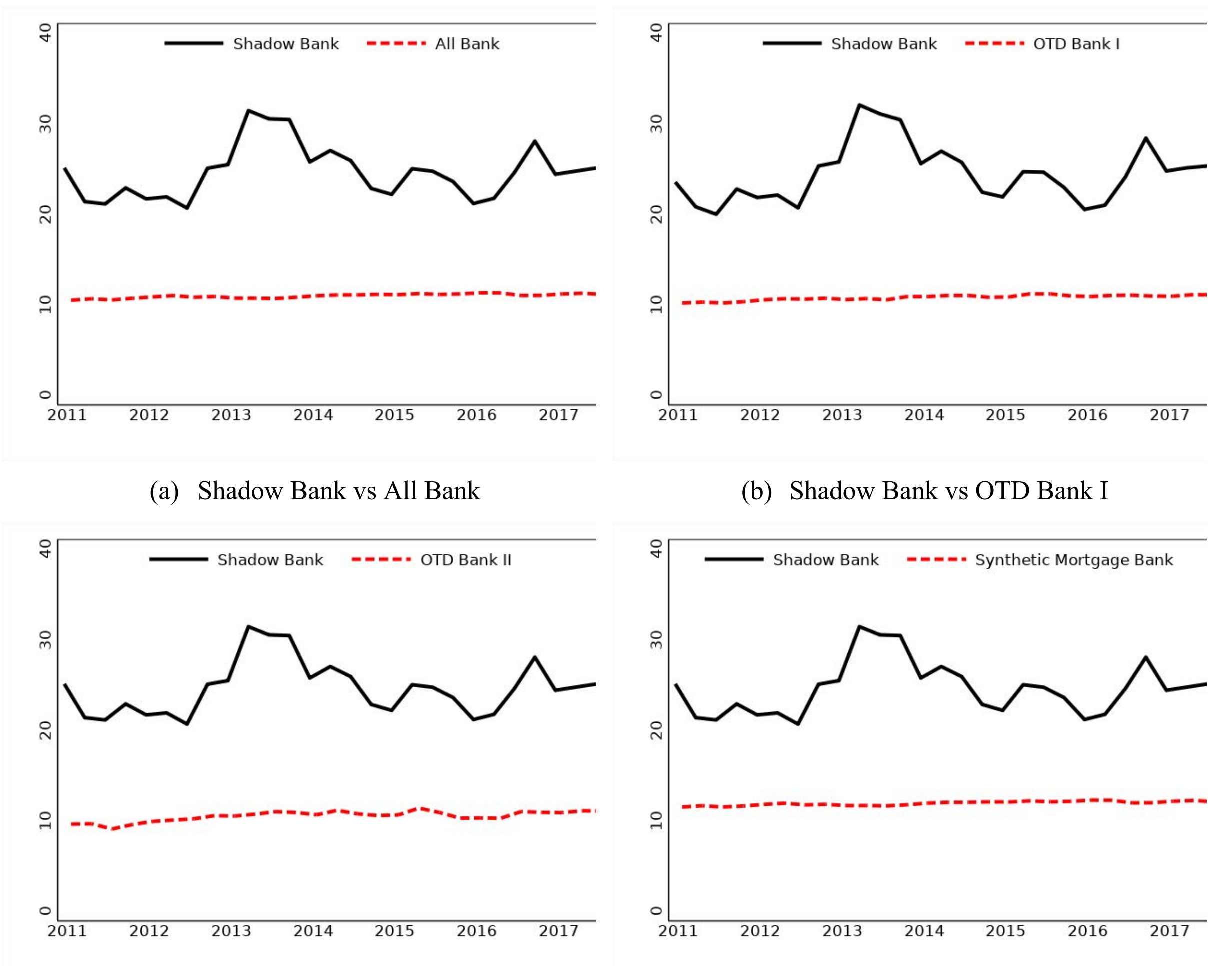
(c) Shadow Bank vs OTD Bank II



(d) Shadow Bank vs Synthetic Mortgage Bank

Figure 4: Equity to Asset Ratio over Time – Shadow Banks vs Banks

This figure plots the time series of equity to asset ratio for shadow banks and banks. Panel (a) compares shadow banks to all banks, panel (b) shadow banks to OTD banks of version I, panel (c) shadow banks to OTD banks of version II, panel (d) shadow banks to synthetic mortgage banks which are constructed by replacing all bank assets with residential mortgages. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. In panel (b) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. *Data Sources:* Shadow banks' quarterly call report filings to state regulators and bank regulatory call report filings.



(a) Shadow Bank vs All Bank

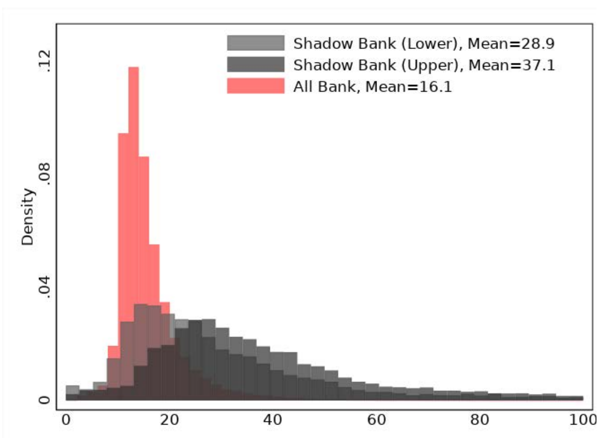
(b) Shadow Bank vs OTD Bank I

(c) Shadow Bank vs OTD Bank II

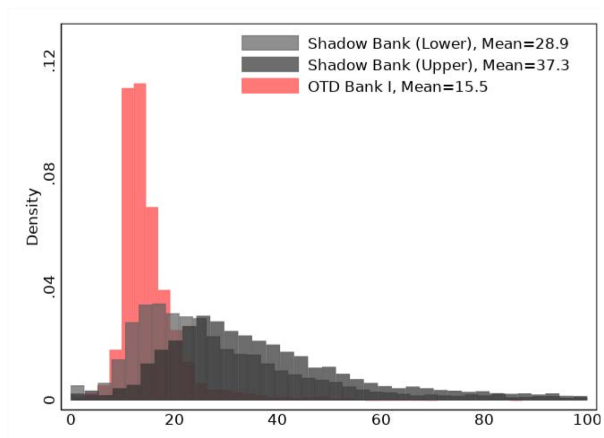
(d) Shadow Bank vs Synthetic Mortgage Bank

Figure 5: Tier 1 Capital Ratio – Shadow Banks vs Banks

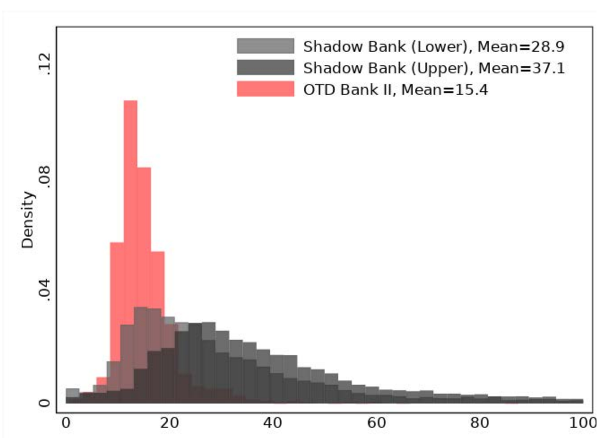
This figure plots the tier 1 capital ratio for shadow banks and banks. Panel (a) compares shadow banks to all banks, panel (b) shadow banks to OTD banks of type I, panel (c) shadow banks to OTD banks of type II, panel (d) shadow banks to synthetic mortgage banks. Since shadow banks do not report risk-based tier 1 capital ratios, we compute this ratio by applying the Basel III risk-based tier 1 capital ratio formula. Since we do not observe the detailed risk profiles for each type of assets held on the shadow banks' balance sheet, we use the upper bound and lower bound of shadow banks' tier 1 capital ratios, respectively. These bounds are computed as described in Section 2.D. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. In panel (b) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. *Data Sources:* Shadow banks' quarterly call report filings to state regulators and bank regulatory call report filings.



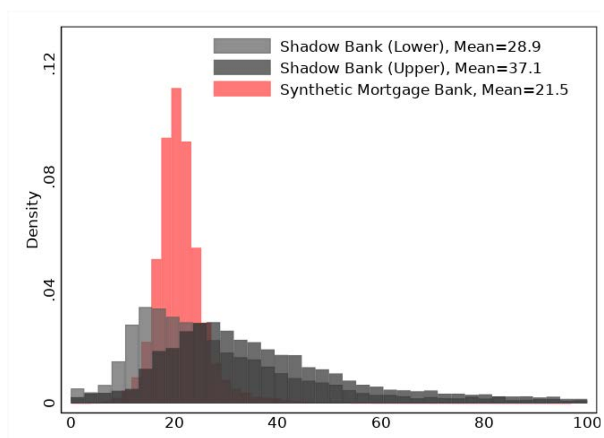
(a) Shadow Bank vs All Bank



(b) Shadow Bank vs OTD Bank I



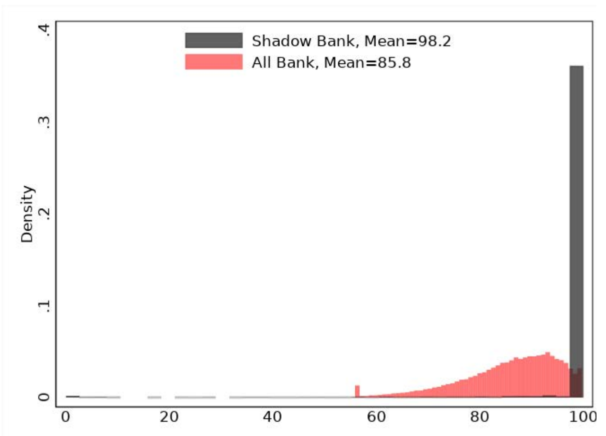
(c) Shadow Bank vs OTD Bank II



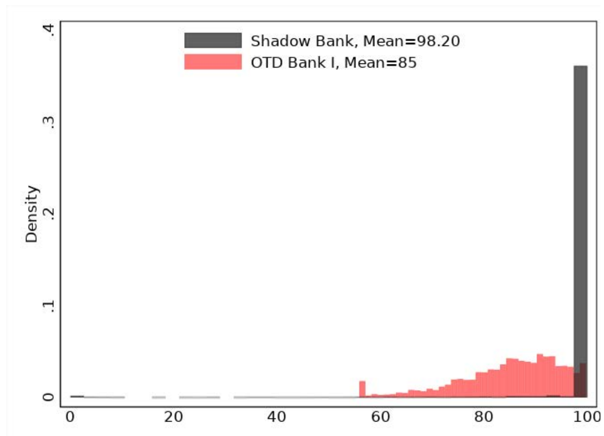
(d) Shadow Bank vs Synthetic Mortgage Bank

Figure 6: Short-Term Debt to Total Debt – Shadow Banks vs Banks

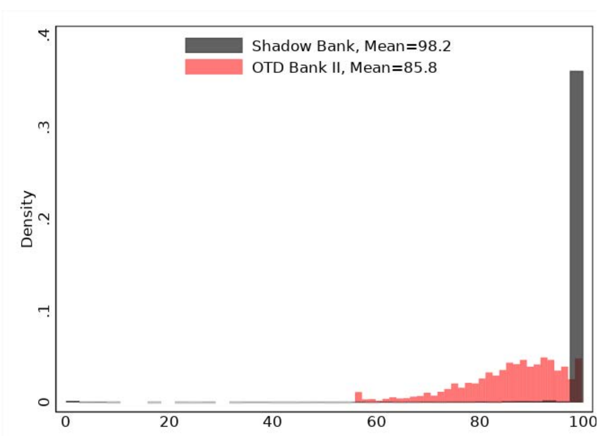
This figure plots the histograms of short-term debt to total debt for shadow banks and banks. Panel (a) compares shadow banks to all banks, panel (b) shadow banks to OTD banks of version I, panel (c) shadow banks to OTD banks of version II, panel (d) shadow banks to synthetic mortgage banks. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. In panel (b) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. *Data Sources:* Shadow banks' quarterly call report filings to state regulators and bank regulatory call report filings.



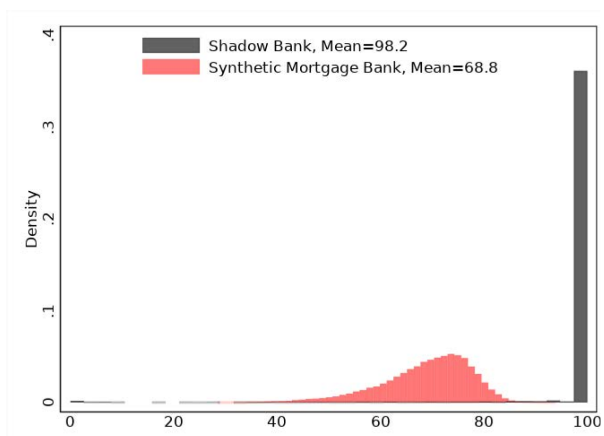
(a) Shadow Bank vs All Bank



(b) Shadow Bank vs OTD Bank I



(c) Shadow Bank vs OTD Bank II



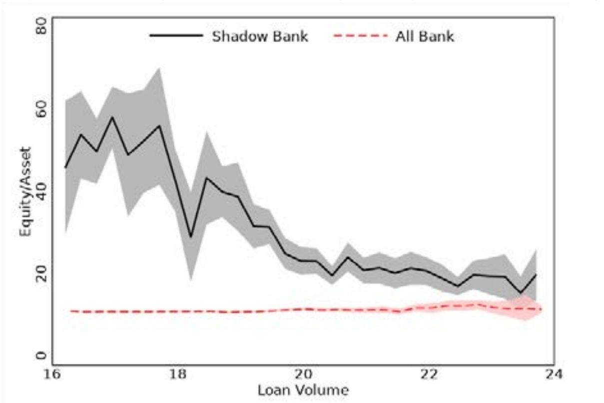
(d) Shadow Bank vs Synthetic Mortgage Bank

Figure 7: Equity to Asset Ratio and Size – Shadow Banks vs Banks

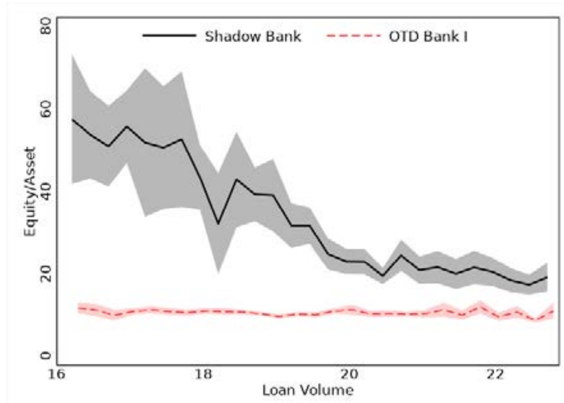
This figure plots the equity to asset ratio of shadow banks and banks against the loan volume. Specifically, using a panel data set of quarterly observations from 2011 to 2017, we estimate the following specification for banks and shadow banks, respectively:

$$Ratio_{i,t} = \Sigma_b \gamma_b I\left(Size_{i,t} \in Bin_b\right) + \epsilon_{i,t}$$

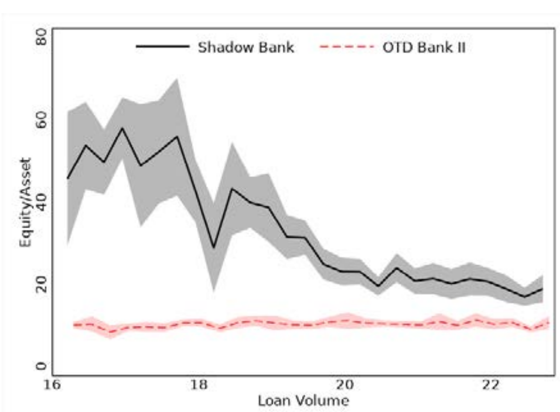
where $Ratio_{i,t}$ is the equity to asset ratio, $I(Size_{i,t} \in Bin_b)$ is an indicator of whether bank (shadow bank) i's size falls within size bucket Bin_b. The plotted coefficients of interest, γ_b, show how the equity to asset ratio vary non-parametrically across the size distribution, where size is measured by the logarithm of annual mortgage origination volume in dollars. Each size bin covers an incremental value of 0.25 in the size distribution. In other words, the difference between the largest firm's size and the smallest firm's size in each size bin is 0.25. The shaded area shows the 95% confidence interval. Standard errors are clustered by institutions. Panel (a) compares shadow banks to all banks, panel (b) shadow banks to OTD banks of version I, panel (c) shadow banks to OTD banks of version II, panel (d) shadow banks to synthetic mortgage banks. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. In panel (b) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.



