Nonbank Lending and Credit Cyclicality*

Quirin Fleckenstein†[1], Manasa Gopal‡[2], Germán Gutiérrez§[3], and Sebastian Hillenbrand¶[4]

[1]HEC Paris

[2]Scheller College of Business, Georgia Tech

[3]Foster School of Business, University of Washington

[4]Harvard Business School

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Abstract

Prior work identifies bank health as a key driver of syndicated lending fluctuations, particularly during the Global Financial Crisis. We show that the relationship between bank health and lending weakens considerably once we account for the impact of nonbanks on loan originations. Weaker banks originated more nonbank loans pre-crisis and reduced their originations more during the crisis, as nonbanks withdrew. Comparing banks and nonbanks over multiple credit cycles, we find that the cyclicality of nonbanks' credit supply is more than three times higher. We show – empirically and theoretically – that theories of heterogeneous financial frictions can explain the evidence.

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†fleckenstein@hec.fr

‡manasa.gopal@scheller.gatech.edu

§gg39@uw.edu

¶shillenbrand@hbs.edu

1 Introduction

The role of the financial sector in amplifying shocks to the real economy has been the subject of growing interest since the Global Financial Crisis (GFC) (e.g. Gertler and Kiyotaki 2010). The health of banks, in particular, has been identified as a key driver of lending fluctuations (Adrian, Colla, and Song Shin 2013, Becker and Ivashina 2014). A deterioration in bank health led to a severe credit crunch during the GFC (Ivashina and Scharfstein 2010a, Santos 2010) and resulted in substantial employment losses (Chodorow-Reich 2013). These findings had a profound impact on financial regulation and research in financial economics. Regulatory responses included the implementation of various measures targeting banks, such as the Dodd-Frank Act and Basel III. Researchers now include a representative banking sector in state-of-the-art macro-finance models (He and Krishnamurthy 2012, Brunnermeier and Sannikov 2014).

Banks, however, are not the only lenders in financial markets, and the importance of nonbanks has grown (Buchak, Matvos, Piskorski, and Seru 2018, Irani, Iyer, Meisenzahl, and Peydro 2021, Gopal and Schnabl 2022). For example, the share of outstanding syndicated loans financed by nonbanks rose from 22% in 2001 to 43% prior to the GFC in 2007 and has since risen to 46% in 2022.[1] This has had large effects on the business model of banks who, now, originate many loans only to immediately distribute them to nonbanks (Bord and Santos 2012, Blickle, Fleckenstein, Hillenbrand, and Saunders 2020).[2] In this paper, we investigate how the rise of nonbanks influences the cyclicality of syndicated loan originations and how this affects our conclusions on the importance of bank and nonbank health for lending fluctuations.

We start by revisiting the relationship between bank health and banks' loan originations during the GFC. To measure bank health, prior work relies on several proxies (e.g., bank's

[1]This is based on outstanding syndicated loans as reported in the Shared National Credit program by the Federal Reserve Bank (https://www.federalreserve.gov/supervisionreg/snc-archive.htm). We assume that all nonbank lending is in drawn (i.e., outstanding) credit rather than committed credit, consistent with undrawn credit lines being primarily provided by banks.

[2]Nonbanks do not directly participate in the primary loan market for tax reasons. Thus, loans targeting the nonbank segment (also called "institutional" loans) are syndicated by banks but then sold within days to nonbanks (Lee, Li, Meisenzahl, and Sicilian 2019). See Blickle, Fleckenstein, Hillenbrand, and Saunders (2020) for more institutional background.

equity ratio (Schwert 2018), trading revenues or the exposure to Lehman Brothers (Ivashina and Scharfstein 2010a, Chodorow-Reich 2013)). We show that these proxies also measure another bank feature: how active banks are in the origination of nonbank loan deals. Banks with weaker health sell a higher share of loans they originate to nonbanks. This previously undocumented bank-nonbank matching means that to understand loan originations we cannot simply look at bank health in isolation, but, we need to take into account the loan demand of nonbanks.