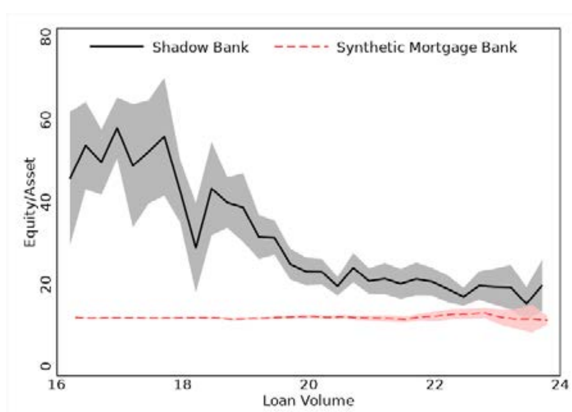
(a) Shadow Bank vs All Bank



(b) Shadow Bank vs OTD Bank I



(c) Shadow Bank vs OTD Bank II



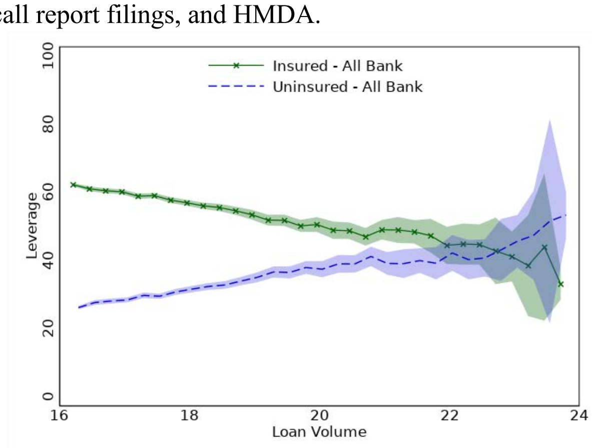
(d) Shadow Bank vs Synthetic Mortgage Bank

Figure 8: Uninsured and Insured Bank Leverage and Size

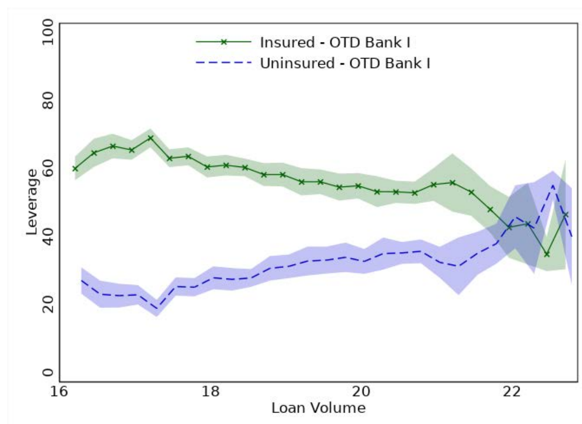
This figure plots uninsured and insured bank debt to asset ratio against loan origination volume. For banks insured debt corresponds to sum of their deposits covered by the FDIC guarantees and uninsured debt is defined as total debt less insured deposits. Specifically, using a panel data set of quarterly observations from 2011 to 2017, we estimate the following specification for banks and shadow banks, respectively:

$$Ratio_{i,t} = \Sigma_b \gamma_b I\left(Size_{i,t} \in Bin_b\right) + \epsilon_{i,t}$$

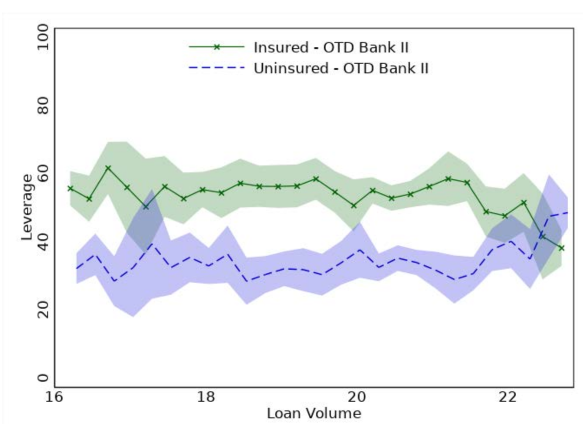
where $Ratio_{i,t}$ is the uninsured and insured bank debt to asset ratio, respectively, $I(Size_{i,t} \in Bin_b)$ is an indicator of whether bank i's size falls within size bucket Bin_b. The plotted coefficients of interest, γ_b, show how a given debt to asset ratios vary non-parametrically across the size distribution, where size is measured by the logarithm of annual mortgage origination volume in dollars. Each size bin covers an incremental value of 0.25 in the size distribution. In other words, the difference between the largest firm's size and the smallest firm's size in each size bin is 0.25. The shaded area shows the 95% confidence interval. Standard errors are clustered by institutions. Panel (a) shows these results for all banks, panel (b) for OTD banks of version I, panel (c) for OTD banks of version II, panel (d) for synthetic mortgage banks. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.



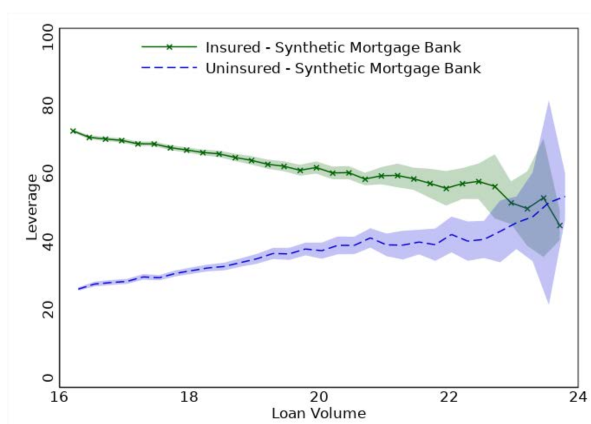
(a) All Bank



(b) OTD Bank I



(c) OTD Bank II



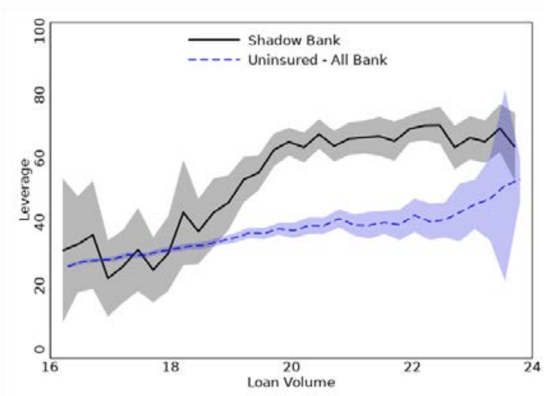
(d) Synthetic Mortgage Bank

Figure 9: Uninsured Leverage and Size – Shadow Banks vs Banks

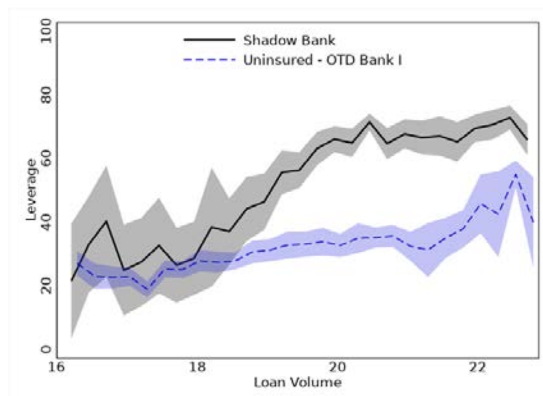
This figure plots uninsured debt to asset ratio against loan origination volume for banks and shadow banks. For banks the uninsured debt is defined as total debt less insured deposits. For shadow banks all debt is uninsured. Specifically, using a panel data set of quarterly observations from 2011 to 2017, we estimate the following specification for banks and shadow banks, respectively:

$$Ratio_{i,t} = \Sigma_b \gamma_b I(Size_{i,t} \in Bin_b) + \epsilon_{i,t}$$

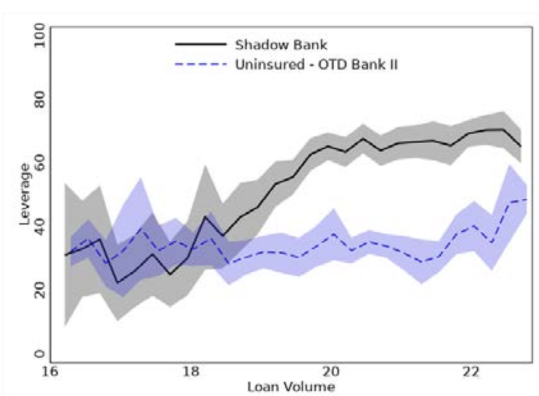
where $Ratio_{i,t}$ is the uninsured and insured bank debt to asset ratio, respectively, $I(Size_{i,t} \in Bin_b)$ is an indicator of whether bank i's size falls within size bucket Bin_b. The plotted coefficients of interest, γ_b, show how a given debt to asset ratios vary non-parametrically across the size distribution, where size is measured by the logarithm of annual mortgage origination volume in dollars. Each size bin covers an incremental value of 0.25 in the size distribution. In other words, the difference between the largest firm's size and the smallest firm's size in each size bin is 0.25. The shaded area shows the 95% confidence interval. Standard errors are clustered by institutions. Panel (a) shows these results for shadow banks and all banks, panel (b) for shadow banks and OTD banks of version I, panel (c) for shadow banks and OTD banks of version II, panel (d) for shadow banks and synthetic mortgage banks. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.



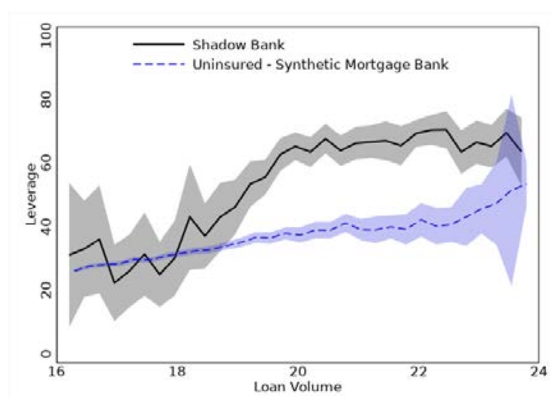
(a) Shadow Banks vs All Bank



(b) Shadow Bank vs OTD Bank I



(c) Shadow Bank vs OTD Bank II



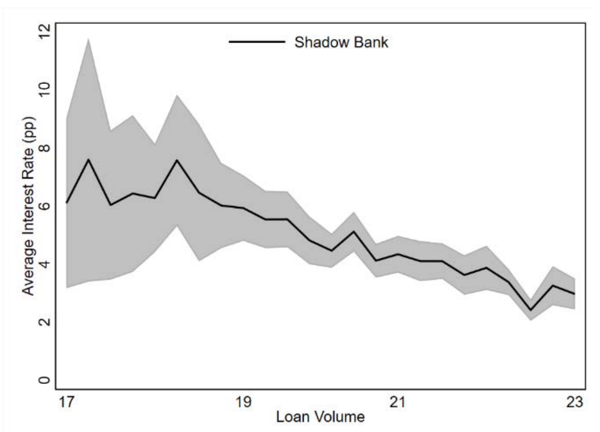
(d) Shadow Bank vs Synthetic Mortgage Bank

Figure 10: Debt Funding Cost and Size – Shadow Banks vs Banks

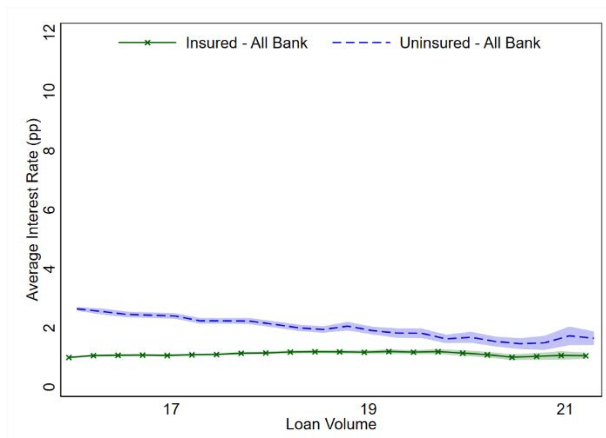
This figure shows average annual interest rate (in %) on debt against loan origination volume. Panel (a) shows these statistics for shadow banks, where uninsured interest rate is calculated as interest expense divided by total debt outstanding. We note that all shadow bank debt is uninsured. Panel (b) shows the results for the average annual interest rate for the uninsured and insured bank debt. Annual interest rates for insured bank debt are calculated as the interest expenses on the insured bank deposits divided by the total insured bank deposits. Due to limitations to bank interest expense data, we modify our definition of insured deposits in this figure based on the breakdown of the interest expense data in bank call reports. We collect interest expense data on transactional accounts and on the time deposit below the deposit insurance limit. We group these deposit categories together and label them insured debt for interest expense analysis. Similarly, we modify our definition of uninsured deposits in this figure based on the breakdown of the interest expense data in bank call reports. We add up saving deposits, time deposits above the deposit insurance limit, repo, foreign deposits, other borrowed money, and subordinate debt and label them uninsured debt for interest expense analysis. We then divide the interest expenses on these debt categories by the total amount of uninsured debt. Panel (c) shows these patterns for annual uninsured-insured interest rate spread for banks, defined as within bank difference between interest rate on uninsured and insured debt. Specifically, using a panel data set of quarterly observations from 2011 to 2017, we estimate the following specification for banks and shadow banks, respectively:

$$Ratio_{i,t} = \Sigma_b \gamma_b I\left(Size_{i,t} \in Bin_b\right) + \epsilon_{i,t}$$

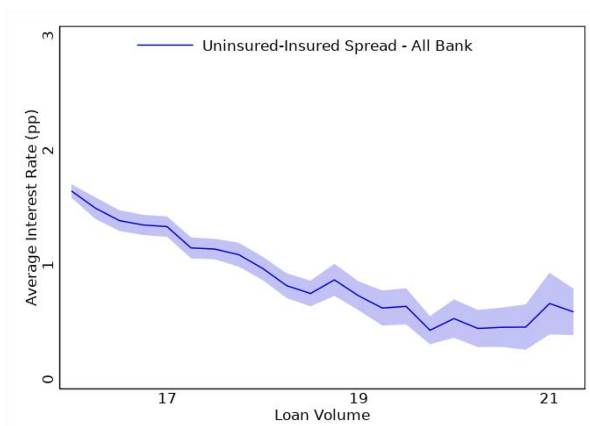
where $Ratio_{i,t}$ is the annual uninsured and insured short-term debt interest rate and the annual uninsured-insured interest rate spread, respectively, $I(Size_{i,t} \in Bin_b)$ is an indicator of whether bank (shadow bank) i's size falls within size bucket Bin_b. The plotted coefficients of interest, γ_b, show how these funding ratios vary non-parametrically across the size distribution, where size is measured by the logarithm of annual mortgage origination volume in dollars. Each size bin covers an incremental value of 0.25 in the size distribution. In other words, the difference between the largest firm's size and the smallest firm's size in each size bin is 0.25. The shaded area shows the 95% confidence interval. Standard errors are clustered by institutions. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.



(a) Shadow Bank Short-Term Debt Cost



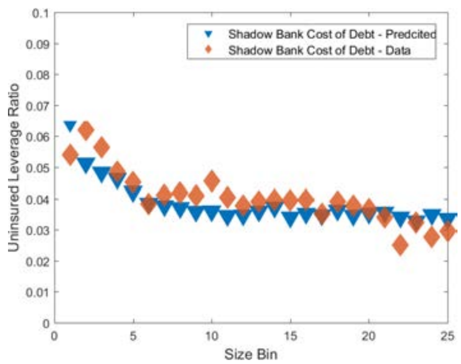
(b) Bank Debt Cost



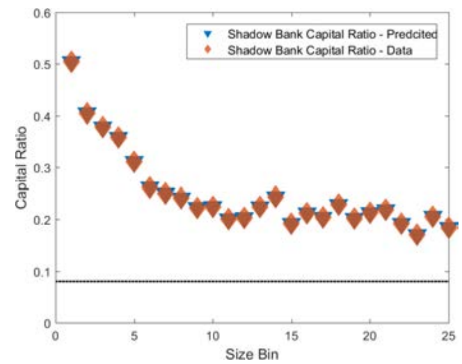
(c) Bank Uninsured-Insured Debt Spread

Figure 11: Model Predictions

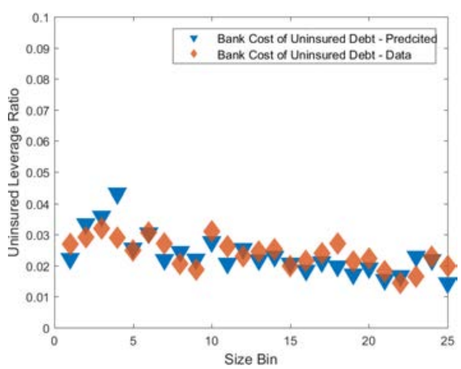
This figure compares the model predicted moments to the observed values against size. Panel (a) shows shadow bank cost of debt. Panel (b) shows shadow banks capital ratio. Panel (c) shows bank cost of uninsured debt. Panel (d) shows bank uninsured leverage ratio. To make these plots, we discretize the intermediary size distribution into 25 size bins of banks and shadow banks. We simulate the model using the calibrated parameters and compare the model predicted values in blue to the observed values in the data in red.



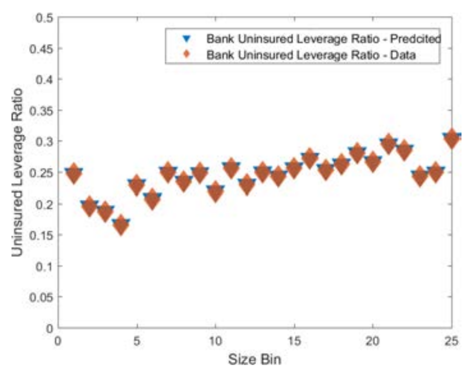
(a) Shadow Bank Cost of Debt



(b) Shadow Bank Leverage



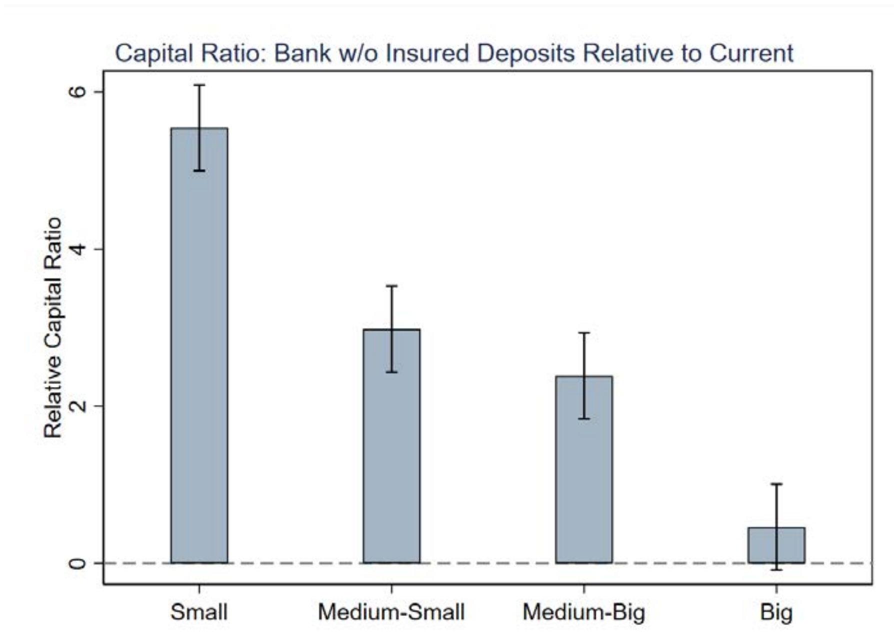
(c) Bank Cost of Uninsured Debt



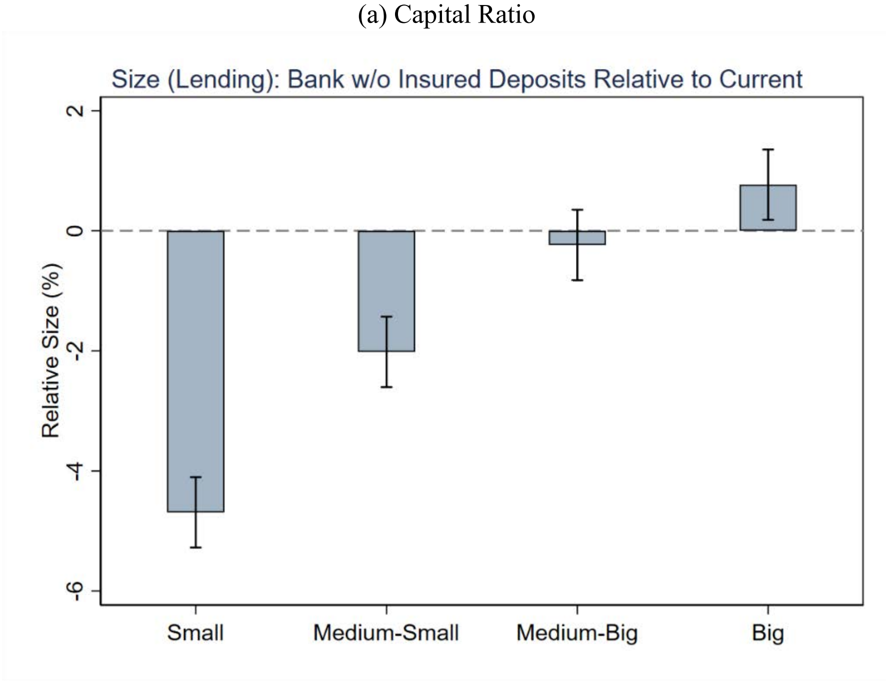
(d) Bank Uninsured Leverage

Figure 12: Counterfactual Capital Ratio and Lending

This figure presents changes in capital ratios and lending in counterfactual without capital requirements and when depositors internalize default. We find the model predicted capital ratio and total lending amount using the calibrated model (baseline). We then simulate a counterfactual world in which there is no capital requirements or deposit insurance on bank debt and find the capital ratio and total lending in this counterfactual. Lastly, we compare them to the baseline values. To make the plots, we divide all banks into four equal-sized buckets based on their initial sizes and plot the average values in each bucket. The bars indicate the average value, and the lines indicate the 95th confidence intervals. Panel (a) presents changes in capital ratios from the baseline to the counterfactual economy. Panel (b) presents changes in lending from the baseline to the counterfactual economy.



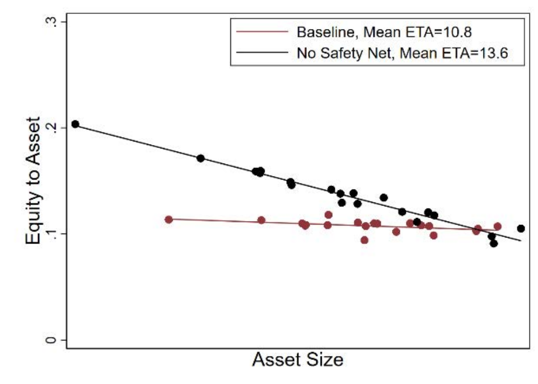
(a) Capital Ratio



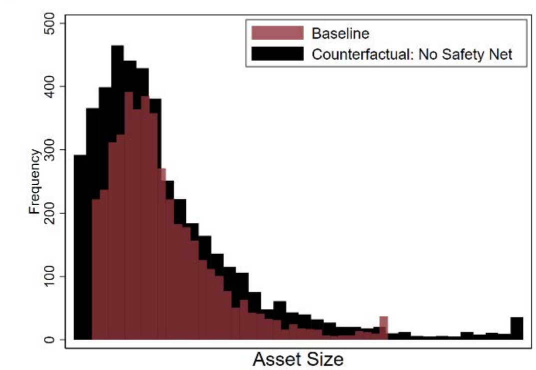
(b) Lending

Figure 13: Counterfactual Capital Ratios and Size (No Safety Nets): Distributional Effects

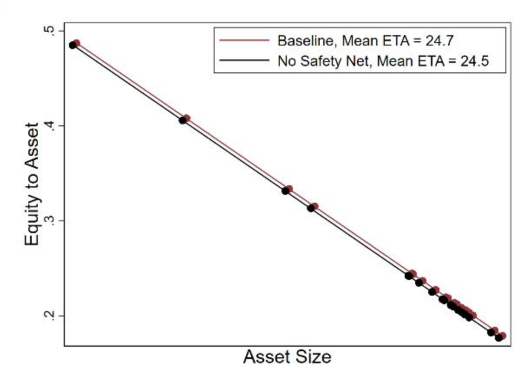
This table presents counterfactual capital ratios and intermediary size when there is no safety nets, i.e., no capital requirement or deposit insurance for banks along with their baseline values. Panel A shows banks' capital ratios. Panel C shows shadow banks' capital ratios. In both panel A and C, we divide the full sample into 20 buckets based on asset size in the data and plot the average equity to asset ratio in each bucket. Panels B and D compare the size distribution in the baseline and that in the counterfactual for banks and shadow banks, respectively.



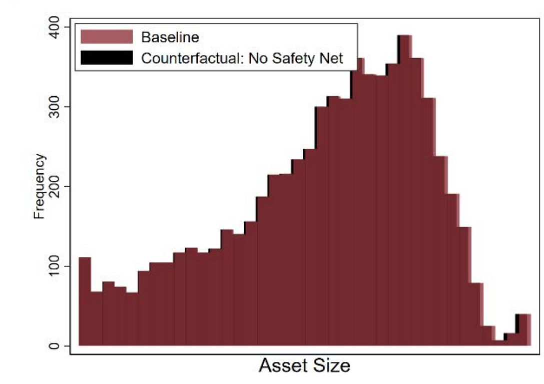
(a) Bank Equity to Asset Ratio



(b) Bank Size



(c) Shadow Bank Equity to Asset Ratio



(d) Shadow Bank Size

A: Supplemental Materials

Appendix A1: Asset and Loan Characteristics – Shadow Banks vs Banks

Panel (a) shows comparable categories of asset composition that are consistently reported in the shadow bank and bank call reports. Column (1) of this table reports the mean asset composition of shadow banks active in the US mortgage market in our sample ranging from 2011 Q1 to 2017 Q4 and the banks. We restrict attention to mortgage companies that are required to file HMDA reports and originate mortgage loans. This restriction leaves us with 429 shadow banks that have a license in the two states that provided us data. Column (2) shows these results for all 4,822 banks in our sample, column (3) for 549 OTD banks of version I, and Column (4) for 257 OTD banks of version II. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). Among shadow banks all reported loans below are real estate loans. Among all bank sample on average 78% of all loans on balance sheet are real estate loans. Among OTD Banks I about 79% of loans are real estate loans. Among OTD Banks II about 82% of loans are real estate loans. Panel (b) shows the fraction of residential loans that are sold for shadow banks and three bank comparison groups based on the 2011-2017 HMDA data files. Panel (c) visually compares the characteristics of shadow bank and bank loans based on Fannie Mae and Freddie Mac loan acquisition files covering our sample period. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank call reports. HMDA, Fannie Mae and Freddie Mac loan acquisition data.

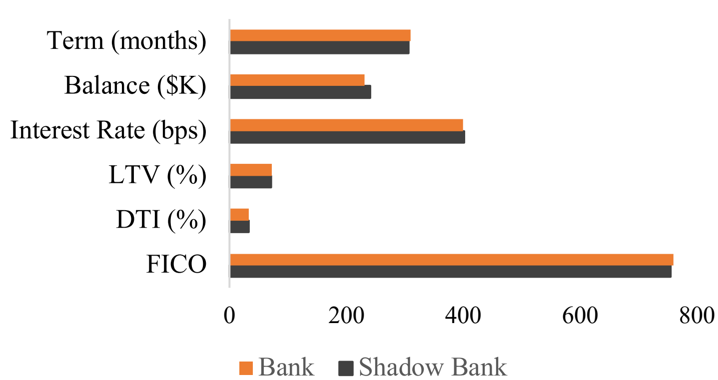
Panel A: Asset composition as a percentage of total assets – shadow banks vs banks

	Shadow Banks	All Bank	OTD Bank I	OTD Bank II
Cash	11.7%	8.5%	9.2%	8.7%
Securities	0.3%	20.5%	16.8%	12.6%
Loans	67.3%	65.2%	67.2%	71.5%
Real Estate Owned	0.3%	0.7%	0.8%	0.8%
Building and Properties	2.0%	1.9%	2.0%	1.7%
Good will and Intangible Assets	0.3%	0.5%	0.8%	1.2%
No. of Institutions	429	4,822	549	257

Panel B: Residential loan characteristics and a percentage of loans sold – shadow banks vs banks (HMDA)

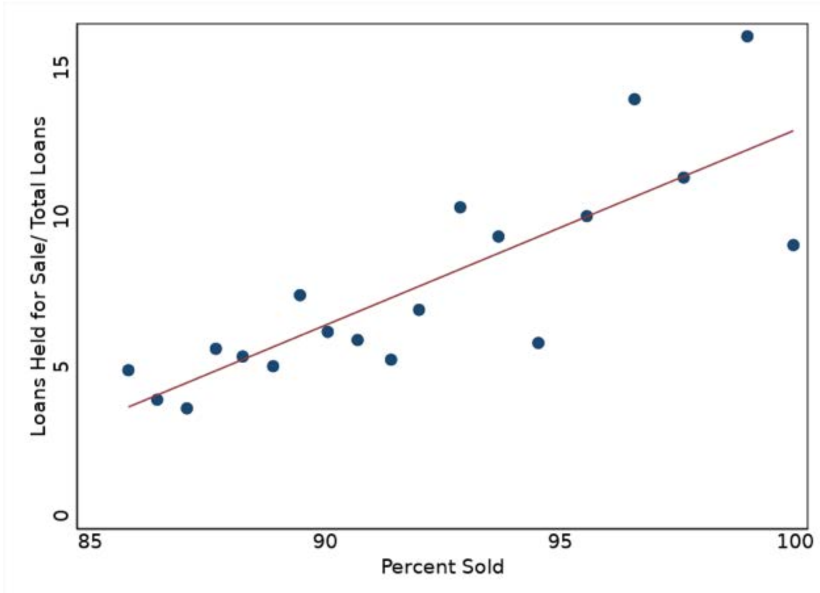
	Shadow Banks	All Bank	OTD Bank I	OTD Bank II
Borrower Income ($K)	101.6	129.9	109.8	114.9
Loan Amount ($K)	225.8	253.5	227.8	225.9
Percentage Loans Sold	93.5%	60.9%	92.1%	88.6%

Panel C: Characteristics of residential loans – shadow banks vs banks (GSE loans)



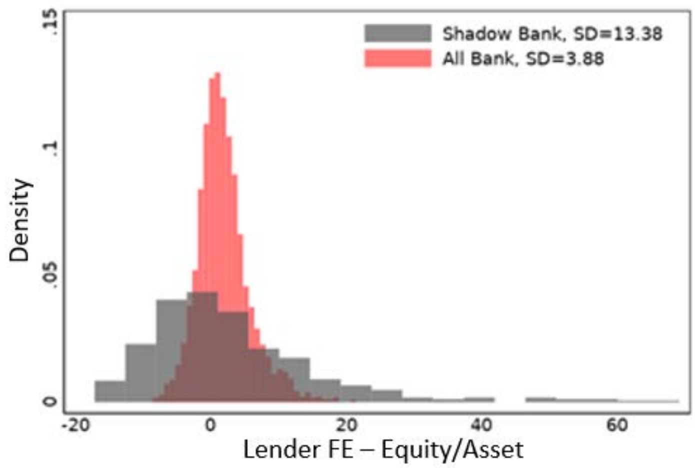
Appendix A2: Percentage of Loans Sold and Loans Held for Sale to Total Loans for Banks

This figure shows the relation between two empirical measures that we use to construct two variants of OTD banks: the percentage of residential mortgage sold (*Percent Sold*) based on HMDA data and the ratio of loans held for sale to total loans (based on call reports). The percent sold scale is divided in twenty bins of equal size in terms of number of banks. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks (greater than 85.5%). As we observe banks that sell more mortgages have on average higher ratio of loans held for sale to total loans (correlation between two measures shown on the figure below equals 0.82). *Data Sources:* Bank call reports, HMDA.

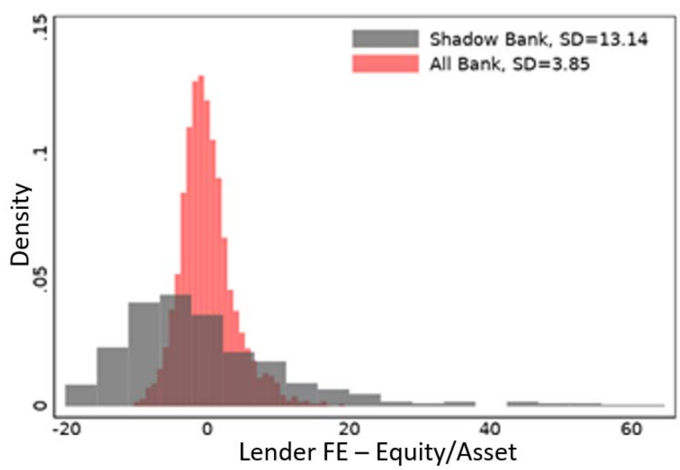


Appendix A3: Equity to Asset Ratio – Lender Fixed Effects

This figure plots the histograms of the estimated lender fixed effects (FEs) from the equity to asset ratio specification similar to one in Table 4, Column (2) but estimated separately for shadow banks and banks. Panel (a) shows the FEs based on the OLS estimates, while panel (b) shows the estimated FEs after Bayesian shrinkage. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filing, and HMDA.



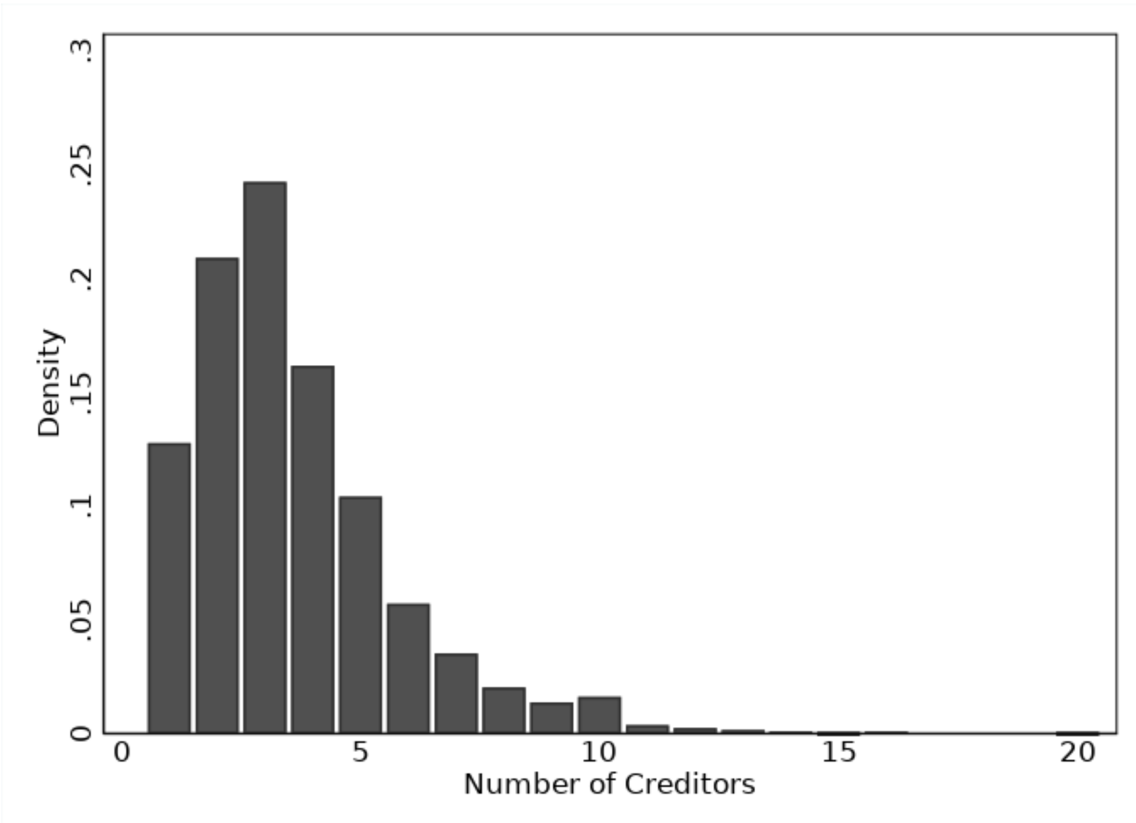
(a) Lender FEs: Shadow Banks vs Banks



(b) Lender FEs (Shrinkage Estimator): Shadow Banks vs Banks

Appendix A4: Number of Providers of Warehouse Lines of Credit to Shadow Banks

This figure plots the histogram (density) of the number of creditors providing the short-term warehouse lines of credit to a given shadow bank. These lines of credit account for most of the shadow banks' debt. *Data Sources:* Shadow banks' quarterly call report filings.

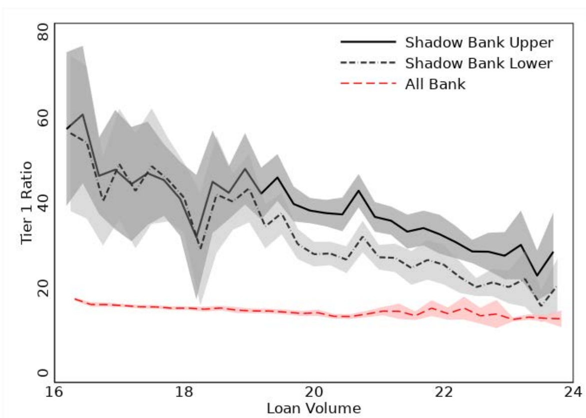


Appendix A5: Tier 1 Capital Ratio and Size – Shadow Banks vs Banks

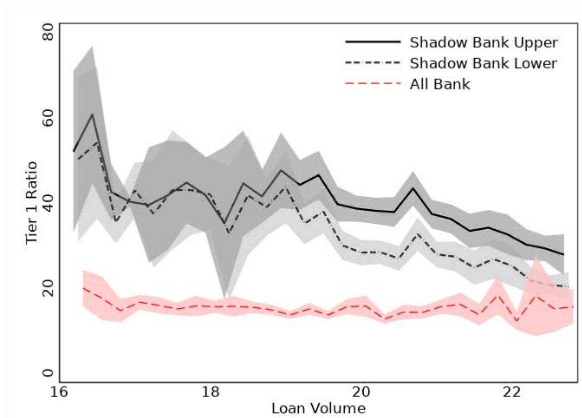
This figure plots the risk-based tier 1 capital ratio of shadow banks (lower and upper bound) and risk-based tier 1 capital ratio banks against the loan volume. Specifically, using a panel data set of quarterly observations from 2011 to 2017, we estimate the following specification for banks and shadow banks, respectively:

$$Ratio_{i,t} = \Sigma_b \gamma_b I\left(Size_{i,t} \in Bin_b\right) + \epsilon_{i,t}$$

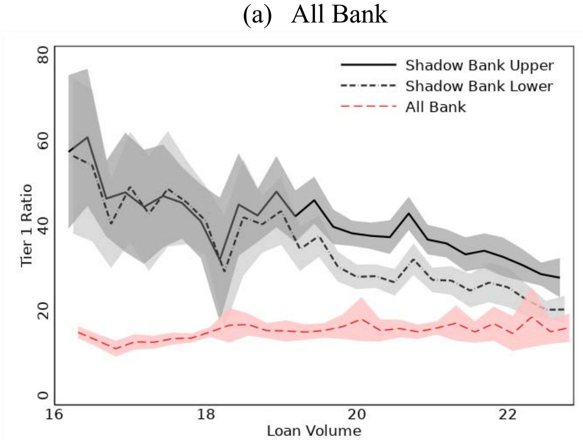
where $Ratio_{i,t}$ is the tier 1 capital ratio ratio, $I(Size_{i,t} \in Bin_b)$ is an indicator of whether bank (shadow bank) i's size falls within size bucket Bin_b. The plotted coefficients of interest, γ_b, show how the funding ratio vary non-parametrically across the size distribution, where size is measured by the logarithm of annual mortgage origination volume in dollars. Each size bin covers an incremental value of 0.25 in the size distribution. In other words, the difference between the largest firm's size and the smallest firm's size in each size bin is 0.25. The shaded area shows the 95% confidence interval. Standard errors are clustered by institutions. Panel (a) compares shadow banks to all banks, panel (b) shadow banks to OTD banks of version I, panel (c) shadow banks to OTD banks of version II, panel (d) shadow banks to synthetic mortgage banks. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. In panel (b) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.