Once we control for banks' nonbank dependence – the share of a bank's loan originations distributed to nonbanks in the pre-crisis period – the relationship between bank health measures and changes in loan originations during the GFC decreases substantially and, in fact, becomes statistically insignificant. On the contrary, we find that nonbank dependence explains most of the variation in bank-level loan originations during this episode. This is not surprising given that all banks, independent of their health, entirely stopped the origination of loan deals meant for sale to nonbanks. Thus, the banks that were most exposed to nonbanks at the onset of the crisis were also the ones which had to reduce their total originations the most. We recover a significant relationship between bank health and lending changes once we focus on bank deals (deals that banks keep on their balance sheet). However, because this is only one part of the market, we find that existing measures of bank health play a less important role in explaining the market-wide credit crunch than what is suggested in prior studies. In contrast, the health of nonbanks seems to matter more. We also conduct a decomposition of the credit-induced employment losses following Chodorow-Reich (2013). Our estimates suggest that the majority of these employment losses are likely due to a reduction in nonbanks' credit supply instead of a reduction in banks' credit supply.

Motivated by this evidence, we then broaden our focus to study lending cyclicality of banks and nonbanks over multiple credit cycles. To identify cyclicality, we estimate the sensitivity of bank and nonbank lending to the Excess Bond Premium (EBP) - a measure of credit conditions that captures the gap between corporate bond spreads and expected credit losses (Gilchrist and Zakrajšek 2012). Thus, it reflects the additional compensation beyond expected losses that investors require to lend to firms. Consistent with our results on the GFC, we find that nonbank lending is far more cyclical than bank lending in the time series, and that the relative cyclicality is remarkably pervasive over multiple cycles. Nonbank originations fall and spreads rise – relative to banks – when economy-wide credit conditions tighten. These results are consistent with the fact that loans held by nonbanks were less likely to be rolled over and experienced greater price volatility during the GFC (Irani, Iyer, Meisenzahl, and Peydro 2021).

These results could be explained by differences in credit demand and borrower risk, or by differences in credit supply between banks and nonbanks. To disentangle these two mechanisms, we exploit the fact that banks and nonbanks often lend to the same borrower under similar contract terms (Ivashina and Sun 2011). This allows us to isolate differences in credit supply by comparing the cyclicality of bank vis-à-vis nonbank loans for the same borrower and at the same time (Khwaja and Mian 2008). We find that a one standard deviation increase in the EBP reduces nonbank loan volumes by 13.9 percentage points more than bank loan volumes (the sensitivity of banks is 5.5 percent). Thus, when aggregate credit conditions tighten, nonbank lending volumes fall more than bank lending volumes, even when controlling for time-varying firm demand and risk. Our estimates suggests that nonbank credit supply is more than three times as cyclical as bank credit supply.

We present a series of tests to confirm that the higher nonbank cyclicality is not driven by alternative explanations such as bank health or the special role of banks as monitors. First, the weaker health of banks originating nonbank loans might explain the higher cyclicality of nonbank loan originations. For example, banks face the risk of not being able to fully sell a loan to nonbanks (Bruche, Malherbe, and Meisenzahl 2020) and thus might be reluctant to originate nonbank loans when facing balance sheet constraints. To address this concern, we compare bank and nonbank loan originations originated by the same bank over the credit cycle. If bank health was the main driver of the cyclicality in bank and nonbank loans, then we would expect that bank loan originations are at least as cyclical as nonbank loan originations since the former requires more balance sheet capacity. However, we find the opposite. For a given bank, nonbank loan originations are more cyclical, suggesting that the health of the originating bank cannot explain the difference in credit cyclicality.

Second, lead arrangers (the key banks in a loan origination) might be tasked with monitoring and screening borrowers (Sufi 2007, Ivashina 2009), and, therefore, possess an informational advantage over other lenders. This might contribute to the documented pattern if the degree of this informational advantage varies over the credit cycle (Ivashina and Scharfstein 2010b). To address this concern, we compare nonbanks with participant banks (who do not have a special role) and find that the bank-nonbank loan cyclicality persists. The degree of the informational advantage should also be stronger for more opaque borrowers. Exploiting opaqueness measures used in prior work (Sufi 2007), we find little evidence that the bank-nonbank cyclicality difference varies with the opaqueness of the borrower.