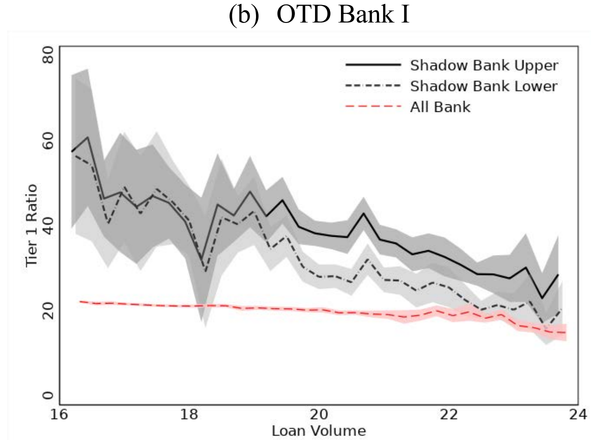
(a) All Bank



(b) OTD Bank I



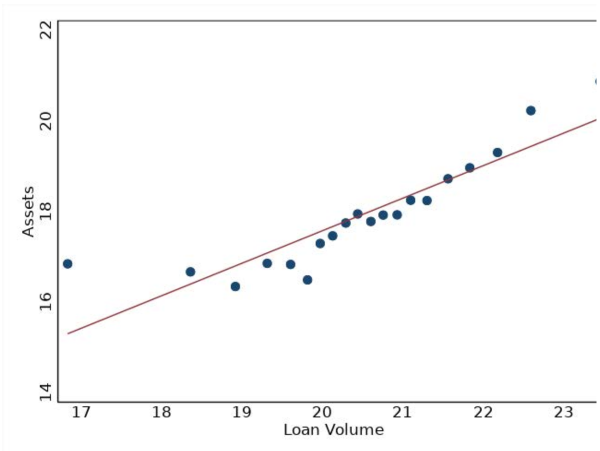
(c) OTD Bank II



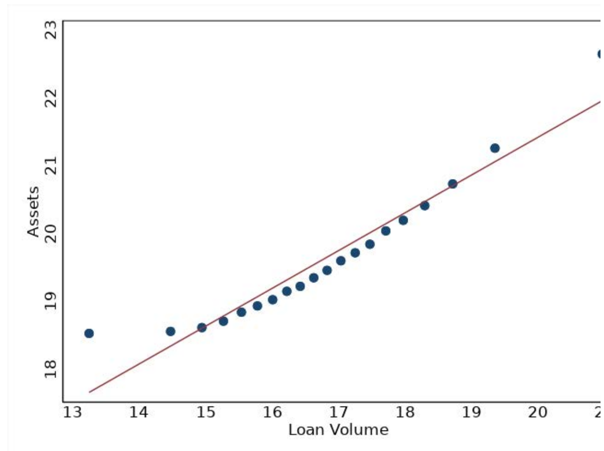
(d) Synthetic Mortgage Bank

Appendix A6: Loan Volume and Assets – Shadow Banks and Banks

This figure plots relation between our two size measures for financial institutions: loan volume (logarithm of annual loan origination volume in dollars) and assets (logarithm of assets in dollars). Panel (a) shows the results for shadow banks while panel (b) shows the results for banks. The loan volume scale is divided in twenty bins of equal size in terms of number of institutions. The correlation of loan volume with size shown on the figures below equals 0.90 for shadow banks and 0.96 for banks.



(a) Shadow banks



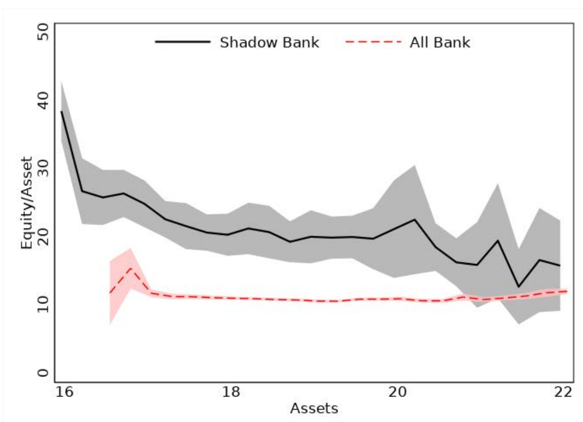
(b) Banks

Appendix A7: Equity to Asset Ratio and Size (Assets) – Shadow Banks vs Banks

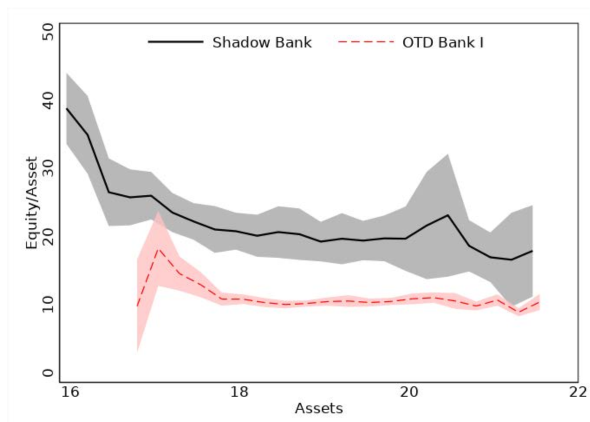
This figure plots the equity to asset ratio of shadow banks and banks against the lender's assets. Specifically, using a panel data set of quarterly observations from 2011 to 2017, we estimate the following specification for banks and shadow banks, respectively:

$$Ratio_{i,t} = \Sigma_b \gamma_b I\left(Size_{i,t} \in Bin_b\right) + \epsilon_{i,t}$$

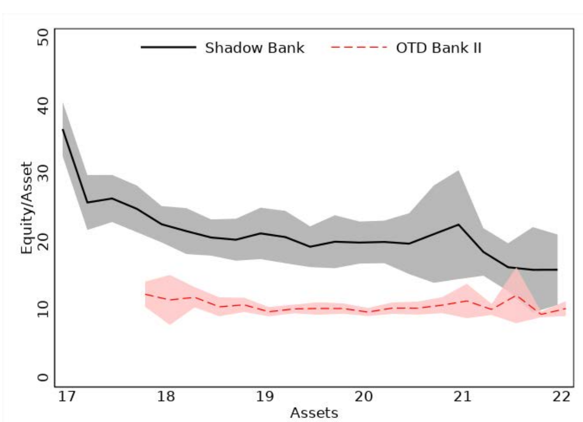
where $Ratio_{i,t}$ is the equity to asset ratio, $I(Size_{i,t} \in Bin_b)$ is an indicator of whether bank (shadow bank) i's size falls within size bucket Bin_b. The plotted coefficients of interest, γ_b, show how the equity to asset ratio vary non-parametrically across the size distribution, where size is measured by the logarithm of assets in dollars. Each size bin covers an incremental value of 0.25 in the size distribution. In other words, the difference between the largest firm's size and the smallest firm's size in each size bin is 0.25. The shaded area shows the 95% confidence interval. Standard errors are clustered by institutions. Panel (a) compares shadow banks to all banks, panel (b) shadow banks to OTD banks of version I, panel (c) shadow banks to OTD banks of version II, panel (d) shadow banks to synthetic mortgage banks. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. In panel (b) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.



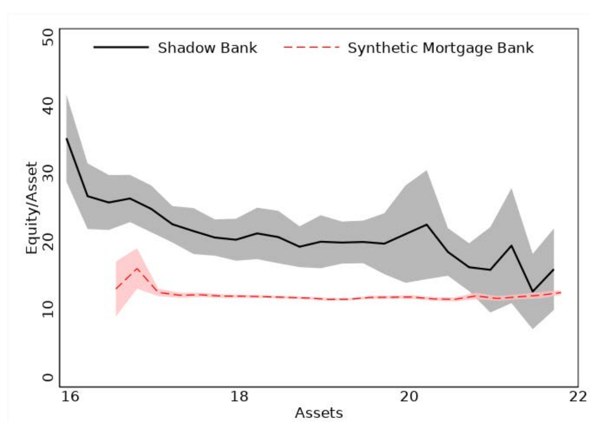
(a) Shadow Bank vs All Bank



(b) Shadow Bank vs OTD Bank I



(c) Shadow Bank vs OTD Bank II



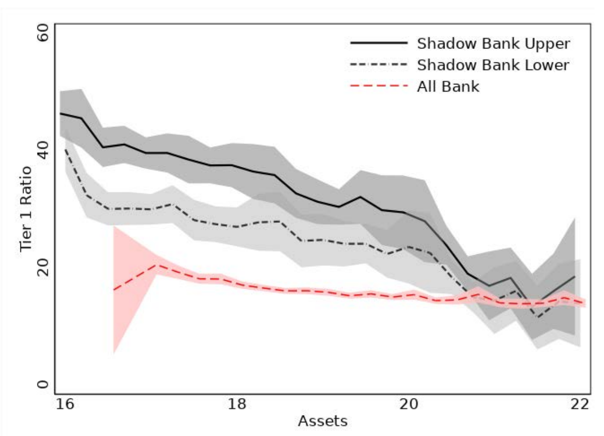
(d) Shadow Bank vs Synthetic Mortgage Bank

Appendix A8: Tier 1 Capital Ratio and Size (Assets) – Shadow Banks vs Banks

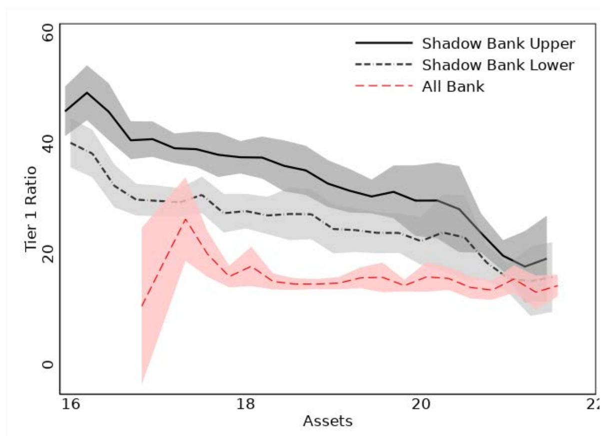
This figure plots the risk-based tier 1 capital ratio of shadow banks (lower and upper bound) and risk-based tier 1 capital ratio banks against the assets. Specifically, using a panel data set of quarterly observations from 2011 to 2017, we estimate the following specification for banks and shadow banks, respectively:

$$Ratio_{i,t} = \Sigma_b \gamma_b I(Size_{i,t} \in Bin_b) + \epsilon_{i,t}$$

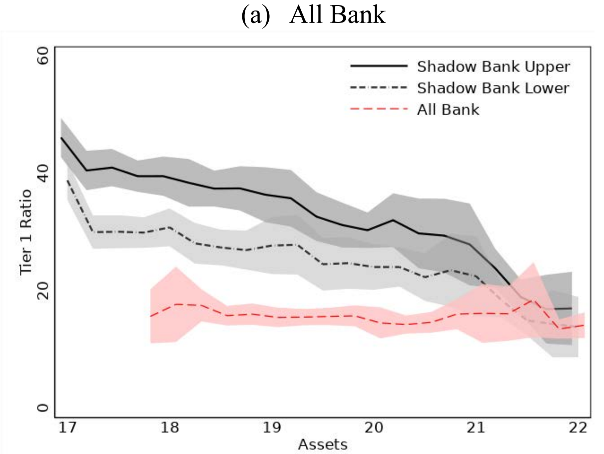
where $Ratio_{i,t}$ is the tier 1 capital ratio ratio, $I(Size_{i,t} \in Bin_b)$ is an indicator of whether bank (shadow bank) i's size falls within size bucket Bin_b. The plotted coefficients of interest, γ_b, show how the funding ratio vary non-parametrically across the size distribution, where size is measured by the logarithm of assets in dollars. Each size bin covers an incremental value of 0.25 in the size distribution. In other words, the difference between the largest firm's size and the smallest firm's size in each size bin is 0.25. The shaded area shows the 95% confidence interval. Standard errors are clustered by institutions. Panel (a) compares shadow banks to all banks, panel (b) shadow banks to OTD banks of version I, panel (c) shadow banks to OTD banks of version II, panel (d) shadow banks to synthetic mortgage banks. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. In panel (b) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.



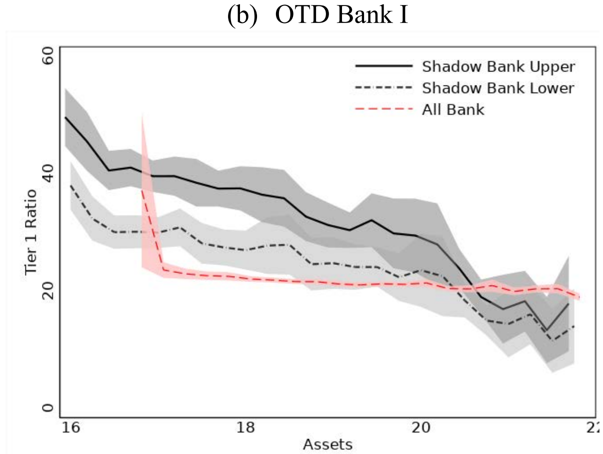
(a) All Bank



(b) OTD Bank I



(c) OTD Bank II



(d) Synthetic Mortgage Bank

Appendix A9: Tier 1 Capital Ratio and Size – Shadow Banks vs Banks

This table reports results of OLS regression of the risk-based tier 1 capital ratio on shadow bank indicator, and its interaction with size. The size is measured by the logarithm of annual mortgage origination volume in dollars (*Loan Volume*). The sample consists of shadow banks and all banks (Column 1), shadow banks and OTD banks of version I (Column 2), shadow banks and OTD banks of version II (Column 3), shadow banks and synthetic mortgage banks which are constructed by replacing all bank assets with residential mortgages (Column 4). Since shadow banks do not report risk-based tier 1 capital ratios, we compute this ratio by applying the Basel III risk-based tier 1 capital ratio formula. Since we do not observe the detailed risk profiles for each type of assets held on the shadow banks' balance sheet, we use the upper bound and lower bound of shadow banks' tier 1 capital ratios in panel (a) and (b), respectively. These bounds are computed as described in Section 2.D. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. In column (2) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. The year-quarter time fixed effects (*Date FE*) are included in all specifications. *Institution controls* include the asset growth, the share of refinanced mortgages out of total mortgage origination volume, the share of government-insured mortgages out of total mortgage origination volume, the logarithm of annual mortgage origination volume in dollars, the geographic loan dispersion, and the logarithm of the weighted average of income per capita in states of operation, where each state income per capita is weighted by the share of institution *i*'s loan origination in this state out of total loan origination of institution *i*, as reported in HMDA. The estimated coefficient of the interaction term of shadow bank indicator with loan volume is scaled by one standard deviation of loan volume. Standard errors in the parentheses are clustered by institution. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.

Panel A: Tier 1 capital ratio (upper bound)

	Shadow Bank vs All Bank	Shadow Bank vs OTD Bank I	Shadow Bank vs OTD Bank II	Shadow Bank vs Synthetic Mortgage Bank
	(1)	(2)	(3)	(4)
Shadow Bank	85.28	86.92	107.68	82.78
	(12.11)	(13.43)	(12.38)	(12.12)
Shadow Bank × Loan Volume	-5.81	-6.01	-8.21	-6.18
	(1.14)	(1.28)	(1.18)	(1.14)
Date FE	Yes	Yes	Yes	Yes
Institution Controls	Yes	Yes	Yes	Yes
Observations	109,411	10,947	8,401	109,411
R^2	0.291	0.408	0.311	0.238
Y-Variable Mean	17.33	27.18	31.59	22.37
Shadow Banks	37.20	37.37	37.20	37.20
Banks	16.13	15.53	15.40	21.47

Appendix A9: Tier 1 Capital Ratio and Size – Shadow Banks vs Banks [continued]

Panel B: Tier 1 capital ratio (lower bound)

	Shadow Bank vs All Bank	Shadow Bank vs OTD Bank I	Shadow Bank vs OTD Bank II	Shadow Bank vs Synthetic Mortgage Bank
	(1)	(2)	(3)	(4)
Shadow Bank	69.47	61.27	80.60	66.97
	(11.27)	(12.14)	(11.84)	(11.28)
Shadow Bank × Loan Volume	-5.33	-4.59	-6.62	-5.70
	(1.05)	(1.15)	(1.11)	(1.05)
Date FE	Yes	Yes	Yes	Yes
Institution Controls	Yes	Yes	Yes	Yes
Observations	109,411	10,947	8,401	109,411
R^2	0.143	0.250	0.208	0.086
Y-Variable Mean	16.77	21.85	24.20	21.80
Shadow Banks	27.25	27.37	27.25	27.25
Banks	16.13	15.53	15.40	21.47

Appendix A10: Equity to Asset Ratio and Size (Assets) – Shadow Banks vs Banks

This table reports results of OLS regression of equity to asset ratio on shadow bank indicator, and its interaction with size. The size is measured by the logarithm of assets in dollars (*Assets*). The sample consists of shadow banks and all banks (Column 1), shadow banks and OTD banks of version I (Column 2), shadow banks and OTD banks of version II (Column 3), shadow banks and synthetic mortgage banks which are constructed by replacing all bank assets with residential mortgages (Column 4). The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. In column (2) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. The year-quarter time fixed effects (*Date FE*) are included in all specifications. *Institution controls* include the asset growth, the share of refinanced mortgages out of total mortgage origination volume, the share of government-insured mortgages out of total mortgage origination volume, the logarithm of assets in dollars, the geographic loan dispersion, and the logarithm of the weighted average of income per capita in states of operation, where each state income per capita is weighted by the share of institution *i*'s loan origination in this state out of total loan origination of institution *i*, as reported in HMDA. The estimated coefficient of the interaction term of shadow bank indicator with assets is scaled by one standard deviation of assets. Standard errors in the parentheses are clustered by institution. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.

	Shadow Bank vs All Bank	Shadow Bank vs OTD Bank I	Shadow Bank vs OTD Bank II	Shadow Bank vs Synthetic Mortgage Bank
	(1)	(2)	(3)	(4)
Shadow Bank	36.14	27.74	28.55	33.68
	(5.34)	(6.49)	(7.48)	(5.34)
Shadow Bank × Assets	-1.95	-1.34	-1.41	-1.84
	(0.41)	(0.49)	(0.57)	(0.41)
Institution Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	109,411	10,947	8,401	109,411
R^2	0.277	0.276	0.218	0.248
Y-Variable Mean	11.56	16.73	18.99	12.47
Y-Var Mean SBs	21.97	22.02	21.97	21.97
Y-Var Mean Bs	10.94	10.68	10.37	11.89

Appendix A11: Tier 1 Capital Ratio and Size (Assets) – Shadow Banks vs Banks

This table reports results of OLS regression of the risk-based tier 1 capital ratio on shadow bank indicator, and its interaction with size. The size is measured by the logarithm of assets in dollars (*Assets*). The sample consists of shadow banks and all banks (Column 1), shadow banks and OTD banks of version I (Column 2), shadow banks and OTD banks of version II (Column 3), shadow banks and synthetic mortgage banks which are constructed by replacing all bank assets with residential mortgages (Column 4). Since shadow banks do not report risk-based tier 1 capital ratios, we compute this ratio by applying the Basel III risk-based tier 1 capital ratio formula. Since we do not observe the detailed risk profiles for each type of assets held on the shadow banks' balance sheet, we use the upper bound and lower bound of shadow banks' tier 1 capital ratios in panel (a) and (b), respectively. These bounds are computed as described in Section 2.D. The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. In column (2) we also remove a few shadow banks whose percentage of mortgages sold is less than the OTD bank I threshold of 85.5%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. The year-quarter time fixed effects (*Date FE*) are included in all specifications. *Institution controls* include the asset growth, the share of refinanced mortgages out of total mortgage origination volume, the share of government-insured mortgages out of total mortgage origination volume, the logarithm of assets in dollars, the lender's geographic loan dispersion, and the logarithm of the weighted average of income per capita in states of operation, where each state income per capita is weighted by the share of institution *i*'s loan origination in this state out of total loan origination of institution *i*, as reported in HMDA. The estimated coefficient of the interaction term of shadow bank indicator with assets is scaled by one standard deviation of assets. Standard errors in the parentheses are clustered by institution. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.

Panel A: Tier 1 capital ratio (upper bound)

	Shadow Bank vs All Bank	Shadow Bank vs OTD Bank I	Shadow Bank vs OTD Bank II	Shadow Bank vs Synthetic Mortgage Bank
	(1)	(2)	(3)	(4)
Shadow Bank	45.57	41.30	57.49	42.21
	(6.49)	(10.41)	(9.69)	(6.48)
Shadow Bank × Assets	-1.97	-1.62	-2.88	-2.18
	(0.50)	(0.78)	(0.73)	(0.50)
Date FE	Yes	Yes	Yes	Yes
Institution Controls	Yes	Yes	Yes	Yes
Observations	109,411	10,947	8,401	109,411
R^2	0.294	0.407	0.311	0.243
Y-Variable Mean	17.33	27.18	31.59	22.37
Shadow Banks	37.20	37.37	37.20	37.20
Banks	16.13	15.53	15.40	21.47

Appendix A11: Tier 1 Capital Ratio and Size (Assets) – Shadow Banks vs Banks [continued]

Panel B: Tier 1 capital ratio (lower bound)

	Shadow Bank vs All Bank	Shadow Bank vs OTD Bank I	Shadow Bank vs OTD Bank II	Shadow Bank vs Synthetic Mortgage Bank
	(1)	(2)	(3)	(4)
Shadow Bank	25.93	23.71	39.17	22.57
	(5.31)	(9.83)	(8.61)	(5.28)
Shadow Bank × Assets	-1.26	-1.10	-2.31	-1.47
	(0.41)	(0.72)	(0.64)	(0.41)
Date FE	Yes	Yes	Yes	Yes
Institution Controls	Yes	Yes	Yes	Yes
Observations	109,411	10,947	8,401	109,411
R^2	0.139	0.240	0.194	0.082
Y-Variable Mean	16.77	21.85	24.20	21.80
Shadow Banks	27.25	27.37	27.25	27.25
Banks	16.13	15.53	15.40	21.47

Appendix A12: Uninsured Bank Leverage and Size (Assets)

This table reports results of OLS regression of uninsured leverage defined as the uninsured debt to asset ratio on size for shadow banks (panel a) and banks (panel b). The size is measured by the logarithm of assets in dollars (*Loan Volume*). For shadow banks all debt items are uninsured. For banks uninsured debt is defined as total debt less insured deposits. In panel (b) the sample consists of all banks (Column 1 and 2), OTD banks I (Column 3 and 4), OTD banks II (Column 5 and 6), and synthetic mortgage banks (Column 7 and 8). The OTD banks of version I are defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA in a given year is in the top five percent among all banks. The average percentage of mortgages sold among OTD banks I is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. The OTD banks II are defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with the 85.5% minimum threshold of mortgages sold out of total originated among OTD banks I (see Section 2E). The synthetic mortgage bank sample is created by replacing all bank loans with mortgage loans while keeping all the other assets fixed. The year-quarter time fixed effects (*Date FE*) are included in all specifications. *Institution controls* include the lender's geographic loan dispersion, asset growth, the share of refinanced mortgages out of total mortgage origination volume, the share of government-insured mortgages out of total mortgage origination volume, and the logarithm of the weighted average of income per capita in states of operation, where each state income per capita is weighted by the share of institution *i*'s loan origination in this state out of total loan origination of institution *i*, as reported in HMDA. The estimated coefficient of assets is scaled by one standard deviation of assets. Standard errors in the parentheses are clustered by institution. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.

Panel A: Debt to asset ratio for shadow banks

	Shadow Bank	
	(1)	(2)
Assets	2.03	0.79
	(0.58)	(0.95)
Date FE	Yes	Yes
Institution Controls	No	Yes
Observations	6,744	6,241
R2	0.884	0.896
Y-Variable Mean	64.30	64.16

Panel B: Uninsured debt to asset ratio for banks

	All Bank		OTD Bank I		OTD Bank II		Synthetic Mortgage Bank	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Assets	2.43	6.03	2.29	5.58	2.79	4.46	2.43	6.03
	(0.03)	(0.23)	(0.09)	(0.86)	(0.29)	(1.03)	(0.03)	(0.23)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Institution Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	108,423	103,170	5,422	5,107	2.248	2,160	108,423	103,170
R^2	0.864	0.882	0.858	0.871	0.864	0.879	0.864	0.882
Y-Variable Mean	29.48	29.63	29.99	30.22	33.68	33.82	29.48	29.63

Appendix A13: Uninsured Debt Cost and Size (Assets) – Shadow Banks vs Banks

This table reports regression results of average annual interest rate on shadow bank debt (Column 1 and 2), uninsured bank debt (Column 3 and 4), and an annual uninsured-insured debt interest rate spread for banks (Column 5 and 6), all in percentage points, on size measured by the logarithm of assets in dollars (*Loan Volume*). We note that all shadow bank debt is uninsured. The annual uninsured-insured interest rate spread is defined as within bank difference between interest rate on uninsured and insured debt. The year fixed effects (*Date FE*) are included in all specifications. *Institution controls* include annual asset growth, the share of refinanced mortgages out of total mortgage origination volume, the share of government-insured mortgages out of total mortgage origination volume, the geographic loan dispersion, and the logarithm of the weighted average of income per capita in states of operation, where each state income per capita is weighted by the share of institution *i*'s loan origination in this state out of total loan origination of institution *i*, as reported in HMDA. The estimated coefficient of assets is scaled by one standard deviation of assets. Standard errors in the parentheses are clustered by institution. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filings, and HMDA.

	Shadow Bank Sample Interest Rate		Full Bank Sample Interest Rate		Full Bank Sample Uninsured-Insured Spread	
	(1)	(2)	(3)	(4)	(5)	(6)
Assets	-0.22	-0.11	-0.38	-0.41	-0.43	-0.45
	(0.06)	(0.06)	(0.01)	(0.01)	(0.01)	(0.01)
Institution Controls	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,015	1,823	27,270	27,137	27,270	27,137
R^2	0.029	0.030	0.348	0.374	0.301	0.332
Y-Variable Mean	4.42	3.97	2.33	2.33	1.25	1.25

Appendix A14: Asset and Loan Characteristics – Shadow Banks vs Banks

We explain here how we construct our "synthetic mortgage banks" group. The idea behind constructing such a group is the following. Suppose mortgage activities require different types of funding than non-mortgage activities. Then banks, which are primarily engaged in mortgage lending should have different capital structures than banks, which are engaged in other activities. We then use variation across banks to extrapolate what the capital structure of banks would be if they only engaged in mortgage activities. We estimate the following specification:

$$Ratio_i = \alpha + \beta MortgageShare_i + \Gamma X_i + \epsilon_i \qquad (1)$$

In which $MortgageShare_i$ is the residential mortgage asset share of total assets, and X_i includes the logarithm of total assets, cash to total assets ratio, security to total asset ratio, fixed assets to total assets. More importantly, it also includes non-residential real estate asset to assets, commercial and industrial loans to assets, agricultural loans to assets, individual loans to assets, and other loans to assets. The dependent variable, $Ratio_i$ is different capital structure ratios such as equity to assets. This specification is then used to construct capital structure ratios of "synthetic banks" that mimic shadow banks -- those whose total *assets* are entirely made up of mortgage loans. To do so, we compute the predicted $\widehat{Ratio_i}$ for each bank while assigning 100-percent weight on mortgage assets and zero on other assets, i.e.

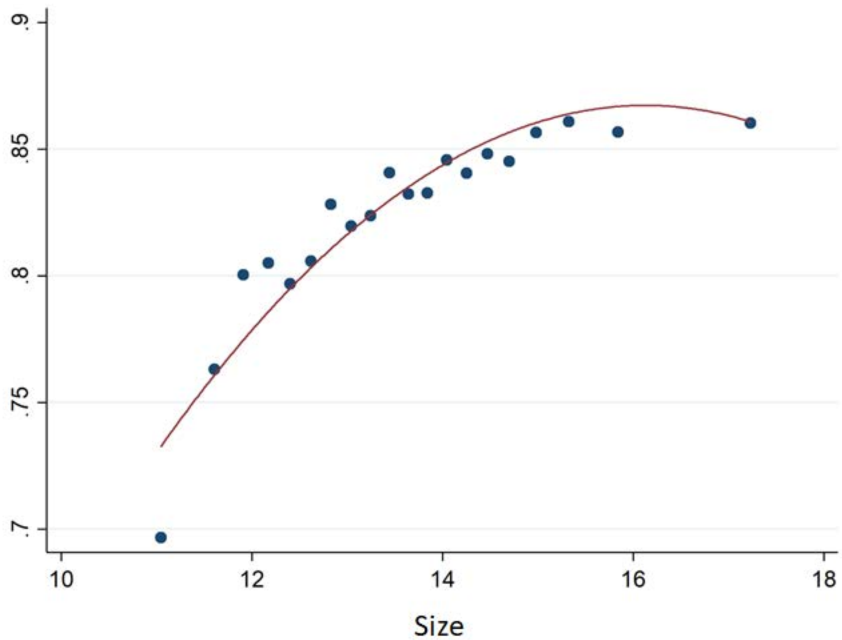
$$\widehat{Ratio_i} = \alpha + \hat{\beta} \times 100\% + \hat{\Gamma} X_i + \hat{\epsilon_i}, \qquad (2)$$

Our third comparison set has 4,822 synthetic mortgage banks. Notably, we also conduct robustness in how we construct the capital structure ratios for synthetic banks. In particular, we compute $MortgageShare_i$ and controls as a function of total loans, rather than assets. That is, $MortgageShare_i$ in this specification is now residential mortgage to total loan ratio, and X_i includes commercial and industrial loans to total loans, agricultural loans to total loans, individual loans to total loans, and other loans to total loans. Similar to the procedure above, we compute the alternative synthetic comparison group of mortgage banks by replacing all bank loans with mortgage loans while keeping all other assets fixed. We obtain very similar results with this alternative synthetic bank comparison group.

Appendix B: External Validity – Bank Financing Prior to the Deposit Insurance

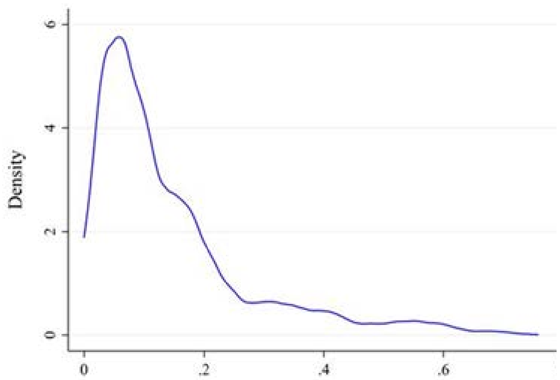
Appendix B1: Bank Leverage Prior to the Deposit Insurance in the United States

This figure plots the US bank leverage across bank size for US banks active in 1928. Since this time period precedes the establishment of the FDIC fund all bank financing including deposits is uninsured, similarly to modern shadow banks. The size is measured by the logarithm of bank assets. First, these pre-deposit insurance banks are substantially better capitalized than modern banks, with average equity to assets of about 18pp, which is close to the capitalization of shadow banks in our sample. Second, we observe that the extent of cross-sectional dispersion of US banks in the pre-deposit insurance period much closer to those of modern shadow banks and much larger than those of modern banks. Third, consistent with our findings about modern shadow banks, bank leverage (capitalization) increases (decreases) with size for pre-deposit insurance banks. *Data Sources:* Hand-collected data on funding ratios of more than six thousand US banks active in 1928 provided to us by Aldunate, Jenter, Korteweg, and Koudijs (2019).

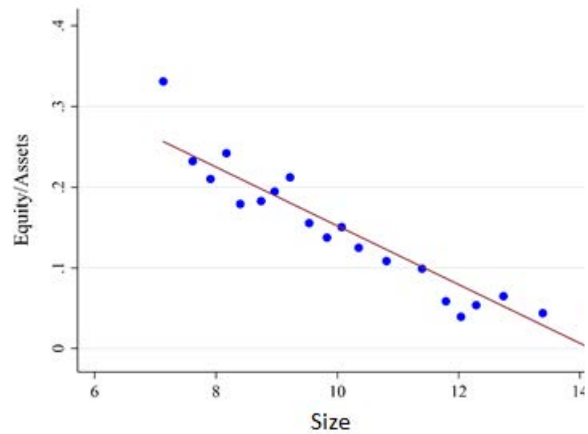


Appendix B2: German Bank Capitalization Prior to the Deposit Insurance

Panel (a) of this figure plots the distribution (density) of equity to asset ratio for German banks in the period preceding the establishment of deposit insurance. We observe that the extent of cross-sectional dispersion of German bank capitalization in the pre-deposit insurance period is similar to those of modern shadow banks and much larger than those of modern banks. Panel (b) plots the equity to asset ratio across size for German banks in the period preceding the establishment of deposit insurance. The size is measured by the logarithm of bank assets. We observe that consistent with our findings about modern shadow banks, bank leverage (capitalization) increases (decreases) with size. *Data Sources:* Hand-collected data from the Federal German Archives on 181 unique banks active in 1928-1933 period provided to us by Blickle, Brunnermeier, and Luck (2019).



(a) Distribution of Equity to Asset Ratio



(b) Equity to Asset Ratio and Size

Appendix C: Asset-Side Subsample Robustness

Appendix C1: Balance Sheet Composition and Mortgage Origination Activities – OTD Banks vs Matched Shadow Banks

Panel A of this table compares the balance sheet composition and mortgage origination activities of OTD banks and shadow banks during our sample period ranging from 2011 Q1 to 2017 Q4. We restrict attention to mortgage companies that are required to file HMDA reports and originate mortgage loans. Removing companies that do not show up in HMDA database, this restriction leaves us with 429 shadow banks that have a license in the two states that provide us data. Column (1) for originate-to-distribute (OTD) banks version I defined as banks whose percentage of mortgages sold in less than 1 year as recorded in HMDA is in the top five percent among all banks. The average percentage of mortgages sold of OTD banks is 92.4%, while the minimum percentage of mortgages sold is 85.5%. The average percentage of mortgages sold of shadow banks is 94.4%. Column (2) shows these statistics for version II OTD banks defined as banks whose shares of loans held for sale out of total loans held on balance sheet are greater than 10% based on their call report data. We note that 10% share of loans held for sale threshold is broadly consistent with about 85.5% minimum threshold of mortgages sold out of total originated for OTD banks of version 1 (see Section 2E). Column (3) shows the statistics for shadow banks. Panel B of this table reports the same statistics after propensity score matching on observables. *Data Sources:* Shadow banks' quarterly call report filings to state regulators, bank regulatory call report filing, and HMDA.