To show how these results advance our understanding of the differences between nonbanks and banks, in particular of why these two types of intermediaries differ in their cyclicality, we develop a conceptual framework in which banks and nonbanks face different financing frictions. We model nonbanks as debt-constrained intermediaries (Brunnermeier and Pedersen 2009, Adrian and Shin 2014) motivated by the empirical observation that the majority of nonbanks in the syndicated loan market (collateralized loan obligations (CLOs)) need to delever in bad times.[3] In contrast, banks are unlikely to face these debt constraints due to explicit and implicit government guarantees for their liabilities. Consistent with this, we show that banks substantially increase their leverage in bad times, and hence can be modeled as equity-constrained intermediaries (Brunnermeier and Sannikov 2014, He and Krishnamurthy 2012). In the model, when economic conditions worsen (improve), nonbanks' debt constraints tighten (relax) leading to a decrease (increase) in leverage, and thus nonbanks' participation in loan originations decreases. In contrast, banks are able to increase their leverage in bad times and, therefore, continue lending. The extent to which banks can offset the decline in nonbank originations depends on the relative constraints of both intermediaries as well as the firm elasticity of demand for credit. The greater the firm demand inelasticity, the greater the cyclicality difference between bank and nonbank lending. The model suggests that debt issuance constraints are a key financial amplification mechanism.

Our paper highlights the key role of nonbanks for syndicated lending and has several important implications. First, we show that measures of bank health proxy for banks' reliance on nonbanks. It is, therefore, necessary to distinguish between nonbank and bank

[3]Besides CLOs, there are also other nonbank lenders that face the risk of runs, for example, due to strategic complementaries (Chen, Goldstein, and Jiang 2010). We show that these nonbanks with fragile liabilities exhibit a similar cyclicality to CLOs.

loans when studying the drivers of syndicated lending fluctuations.[4] Second, we highlight the important role of nonbanks in the credit cycle. The secular rise of nonbank lenders could, therefore, result in larger lending fluctuations. Finally, we provide a generalized framework to understand how the different financing frictions affect lending cyclicality in markets with both banks and nonbanks.

Related Literature. Our paper makes several contributions to the existing literature. First, our paper contributes to the empirical macro-finance literature studying how financial intermediation affects lending and real outcomes.[5] While prior studies mostly focus on single episodes and one type of intermediary, we quantify the fluctuations in credit supply of bank and nonbank intermediaries over the entire credit cycle. We show that the high cyclicality of the loan market compared to the bond market Adrian, Colla, and Song Shin (2013), Becker and Ivashina (2014), stems from *nonbanks* and instead of *banks* as argued by the prior literature. Our conclusion is consistent with studies focusing on single epsiodes. (Ivashina and Sun 2011, Shivdasani and Wang 2011) document that the pre-crisis boom was caused by nonbanks and Irani, Iyer, Meisenzahl, and Peydro (2021) show that nonbanks refused to roll over loans during the GFC.

Second, our analysis on the credit crunch in the primary loan market during the GFC is related to a number of studies (e.g., Ivashina and Scharfstein 2010b, Santos 2010, Chodorow-Reich 2013). We show that the exit of nonbank lenders was quantitatively important for overall primary loan originations and, ultimately, employment. We also show why prior studies have over-emphasized bank health as the main culprit for the credit crunch.

Third, our paper relates to often-theoretical studies on how financial intermediation affects asset prices and the real economy (e.g., He and Krishnamurthy 2013, Brunnermeier and Sannikov 2014). We show that theories of financing frictions can be directly applied to nonbanks and banks in the syndicated loan market. We provide an explanation for why even long-term financed nonbanks, which provide the majority share of nonbank lending in

[4] In fact, such separation is common in other markets, such as mortgage lending. See, for example, Mian and Sufi (2021).