Panel A: Raw Sample

	OTD V1		OTD V2		Shadow Bank	
	Mean	Stdev	Mean	Stdev	Mean	Stdev
Total Asset ($Million)	949	3820	1466	7206	564	2298
Cash/TA	8.99	7.86	8.25	8.09	11.66	13.20
Mortgage/TA	53.01	16.56	58.84	16.64	67.21	25.39
MSR/TA	0	0	0	0	7.65	11.34
Ln(Loan Volume)	496	1870	1100	3150	2250	5480
Jumbo Share	8.18	14.72	20.96	27.84	7.27	10.6
Percent Sold	92.37	4.46	65.62	39.16	94.42	15.11
Refinance Share	52.51	23.77	48.92	24.1	45.25	26.47
Government Loan Share	19.13	20.72	21.7	22.36	36.94	25.28
Observations	5428		2260		7340	

Panel B: Matched Sample – OTD V1

	OTD V1		Shadow Bank		Difference
	Mean	Stdev	Mean	Stdev	Mean
Total Asset ($Million)	938.73	3969.75	703.06	2762.97	236
Cash/TA	9.55	8.28	10.25	11.22	-0.7
Mortgage/TA	55.11	16.74	62.52	27.04	-7.41
MSR/TA	0	0	10.07	13	-10.07
Ln(Loan Volume)	18.7	1.73	20.57	1.62	-1.87
Jumbo Share	8.57	14.55	9.06	12.63	-0.49
Percent Sold	92.65	4.45	93.45	17.18	-0.8
Refinance Share	50.15	23.56	48.11	25.84	2.04
Government Loan Share	22.04	21.38	25.17	18.82	-3.13
Observations	4486		4486		

Panel C: Matched Sample – OTD V2

	OTD V2		Shadow Bank		Difference
	Mean	Stdev	Mean	Stdev	Mean
Total Asset ($Million)	1392.19	7932.99	1508.25	4260.82	-116
Cash/TA	8.42	8.23	7.24	7	1.18
Mortgage/TA	59.82	16.34	52	30.83	7.82
MSR/TA	0	0	13.7	16.26	-13.7
Ln(Loan Volume)	19.62	2	20.48	1.93	-0.86
Jumbo Share	11.53	16.63	12.21	17.56	-0.68
Percent Sold	82.03	24.56	85.18	27.62	-3.15
Refinance Share	49.2	22.54	58.54	26.94	-9.34
Government Loan Share	27.09	21.94	22.85	23.38	4.24
Observations	1797		1797		

Appendix C2: Size and Institution Characteristics – Loan Volume

This table reports the correlation between size and institution characteristics. Panel A analyzes mortgage loan geographic concentration and size. Size is measured by log of loan volume. Mortgage loan geographic concentration is measured by sum of the squares of mortgage origination share in each county. The larger this value the more concentrated a bank or shadow bank's mortgage lending activity is. Sample includes quarterly observations from 2011 to 2017. Panel B analyzes the correlation between cash flow volatility and size and correlation between growth and size. We keep only shadow banks and banks that have call reports and HMDA filings in all years from 2012 and 2016. Cash flow volatility is calculated as standard deviation of quarterly net income to asset ratios from 2012 to 2016. Growth is calculated as change in loan volume from 2012 to 2016. Loan Volume is the average loan volume over this sample period.

Panel A: Mortgage Loan Geographic Concentration

	Bank		Shadow Bank		Full Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Loan Volume	-0.07***	-0.05***	-0.03***	-0.02***	-0.07***	-0.05***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Shadow Bank					-0.89***	
					(0.07)	
Shadow Bank x Loan Volume					0.04***	0.03***
					(0.00)	(0.01)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Institution FE	No	Yes	No	Yes	No	Yes
N	108495	108495	7340	7340	115835	115835
R^2	0.3	0.1	0.1	0.1	0.3	0.1

Panel B: Cash Flow Volatility and Loan Growth

	Bank		Shadow Bank		Full Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
	CF Vol	Growth	CF Vol	Growth	CF Vol	Growth
Loan Volume	-0.001	-0.04***	-0.05	0.15***	-0.001	-0.04***
	(0.00)	(0.01)	(0.05)	(0.04)	(0.00)	(0.01)
Shadow Bank					2.44***	-3.58***
					(0.31)	(0.87)
Shadow Bank x Loan Volume					-0.05***	0.18***
					(0.02)	(0.04)
N	3468	3468	241	241	3709	3709
R^2	0.00	0.00	0.00	0.05	0.54	0.01

Appendix C3: Size and Institution Characteristics – Asset

This table reports the correlation between size and institution characteristics. Panel A analyzes mortgage loan geographic concentration and size. Size is measured by log of assets. Mortgage loan geographic concentration is measured by sum of the squares of mortgage origination share in each county. The larger this value the more concentrated a bank or shadow bank's mortgage lending activity is. Sample includes quarterly observations from 2011 to 2017. Panel B analyzes the correlation between cash flow volatility and size and correlation between growth and size. We keep only shadow banks and banks that have call reports and HMDA filings in all years from 2012 and 2016. Cash flow volatility is calculated as standard deviation of quarterly net income to asset ratios from 2012 to 2016. Growth is calculated as change in asset size from 2012 to 2016. Asset is the average asset over this sample period.

Panel A: Mortgage Loan Geographic Concentration

Panel B: Cash Flow Volatility and Loan Growth

	Bank		Shadow Bank		Full Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Asset	-0.07***	-0.06***	-0.01***	-0.002*	-0.07***	-0.06***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Shadow Bank					-1.57***	
					(0.05)	
Shadow Bank x Asset					0.06***	0.06***
					(0.00)	(0.01)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Institution FE	No	Yes	No	Yes	No	Yes
N	108495	108495	7340	7340	115835	115835
R^2	0.19	0.05	0.07	0.05	0.26	0.05

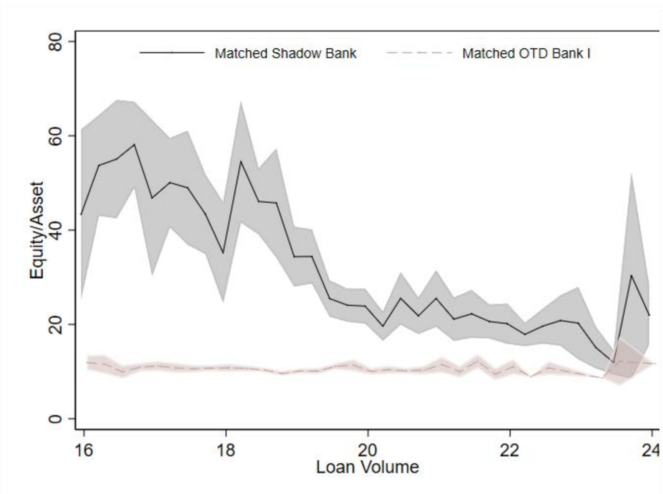
	Bank		Shadow Bank		Full Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
	CF Vol	Growth	CF Vol	Growth	CF Vol	Growth
Average Loan Volume	-0.002	0.06***	-0.06*	0.15**	-0.002	0.06***
	(0.00)	(0.00)	(0.03)	(0.08)	(0.00)	(0.01)
Shadow Bank					2.51***	-0.99**
					(0.20)	(0.43)
Shadow Bank x Average Loan Volume					-0.06***	0.09***
					(0.01)	(0.02)
N	3468.00	3468.00	241.00	241.00	3709.00	3709.00
R^2	0.00	0.00	0.00	0.05	0.54	0.01

Appendix C4: Equity to Asset Ratio and Size – Matched Sample, Non-MSR, Non-FinTech

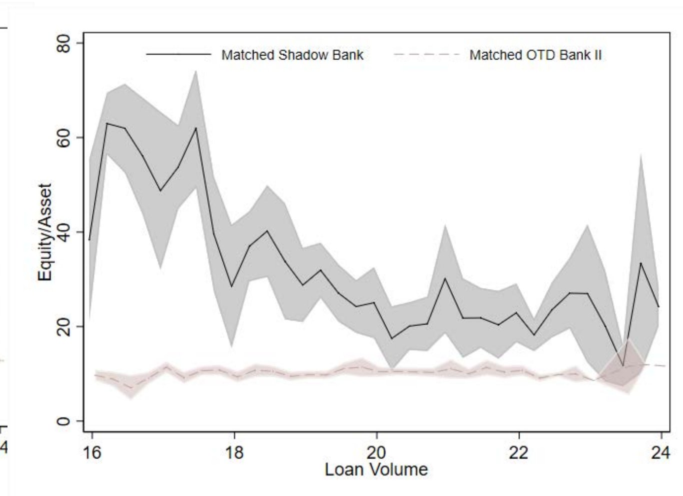
This figure plots the equity to asset ratio of shadow banks and banks against the loan volume. Using a panel data set of quarterly observations from 2011 to 2017, we estimate the following specification for banks and shadow banks, respectively:

$$Ratio_{i,t} = \Sigma_b \gamma_b I(Size_{i,t} \in Bin_b) + \epsilon_{i,t}$$

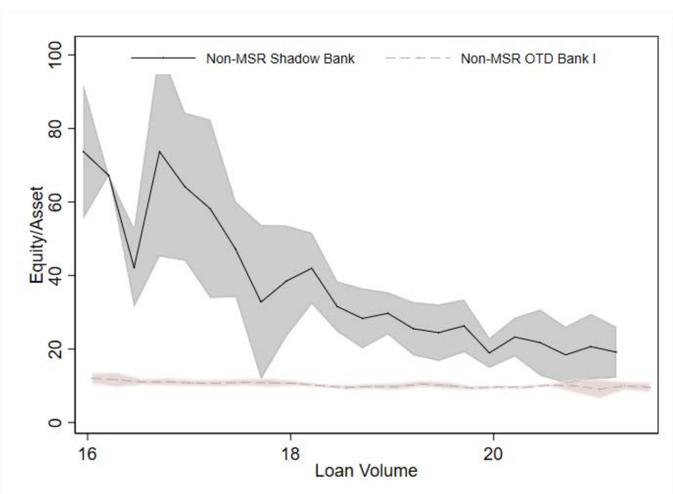
where $Ratio_{i,t}$ is the equity to asset ratio, $I(Size_{i,t} \in Bin_b)$ is an indicator of whether bank (shadow bank) i's size falls within size bucket Bin_b. The plotted coefficients of interest, γ_b, show how the equity to asset ratio vary non-parametrically across the size distribution, where size is measured by the log of annual mortgage origination volume in dollars. Each size bin covers an incremental value of 0.25 in the size distribution. The shaded area shows the 95% confidence interval. Standard errors are clustered by institutions. Panel (a) compares shadow banks to OTD bank of version 1 after matching on observables, panel (b) compares shadow banks to OTD banks of version 2 after matching on observables, panel (c) compares non-MSR shadow banks to non-MSR OTD banks of version 1, and panel (d) compares non-FinTech shadow banks to OTD banks of version 1. Summary statistics of matched shadow banks and OTD banks can be found in Table C1.



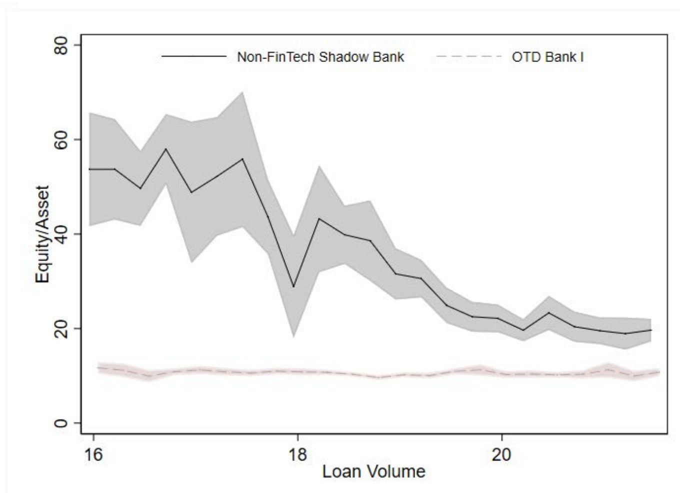
(a) Shadow Banks vs Matched OTD Bank I



(b) Shadow Banks vs Matched OTD Bank II



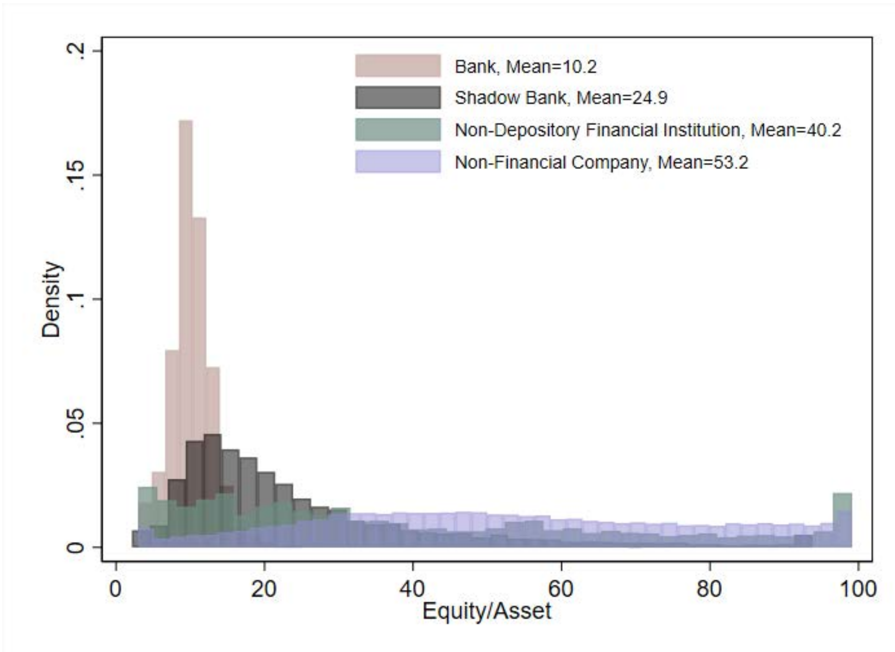
(c) Non-MSR Shadow Bank vs Non-MSR OTD Bank I



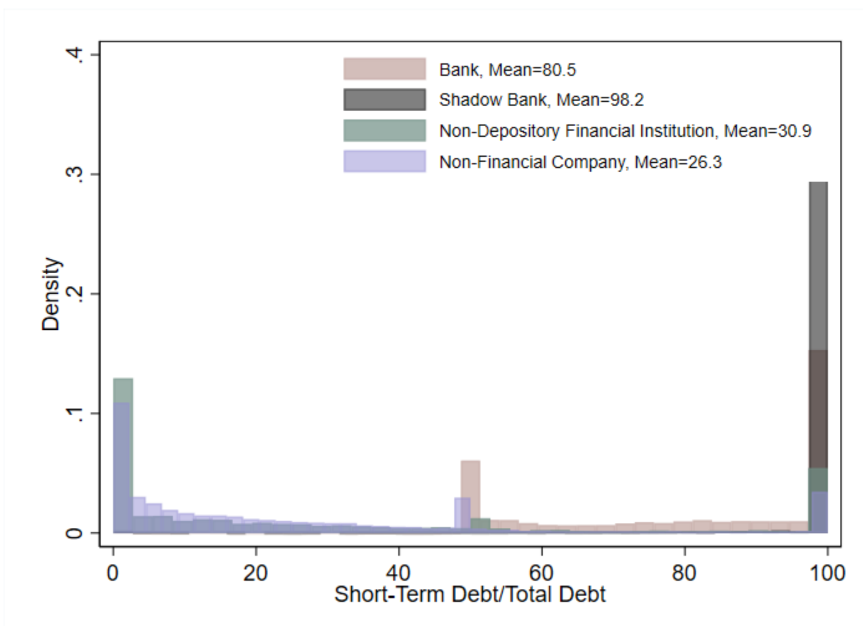
(d) Non-FinTech Shadow Bank vs OTD Bank I

Appendix C5: Dispersion in Funding Structure - Compustat

This figure compares shadow banks, banks (NAICS is 522110, Commercial Banks), other financial companies (2-digit NAICS is 52, other than commercial banks), and non-financial companies (2-digit NAICS code is not equal to 52) in Compustat from 2011 to 2017. The observations are at annual frequencies for Compustat data and quarterly for shadow bank call reports. Panel (a) plots equity to asset ratios. Panel (b) plots short-term debt to total debt ratios.



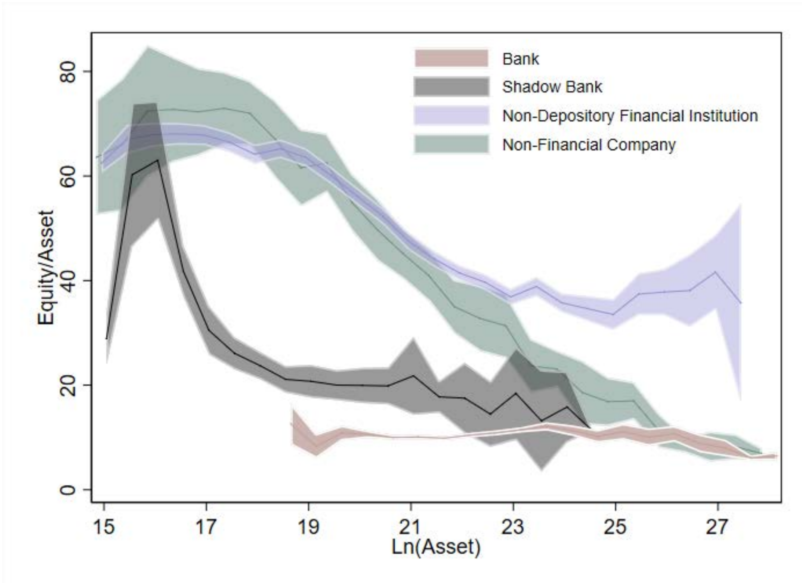
(a) Equity to Asset Ratio



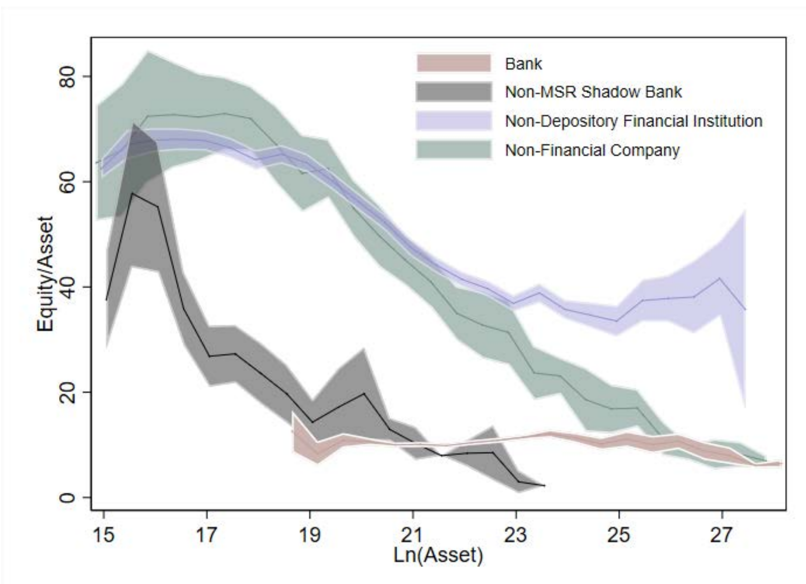
(b) Short-Term Debt to Total Debt

Appendix C6: Equity to Asset and Size - Compustat

This figure plots equity to asset ratio against size as measured by log of total assets for shadow banks, banks (NAICS is 522110, Commercial Banks), other financial companies (2-digit NAICS is 52, other than commercial banks), and non-financial companies (2-digit NAICS code is not equal to 52) in Compustat from 2011 to 2017. The observations are at annual frequencies for Compustat data and quarterly frequencies for shadow bank call reports. Panel (a) plots all shadow banks, while Panel (b) plots only non-MSR shadow banks.