[5] See for example Peek and Rosengren (2000), Khwaja and Mian (2008), Paravisini (2008), Ivashina and Scharfstein (2010a), Chava and Purnanandam (2011), Schnabl (2012), Chodorow-Reich (2013), Amiti and Weinstein (2018), Huber (2018), Acharya, Eisert, Eufinger, and Hirsch (2018).

the syndicated loan market, are more cyclical than banks.

The rest of the paper is organized as follows. Section 2 provides institutional background information. Section 3 discusses the data. Section 4 examines the contribution of nonbanks and banks to the credit crunch during the GFC. Section 5 extends our analysis to multiple credit cycles and contrasts the credit supply cyclicality of banks and nonbanks. Section 6 develops a simple framework to rationalize our empirical findings. Section 7 concludes.

2 Institutional Setting

Our analysis focuses on the primary market of US syndicated loans – a market through which banks and nonbanks lend to medium and large corporations. This is an important market to study for several reasons. First, it is large and quantitatively important. As of 2022, we estimate that syndicated loans accounted for more than half of all loans outstanding to non-financial corporations and about three-fourths of outstanding corporate bonds.[6] Second, credit contractions in this market have significant real effects (Chodorow-Reich 2013), especially, because (i) these loans provide *new* credit to firms; and (ii) many of these firms depend on this market for credit (Schwert 2018). Last, this market has been the subject of several influential studies (e.g., Chodorow-Reich 2013, Ivashina and Scharfstein 2010a, Santos 2010, Adrian, Colla, and Song Shin 2013, Becker and Ivashina 2014).

In addition, the syndicated lending market has several unique features that make it attractive for studying the credit cyclicality of banks and nonbanks. First, we have data measuring bank and nonbank originations since 2000, which allows us to study cyclicality over multiple credit cycles rather than select events such as the GFC. Second, this is one of the few markets where banks and nonbanks lend to the same borrower, at the same time

[6]These estimates are based on the Shared National Credit Program, which tracks all syndicated loans held by at least two U.S.-supervised banks with an outstanding balance at origination over \$100mm. As such, it provides a lower bound on the total amount of syndicated loans. As of Q2 2022, SNC reports \$5.9 trillion total outstanding commitments and \$2.9 trillion outstanding balances (see SNC), of which \$4.9 trillion and \$2.5 trillion were lent to U.S. corporations, respectively (see SNC Domestic Entities). The Financial Accounts of the US reports that non-financial businesses in the U.S. had \$5.1 trillion non-mortgage loans outstanding and \$6.7 trillion in outstanding corporate bonds. Thus, outstanding loans in the syndicated loan market represent at least 57% of total loans outstanding to all firms in the U.S and the syndicated loan market is about three-fourths the size of the corporate bond market.

and under the same contract. As described in more detail below, this allows us to causally identify the effect of credit supply while controlling for credit demand.

We begin by providing a brief overview of the market and origination process, with an emphasis on the institutional features that may affect bank and nonbank lending cyclicality.[7]

Syndicated deals. Syndicated loans are originated as part of "deals" or "packages" that contain multiple "facilities" for a single borrower. The average deal contains total commitments of $483mm split across 1.6 facilities. Facilities can include revolving and Term Loan A (TLA) facilities designed to appeal to *banks* and Term Loan B (TLB) facilities designed to appeal to *nonbanks*. Importantly, different facilities within the same deal have the same seniority and term loans are also backed by the same collateral (Ivashina and Sun 2011). Figure 1 provides an example of a deal originated for Yum! Brands Inc in 2016. As shown, this deal included a $2bn Term Loan B with 7 years maturity, a $0.5bn Term Loan A with 5 years maturity and a $1bn revolving facility with 5 years maturity.

Origination process. Syndicated deals are arranged by a group of syndicating banks, which include at least one "lead arranger" and potentially other "underwriting" banks. In the case of Yum! Brands Inc, several investment and universal banks acted as "arrangers" while JP Morgan received the additional title of "admin agent". We refer to them as lead banks in the remainder of the paper (see Ivashina 2009).

Lead banks are responsible for "structuring" the deal (i.e., splitting the required funding amount into facilities, setting the maturity for each facility, and defining other non-price characteristics), setting the target rate on each facility and leading the book-building process prior to origination, in exchange for fees. Arrangers internalize the expected nonbank supply at initial discussions. Thus, the existence and structure of a deal depends crucially on the expected credit supply from each group of lenders. If lead arrangers expect limited demand from nonbanks, for example, they will reduce the size and increase the spread of TLB facilities; or may be reluctant to commit to originate a deal altogether.

[7]For additional details on the syndication process, see Ivashina and Sun (2011) and Bruche, Malherbe, and Meisenzahl (2020). For a more detailed description of the institutional features of CLOs, see Kundu (2021), Fleckenstein (2022), and Cordell, Roberts, and Schwert (2023). Last, for additional details on the composition of nonbanks, see Irani, Iyer, Meisenzahl, and Peydro (2021).

Since arrangers often build relationships with borrowers and perform due diligence on them, they might have an informational advantage over other lenders. Sufi (2007) and Ivashina (2009) argue that banks therefore need to retain part of a loan deal to signal the quality of the loan. While the arranging banks typically hold the bank tranches, they almost always sell nonbank tranches – often immediately after origination. Thus, even if arranging banks hold TLB facilities at origination, their ultimate intent is to offload them to nonbanks (Bord and Santos 2012). This is especially common because many nonbanks never participate in the "primary market" for tax reasons. Instead, they buy loan commitments shortly after origination (Blickle, Fleckenstein, Hillenbrand, and Saunders 2020).[8] Last, arranging banks face the risk of not being able to sell all nonbank tranches if demand for them is surprisingly weak which is termed pipeline risk (Bruche, Malherbe, and Meisenzahl 2020).[9]

Lenders. Both banks and nonbanks are important lenders in the syndicated loan market. The latter tend to focus on lower-rated borrowers, but there is substantial overlap between both lender types. The importance of nonbanks has risen over time. According to the Shared National Credit program, the share of outstanding loans held by nonbanks increased from 22% in 2001 to 46% in 2022.

Figure 2 plots the share of outstanding nonbank balances by type of nonbank. As shown, CLOs hold between 50% and 80% of total nonbank loan holdings, while open-end loan funds, ETFs and separate accounts at asset management companies hold around 20%. Hedge funds, private debt funds, pension funds and insurance companies hold the remaining share. We provide further information on the lenders when we study the reasons for their cyclicality in Section 6.

[8]For example, most CLOs investing in USD loans are domiciled in the Cayman islands (Liu and Schmidt-Eisenlohr 2019) and can avoid US taxes by not engaging in so-called "US trade or business". Since originating loans would be considered "US trade or business", they instead purchase loans on the secondary market – often immediately after origination in so-called "primary assignments" (Blickle, Fleckenstein, Hillenbrand, and Saunders 2020).

[9]In particular, deals that are unsubscribed take longer to find investors (i.e., have a longer "time-on-the-market") and may have their spread adjusted to increase demand (i.e., "flexed-up"). In extreme cases where demand for particular facilities dry up, arranging banks may adjust the deal structure in addition to spreads (e.g., link) or may be forced to retain a larger share of the deal than initially planned (Bruche, Malherbe, and Meisenzahl 2020). Note that this only affects "underwritten" deals, but not so-called "best efforts" deals.

3 Data Sources

In order to study the relative cyclicality of bank and nonbank lending, we gather data from three sources.