(a) Full Shadow Bank Sample vs Other Institution Types



(b) Non-MSR Shadow Bank Sample vs Other Institution Types

Appendix D: Deposit Breakdown

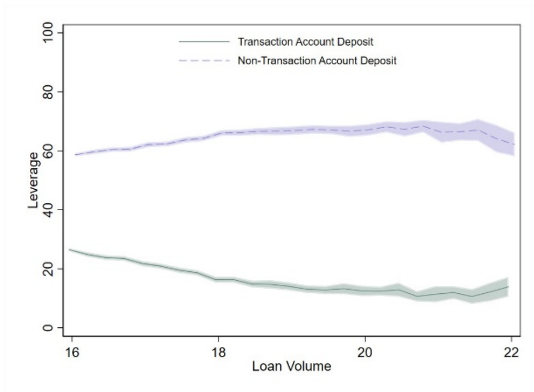
Appendix D1: Bank Deposit Breakdown

This table shows bank deposit composition. We restrict attention to institutions that have a match in HMDA reports. Columns (1) and (2) show full sample mean and standard deviation. Columns (3) and (4) show OTD bank version I. Columns (5) and (6) show OTD bank version II. Brokered deposits, item RCON 2365 in bank 031/041 filings, and non-transaction account deposits, item RCON 2385 in bank 031/041 filings, are not two mutually exclusive categories. Brokered deposits may include both transaction accounts and non-transaction accounts.

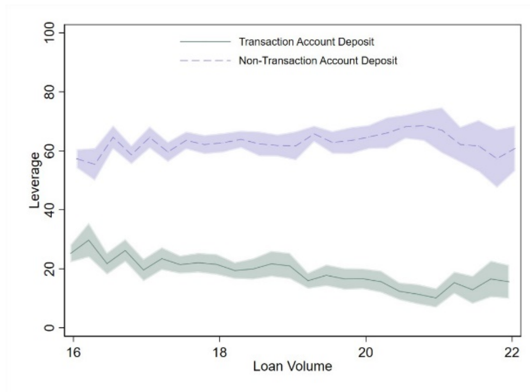
	All Banks		OTD I		OTD II	
	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	Stdev	Mean	Stdev	Mean	Stdev
Asset (Billion)	3.4	51.0	0.9	3.8	1.5	7.2
Deposit/Asset	83.7	6.1	82.4	7.2	80.3	8.1
Brokered Deposit/Asset	2.7	5.8	4.8	9.8	5.9	11.0
Non-Transaction Account Deposit/Asset	61.6	12.7	62.7	13.6	61.2	15.2
Time Deposit/Asset	29.0	13.2	29.9	14.3	30.9	16.3
Savings Deposit/Asset	32.6	15.4	32.8	16.3	30.3	16.6
No. of Institutions	4,821		550		256	

Appendix D2: Transaction Account Deposit and Size

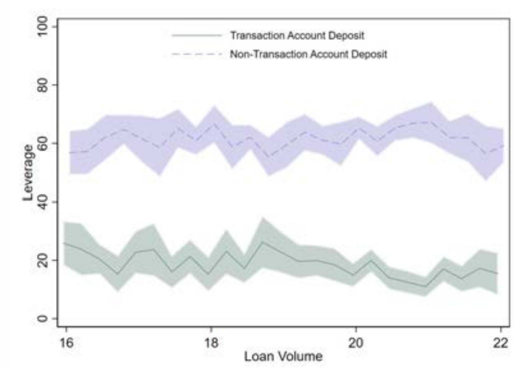
This figure plots transaction account deposit and non-transaction account deposit ratios of banks against the loan volume. Panel (a) compares shadow banks to bank full sample. Panel (b) compares shadow banks to OTD bank of version 1, and Panel (c) compares shadow banks to OTD banks of version 2. The shaded area shows the 95% confidence interval. Standard errors are clustered by institutions.



(a) Full Sample



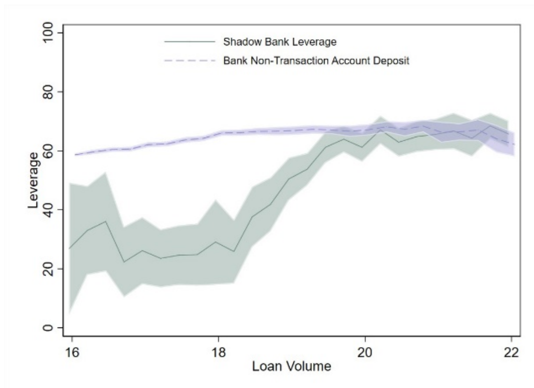
(b) OTD Bank I



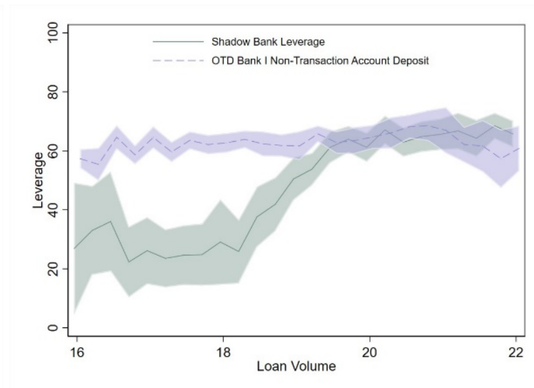
(c) OTD Bank II

Appendix D3: Non-Transaction Related Leverage and Size

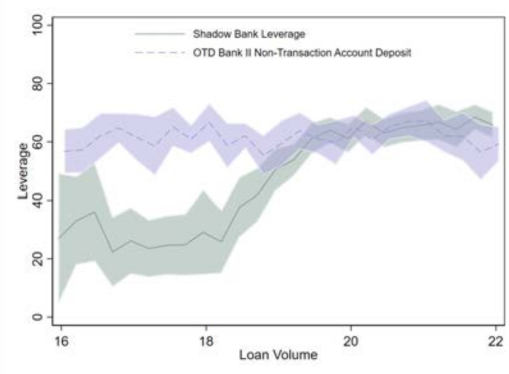
This figure plots non-transaction related leverage of shadow banks and banks against the loan volume. Panel (a) compares shadow banks to bank full sample. Panel (b) compares shadow banks to OTD bank of version 1, and Panel (c) compares shadow banks to OTD banks of version 2. The shaded area shows the 95% confidence interval. Standard errors are clustered by institutions.



(a) Full Sample



(b) OTD Bank I



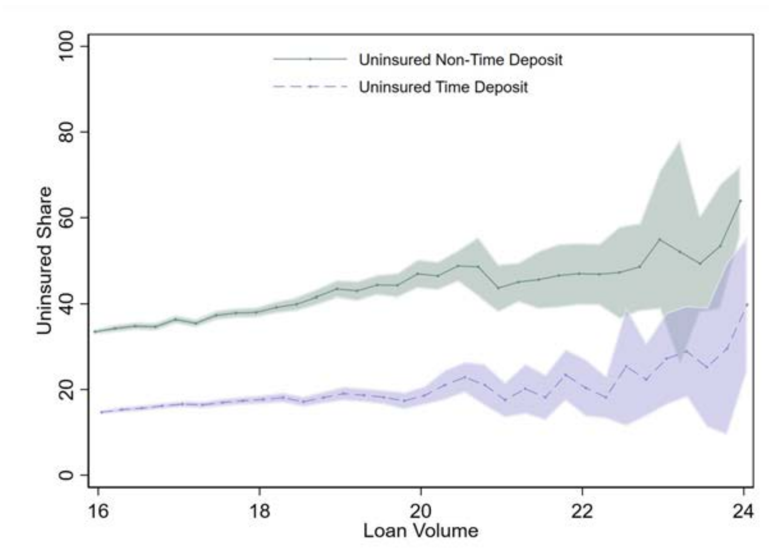
(c) OTD Bank II

Appendix D4: Time Deposit and Size

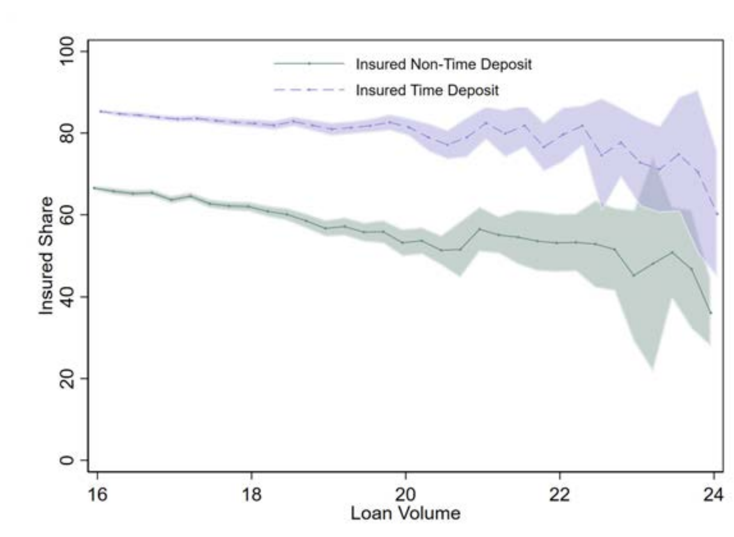
This figure compares time deposit and non-time deposit of banks against the loan volume. Using a panel data set of quarterly observations from 2011 to 2017, we estimate the following specification for banks and shadow banks, respectively:

$$Ratio_{i,t} = \Sigma_b \gamma_b I\left(Size_{i,t} \in Bin_b\right) + \epsilon_{i,t}$$

where Ratio are uninsured share of total time deposit and of total non-time deposit, respectively, in panel (a) and insured share of total time deposit and of total non-time deposit, respectively, in panel (b). The plotted coefficients of interest, γ_b, show how the uninsured(insured) leverage vary non-parametrically across the size distribution, where size is measured by the logarithm of annual mortgage origination volume in dollars. The shaded area shows the 95% confidence interval. Standard errors are clustered by institutions.



(a) Uninsured Leverage



(b) Insured Leverage

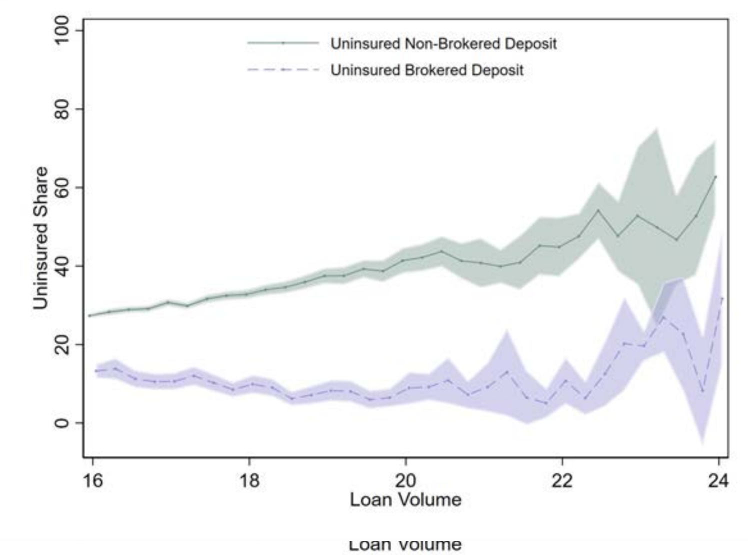
Appendix D5: Brokered Deposit and Size

This figure compares brokered deposit and non-brokered deposit of banks against the loan volume. Using a panel data set of quarterly observations from 2011 to 2017, we estimate the following specification for banks and shadow banks, respectively:

$$Ratio_{i,t} = \Sigma_b \gamma_b I\left(Size_{i,t} \in Bin_b\right) + \epsilon_{i,t}$$

where Ratio are uninsured share of brokered deposit and of non-brokered deposit, respectively, in panel (a), and insured share of brokered deposit and of non-brokered deposit, respectively, in panel (b). The plotted coefficients of interest, γ_b, show how the uninsured(insured) leverage vary non-parametrically across the size distribution, where size is measured by the logarithm of annual mortgage origination volume in dollars. The shaded area shows the 95% confidence interval. Standard errors are clustered by institutions.

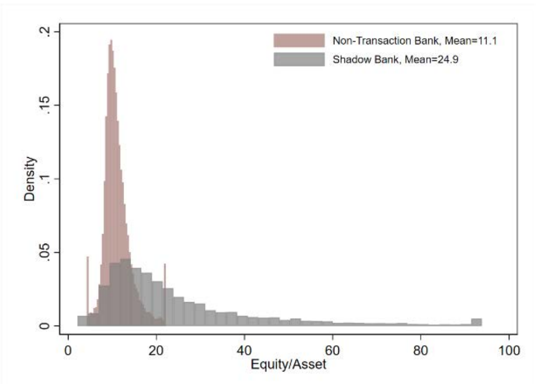
(a) Uninsured Leverage



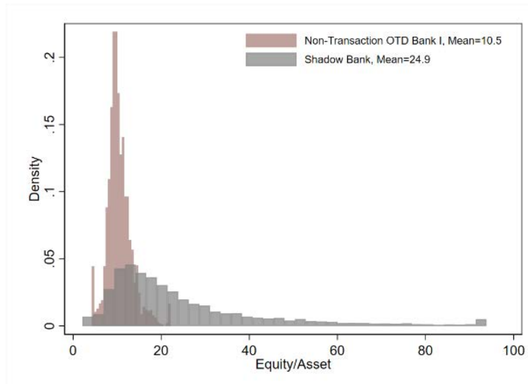
(b) Insured Leverage

Appendix D6: Non-Transaction Bank Equity to Asset

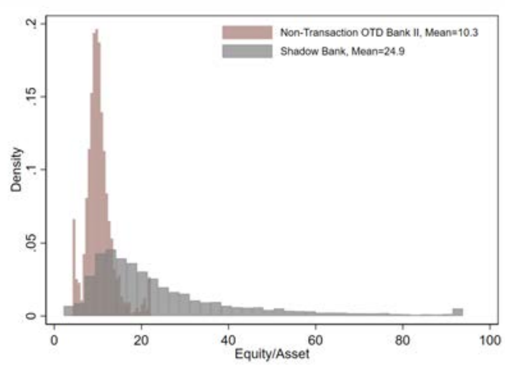
This figure plots the histograms (density) of equity to asset ratio for shadow banks and non-transaction banks. ***Non-transaction banks*** are defined as banks whose non- transaction account deposits make up more than 75% of their total deposits. Panel (a) compares shadow banks to bank full sample. Panel (b) compares shadow banks to OTD bank of version 1, and Panel (c) compares shadow banks to OTD banks of version 2.



(a) Full Sample



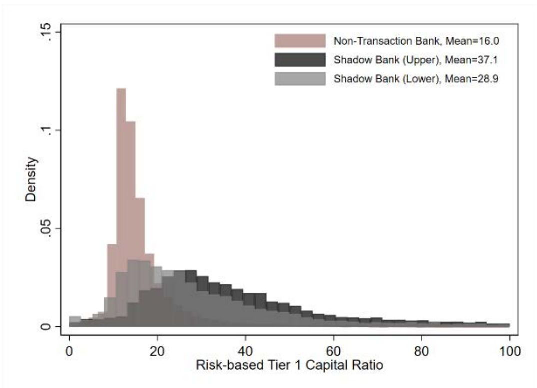
(b) OTD Bank I



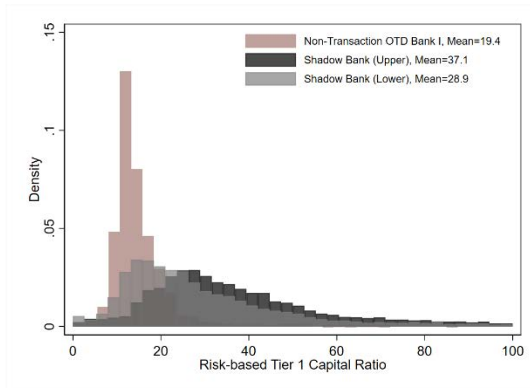
(c) OTD Bank II

Appendix D7: Non-Transaction Bank Risk-Based Tier 1

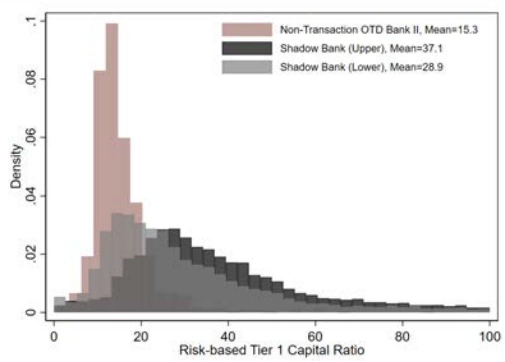
This figure plots the histograms (density) of risk-based tier 1 ratio for shadow banks and ***non-transaction banks.*** Non-transaction banks are defined as banks whose non- transaction account deposits make up more than 75% of their total deposits. Panel (a) compares shadow banks to bank full sample. Panel (b) compares shadow banks to OTD bank of version 1, and Panel (c) compares shadow banks to OTD banks of version 2.



(a) Full Sample



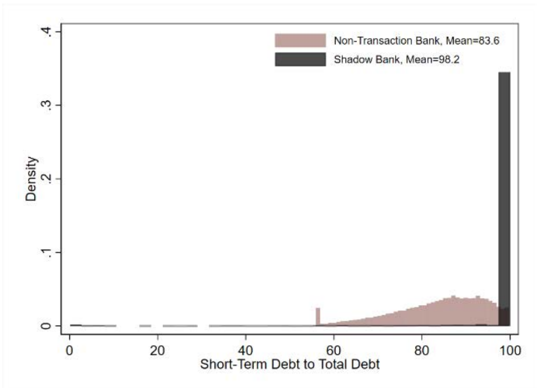
(b) OTD Bank I



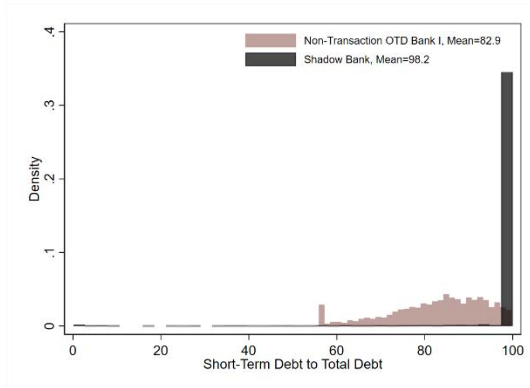
(c) OTD Bank II

Appendix D8: Non-Transaction Bank Debt Structure

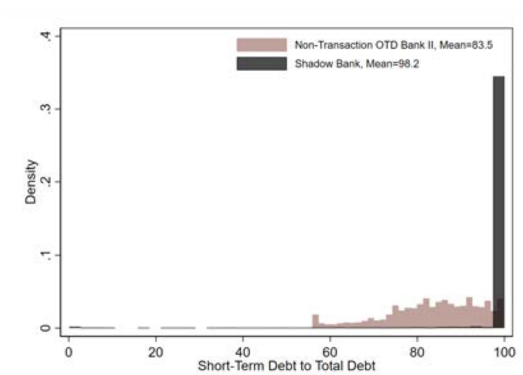
This figure plots the histograms (density) of short-term debt to total debt for shadow banks and ***non-transaction banks***. Non-transaction banks are defined as banks whose non-transaction account deposits make up more than 75% of their total deposits. Panel (a) compares shadow banks to bank full sample. Panel (b) compares shadow banks to OTD bank of version 1, and Panel (c) compares shadow banks to OTD banks of version 2.