DealScan. First, we obtain data on new originations of syndicated loans from Thomson Reuters DealScan[10] and focus on syndicated loans originated in the United States to non-financial companies between 2000Q1 and 2020Q4. Our sample consists of loan originations and loan refinancings. We proxy for a loan refinancing if an already originated loan is amended with a change in loan spread and maturity. Each origination and refinancing is considered a new loan.[11]

To classify the main lender type behind each loan tranche, we exploit the classification of tranches following industry practice (Standard and Poors 2020) and the prior academic literature (Ivashina and Sun 2011, Nini 2008). Specifically, we classify Term Loan Bs (as well Term Loans C to K) as "nonbank loans" and all other term loans and credit lines as "bank loans". In Table A1 of the Appendix, we provide further support for this classification, showing that almost all loans held by CLOs (86%) are indeed Term Loan Bs. All our results remain unchanged when we focus exclusively on the comparison of term loans, i.e. when we only classify Term Loan As as "bank loans" (and ignore credit lines).

Table 1 compares bank and nonbank loans. Nonbank loans (i.e., Term Loan Bs) are non-amortizing loans with a bullet payment at maturity in contrast to many types of bank loans (e.g., credit lines and term loan As), which require the borrower to repay the principal over time. Panel A shows that most bank loans are credit lines, which tend to be issued frequently due to their short maturity, while almost 16% are Term Loan As. Bank and nonbank loans differ beyond their amortization schedule. Panel A shows that nonbank loans are significantly larger than bank loans ($381mm vs. $277mm), more expensive (390 bps vs. 275 bps),[12] tend to have a longer maturity (67 months vs. 49 months), and fund riskier

[10] We use "Refinitiv LoanConnector Dealscan" for the main analyses and the legacy version "LPC Dealscan" when we analyze lending during the GFC to be comparable to earlier literature.

[11] We follow this procedure to line up the facility files in the legacy Dealscan to the tranche files in the updated Dealscan. Amendments were treated as new facilities in legacy Dealscan. Our results are unchanged when we focus purely on new originations.

[12] Chernenko, Erel, and Prilmeier (2022) focus on middle-market firms and also find that nonbank loans

firms (87% vs. 52% are "leveraged loans"). However, bank and nonbank loans tend to fund projects with similar purposes. As shown in Panel C, more than half of the bank and nonbank credit is supplied for general corporate purposes, while only around 3% of bank and 19% of nonbank loans fund LBOs. Thus, bank and nonbank lending are both important for real economic activity.

Importantly, there is a substantial overlap between bank and nonbank lending: 18% of bank loans are part of loan deals which contain at least one nonbank loan (Panel B). The overlap is concentrated among borrowers with a rating that is slightly below investment grade (see also Lee, Li, Meisenzahl, and Sicilian (2019)). We exploit this overlap for identification. Throughout the paper, we also refer to overlapping deals as "nonbank deals", i.e., as deals that contain at least one nonbank tranche, and to deals which contain only bank loans (credit lines and Term Loan As) as "bank deals".

Compustat. We use Compustat to obtain opaqueness measures for firms following Sufi (2007) and equity ratios for banks following Schwert (2018). To obtain the former, we merge the borrowers in Dealscan to Compustat via the legacy Dealscan version using the link provided by WRDS and the latest legacy Dealscan-Compustat link file provided by Chava and Roberts (2008). To obtain the latter, we use the linking file provided by Schwert (2018) to match Dealscan lenders to bank holding companies. We follow Schwert (2018) and compute the equity ratio as the market capitalization relative to quasi-market assets. We obtain additional measures of bank health during the GFC directly from the website of Chodorow-Reich.

Excess Bond Premium. Our main measure for the credit cycle is the Excess Bond Premium (EBP) from Gilchrist and Zakrajšek (2012). The EBP is constructed by averaging the residual bond spread across all firms after controlling for firm-specific default risk. Since it controls for default risk, it can be interpreted as the (time-varying) risk premium that investors require for holding risky corporate bonds. It therefore provides a good proxy for economy-wide credit supply. The mean and standard deviation of the EBP in our sample

are more expensive for firms than bank loans.

are 0.1 and 0.7 percent, respectively.