(a) Full Sample



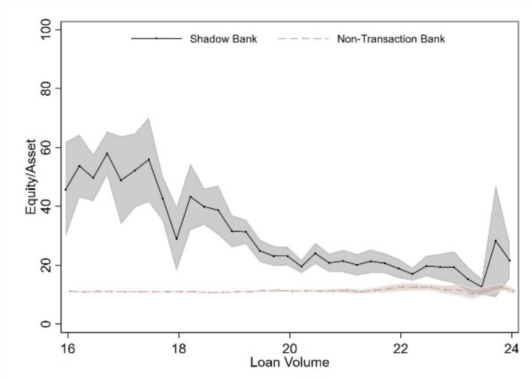
(b) OTD Bank I

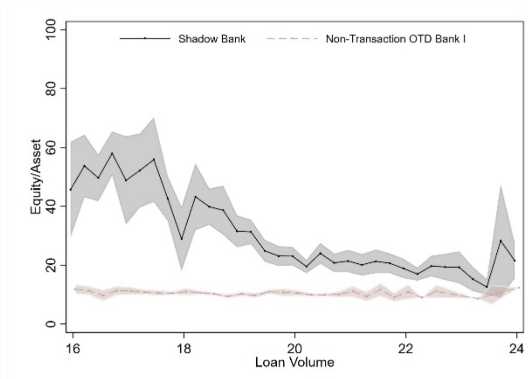


(c) OTD Bank II

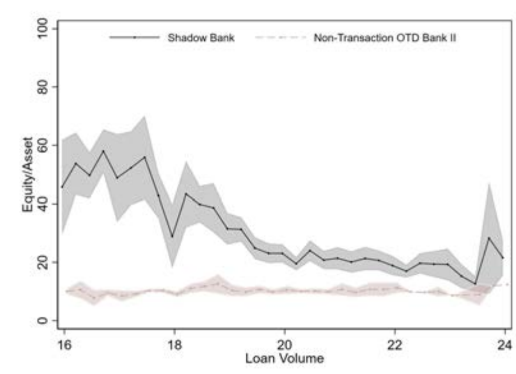
Appendix D9: Non-Transaction Bank Capital Ratio and Size

This figure plots the equity to asset ratio of shadow banks and ***non-transaction banks*** against the loan volume. Panel (a) compares shadow banks to bank full sample. Panel (b) compares shadow banks to OTD bank of version 1, and Panel (c) compares shadow banks to OTD banks of version 2. The shaded area shows the 95% confidence interval. Standard errors are clustered by institutions.





(a) Full Sample (b) OTD Bank I



(c) OTD Bank II

Appendix E: Model Proofs

Appendix E1: Shadow Bank Equilibrium Leverage, Size, and Cost of Debt

In choosing its capital structure, a shadow bank accounts for the fact that its choice will affect the pricing of uninsured debt. Equity holders are protected by limited liability, and maximize the expected value of equity, $v_i^{j=s}$:

$$v_i^{j=s} = \max_{E_i, D_i^U} \quad p \underbrace{max\left(f \quad (a_i) - D_i^U\left(1 + r_i^U\right), 0\right)}_{Good\ state} + (1-p)\underbrace{\max\left(\lambda_i f \quad (a_i) - D_i^U\left(1 + r_i^U\right), 0\right)}_{Bad\ state} - E_i \tag{AE1}$$

In equilibrium, cost of debt accounts for potential distress and money-like premium:

$$D_i^U = pD_i^U(1 + r_i^U) + (1-p)\min\left(D_i^U(1 + r_i^U), \underbrace{f(a)\lambda_i - a_i\delta\left(\frac{D_i^U}{a_i} - \lambda_i\right)^2}_{Recovery\ in\ default}\right) + \underbrace{D_i^U\gamma^s}_{Liquidity\ benefit} \tag{AE2}$$

When the uninsured debt is not risky, i.e., $D_i^U\left(1 + r_i^U\right) \leq f \quad (a_i)\lambda_i$, $r_i^U = -\gamma^s$, and the intermediary will want to maximize leverage. Intuitively, since uninsured debt provides money-like premium, the intermediary benefits from increasing leverage.

On the margin at which the debt becomes risky, the marginal benefit of having an extra dollar of debt is positive, which is equal to the money-like premium, while the marginal cost of having an extra dollar of debt is zero. Thus, it is optimal to increase uninsured leverage. Once the debt becomes risky, the intermediary faces a tradeoff between the money-like premium and the dead-weight loss in default as it increases uninsured debt. Therefore, the intermediary chooses enough uninsured debt such that shadow bank debt is risky in equilibrium, i.e., $D_i^U\left(1 + r_i^U\right) > f \quad (a_i)\lambda_i$.

We then have the following pricing condition:

$$r_i^U = \frac{1-\gamma^s}{p} - \frac{1-p}{p}\frac{f(a_i)\lambda_i - a_i\delta\left(\frac{D_i^U}{a_i} - \lambda_i\right)^2}{D_i^U} - 1 \tag{AE3}$$

Plugging (A3) into (A1) yields the following optimization problem:

$$v_i^{j=s} = \max_{a_i, l_i^U} \underbrace{f \quad (a_i)(p + (1-p)\lambda_i) - a_i}_{Profits\ from\ lending} + \underbrace{a_i l_i^U \gamma^j}_{Money-like\ \ benefit} - \underbrace{(1-p)a_i\delta\left(l_i^U - \lambda_i\right)^2}_{Run\ cost} \tag{AE4}$$

where $l_i^U \equiv \frac{D_i^U}{a_i}$ denotes the leverage ratio. The first order conditions yield the following equilibrium leverage ratio and asset size:

$$(l_i^U)^* = \frac{\gamma^s}{2(1-p)\delta} + \lambda_i \tag{AE5}$$

$$f_a{}'(a_i^*)(p + (1-p)\lambda_i) = 1 - \lambda_i\gamma^s - \frac{(\gamma^s)^2}{4(1-p)\delta} \tag{AE6}$$

In words, in choosing leverage and size, shadow banks trade off profits from lending, the liquidity benefits of leverage, and the run cost of financing with debt. The marginal run cost of debt, $(1-p)2\delta(l_i^U - \lambda_i)$, has to equal the marginal liquidity benefit of debt, γ. Intuitively, more productive shadow banks, with a higher λ_i, have a higher recovery in the bad state. Therefore, runs result in lower inefficient liquidations and are less costly, which leads to more productive shadow bank's choosing higher equilibrium leverage.
Shadow banks choose optimal intermediary size by trading off marginal costs and benefits of capital, accounting for the fact that leverage changes the cost of capital. More productive shadow banks have a higher marginal benefit from lending for a given size. The marginal cost of capital is a function of leverage. As the logic above suggests, more productive shadow banks optimally choose higher leverage, resulting in a lower equilibrium marginal cost of capital, which arises from liquidity benefits of debt.

Appendix E2: Bank Equilibrium Leverage, Size, and Cost of Debt

Banks face a similar problem to shadow banks. They have their lending technology and choose their capital structure and size. They differ from shadow banks because they can also access insured deposits but are constrained by capital requirements. Formally, a bank chooses its financing to maximize dividends to shareholders. It chooses how much external equity E_i to raise, how much uninsured and insured debt (D_i^U, D_i^I) to issue, resulting in total assets of a_i. In choosing its capital structure, the bank accounts for the fact that its choices will affect the pricing of (uninsured) debt. Equity holders are protected by limited liability, and maximize the expected value of equity:

$$\begin{aligned} v_i^{j=b} = \max_{E_i, D_i^U, D_i^I} p \underbrace{\left(f(a_i) - D_b^U r_b^U - D_b^I\left(r_b^I + \Delta\right)\right)}_{Good\ state} \\ + (1-\mathrm{p}) \underbrace{\max\left(\lambda^{\mathrm{b}} f(a_i) - D_i^U r_i^U - D_i^I\left(r_i^I + \Delta\right), 0\right)}_{Bad\ state} - E_i \end{aligned} \tag{AE7}$$

$$s.t.\ \frac{D_i^U + D_i^I}{a_i} \le \bar{l}$$

The equity holders' problem is very similar to that of shadow banks but accounts for the repayment of insured deposits, as well as the acquisition cost of insured deposits.
Debt holders are competitive and account for default and recovery in default when setting interest rates. Because insured depositors are sleepy, and the assets are used to first repay uninsured depositors who run, the uninsured depositor problem is the same as the one for shadow banks:

$$\begin{aligned} D_i^U = pD_i^U(1 + r_i^U) + (1-p) \min\left(D_i^U(1 + r_i^U), \underbrace{f(a)\lambda_i - a_i\delta\left(\frac{D_i^U}{a_i} - \lambda_i\right)^2}_{Recovery\ in\ default} \right) \\ + \underbrace{D_i^U\gamma^s}_{Liquidity\ benefit} \end{aligned} \tag{AE8}$$

Insured depositors, on the other hand, do not account for default, because they are insured by the FDIC, so their problem simply boils down to:

$$D_i^U = D_i^I = D_i^I\left(1 + r_i^I\right) + \underbrace{D_i^I \gamma^b}_{liquidity\ benefit} \quad \text{(AE9)}$$

Because insured depositors earn a liquidity benefit, they are willing to supply deposits below the cost of capital, which we normalize at 1. Therefore, insured depositors earn a negative real interest rate on their deposits.

Give that insured deposits are subsidized, why would shadow banks choose any uninsured debt at all? If uninsured debt were risk free, then it is a preferred mode of funding, since it does not require costly acquisition associated with insured deposits, such as operating branches, advertise, and incur other costs that are typically associated with these typically small accounts. This intuition carries over to the first dollar of risky uninsured debt, where $\frac{D_i^U}{a_i} = \lambda_i$. The marginal benefit of uninsured debt is the same as that of insured debt, equaling to the money-like premium, γ^b. On the other hand, a marginal dollar of insured debt has an acquisition cost of Δ. The marginal cost of the first risky dollar, on the other hand, is 0. Once uninsured debt is risky, on the other hand, the insured depositors collect the deposit subsidy, so the marginal benefit increases. The bank is therefore financed entirely with uninsured deposits, or a mixture of the two. If they choose to finance themselves with any insured deposits, then banks will always borrow the maximum allowable amount. In other words, the capital requirements bind.

Because of deposit insurance, banks would always want to borrow an additional unit of insured deposits, if they were not subject to capital requirements. However, once they are subject to capital requirements, bank choose to fund themselves at least partially with uninsured debt.

(AE7) can be written as the constrained maximization problem below, with the Lagrange multiplier on the capital requirement constraint capturing the shadow cost of capital requirements from the perspective of the banks' equity holders.

$$\begin{aligned} v_i^{j=b} = \max_{\mathrm{a_i}, l_i^I, l_i^U} & \underbrace{f\ \ (a_i)(p + (1-p)\lambda_i) - a_i}_{Profits\ from\ lending} + \underbrace{\boldsymbol{a_i}(\boldsymbol{l_i^I} + l_i^U)\gamma^j}_{Money-like\ benefit} \\ & - \underbrace{(1-p)a_i\delta\left(l_i^U - \lambda_i\right)^2}_{Run\ cost} \quad \underbrace{-\boldsymbol{a_i l_i^I \Delta}}_{Insured\ deposit\ acquistion\ cost} \\ & + \underbrace{\boldsymbol{a_i l_i^I (1-p)}}_{Deposit\ insurance\ benefit} + \underbrace{\boldsymbol{\Lambda_i(\bar{l} - l_i^I - l_i^U)}}_{Shadow\ cost\ of\ capital\ requirements} \end{aligned} \quad \text{(AE10)}$$

The first order conditions yield the following equilibrium choices:

$$l_i^U = \frac{\Delta - p}{2p\delta} + \lambda_i, l_i^I = \bar{l} - l_i^U \quad \text{(AE10)}$$

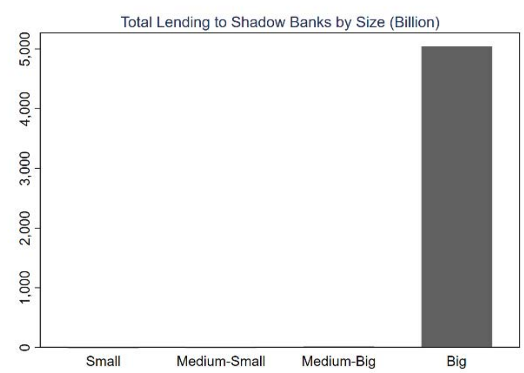
$$\begin{aligned} & \underbrace{f_a\ '(a_i)(p + (1-p)\lambda_i)}_{MB\ of\ capital} \\ & = 1 \quad \underbrace{-\gamma^j\left(l_i^U + \boldsymbol{l_i^I}\right)}_{Money-like\ benefit} \quad \underbrace{+(1-p)\delta\left(l_i^U - \lambda_i\right)^2}_{Run\ cost\ of\ uninsured\ \ debt} \quad \underbrace{-\boldsymbol{l_i^I(1-p)}}_{\boldsymbol{Deposit\ insurance\ benefit}} \quad \underbrace{+\boldsymbol{l_i^I \Delta}}_{\boldsymbol{Cost\ of\ i.\ deposits}}. \end{aligned} \quad \text{(AE11)}$$

Appendix F: Funding Relationship Between Banks and Shadow Banks

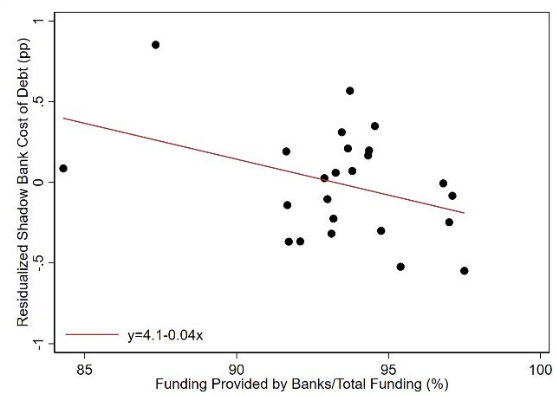
Appendix F1: Total Lending to Shadow Banks by Bank Size

Panel (a) shows the total bank lending to shadow banks by bank asset size. We divide the entire sample into four equal-sized buckets, where small corresponds to the bottom size quartile, and big corresponds to the top size quartile. We then sum up lending to non-depository financial institutions reported by each bank during 2012 to 2017. Panel (b) plots the average residualized shadow bank cost of debt against the share of total debt funding shadow banks obtain from banks. To obtain the residualized values, we purge out size-related variation as well as the time trend. *Data sources:* bank and shadow bank call reports.

	Size bin			
	1	2	3	4
Total Lending to Shadow Banks (Billion)	1.08	3.76	15.93	5045.16



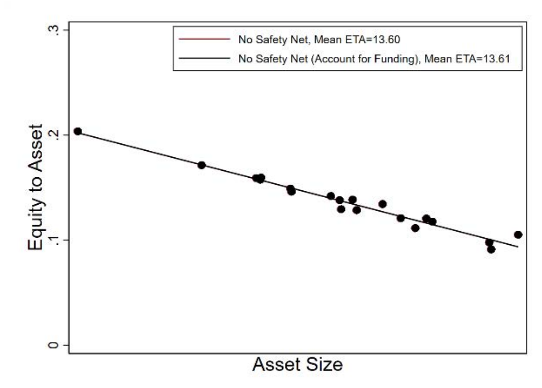
(a) Total Bank Lending to Shadow Bank



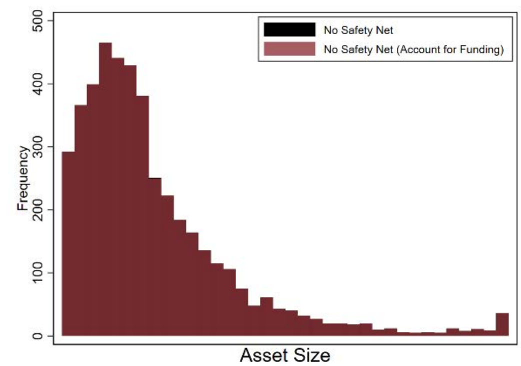
(b) Residualized Shadow Bank Cost of Debt

Appendix F2. Counterfactual: Bank-Shadow bank Funding Relationship

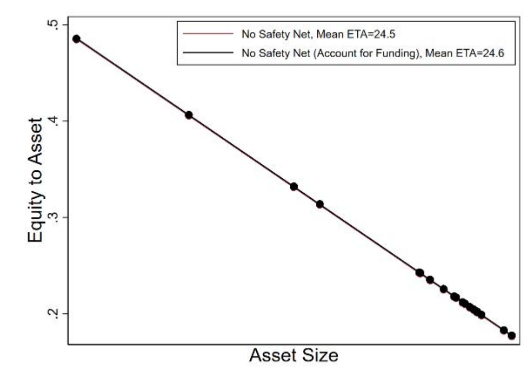
This figure presents no safety nets counterfactual capital ratios and intermediary size when we consider the intermediation wedge created by bank-shadow bank funding relationship. Panels A and C show banks' and shadow banks' capital ratios, respectively. We divide the full sample into 20 buckets based on asset size in the data and plot the average equity to asset ratio in each bucket. Panels B and D compare the size distribution in the baseline and that in the counterfactual for banks and shadow banks, respectively. *Data sources:* bank and shadow bank call reports.



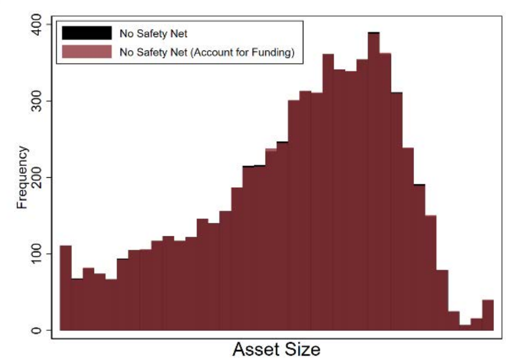
(a) Bank Equity to Asset Ratio



(b) Bank Size



(c) Shadow Bank Equity to Asset Ratio



(d) Shadow Bank Size