Creditflux. We obtain data on CLO tranches and holdings from Creditflux, which in turn extracts these data from the monthly trustee reports that CLOs provide to their investors. Creditflux captures the near universe of CLO tranches and the majority of holdings since approximately 2005. This data allows us to measure the evolution of CLO leverage through the cycle.

4 Banks vs. Nonbanks During the Global Financial Crisis

The impact of financial sector health on lending and real outcomes has been studied extensively, most often for the GFC. In particular, the health of banks has been identified as a key driver of the credit crunch during the GFC (e.g., Ivashina and Scharfstein 2010a, Santos 2010, Chodorow-Reich 2013). Prior work typically studies the effect of bank health on bank-level loan originations in isolation. However, many syndicated loans are originated for distribution to nonbanks (Bord and Santos 2012). Thus, nonbanks play an important role for loan origination. Importantly, banks' activity in the originate-to-distribute or nonbank loan segment might interact with bank health.

In the following, we provide evidence for a bank-nonbank matching pattern. The documented pattern has wide-ranging implications for the relationship between financial sector health and real activity. Firstly, the relationship between bank health and lending changes during the GFC is weaker than what is suggested by prior estimates. Secondly, the health of nonbanks was likely a more important factor in the credit crunch during the GFC than bank health.

4.1 Bank-Nonbank Matching

We start by studying how a bank's health interacts with its activity in the nonbank loan segment for the period prior to the GFC. Prior work uses several proxies for bank health, such as banks' equity ratio (Schwert 2018), banks' syndication exposure to Lehman Brothers, banks' deposit share, or banks' business model amongst other measures (Ivashina and Scharfstein 2010b, Chodorow-Reich 2013).

We compute a bank's "nonbank dependence" as the fraction of loans originated by a bank through nonbank deals, i.e. deals that contain a nonbank tranche. We focus on loans where the bank acts as the lead arranger.[13] For example, Goldman Sachs was the lead arranger on 209 loans in 2006 of which 183 loans were originated as part of nonbank deals. This implies a nonbank dependence of 87.6% for Goldman Sachs in 2006.

We then simply relate banks' capital ratio (as a proxy for their health) to their nonbank dependence in 2006. Figure 3 documents a strong negative relationship between banks' capital ratios and their nonbank dependence. Banks with lower capital ratios originated more nonbank deals prior to the GFC. For example, Goldman Sachs was very active in nonbank loan originations (87.6%) and had a low capital ratio of 10.0%. On the contrary side, Wells Fargo originated much fewer nonbank deals (14.4%), but had a considerably higher capital ratio (21.6%). Thus, banks that were considered the have the weakest health going into the GFC were also the ones that were the most active in their origination of nonbank loans.

The figure additionally shows that banks' business model – as an alternative proxy for bank health – has an even higher explanatory power for banks' nonbank activity. Investment banks collaborated the most with nonbanks, universal banks collaborated less with nonbanks, while regional banks collaborated the least with nonbanks.[14] Thus, investment banks who were arguably most exposed to financial shocks (for example, through their increased use of wholesale funding), were the ones whose origination business was most exposed to nonbanks. We reach the same conclusion using other bank health proxies constructed in Chodorow-Reich (2013): A bank's nonbank dependence is highly correlated with a bank's syndication exposure to Lehman Brothers, as well other bank health measures, such as the share of

[13] All our results are robust to focusing on including loans were a bank only participated in the syndicate without being the lead arranger.

[14] We classify Morgan Stanley, Jefferies, Goldman Sachs, Lehman Brothers, Bear Stearns, and Merrill Lynch as investment banks; JP Morgan Chase, Wachovia, Citigroup, Bank of America, and Wells Fargo as universal banks; KeyBank, SunTrust Banks, US Bank, Regions Financial, Fifth Third Bank, Capital One, PNC Financial Services as regional banks.

revenues generated through trading activities, exposure to mortgage backed-securities, etc.

The documented bank-nonbank sorting pattern does not just exist prior to the GFC, but prevails over the past two decades as shown in the Appendix. In particular, a bank's business model explains most of the cross-sectional nonbank dependence. This suggests that the sorting pattern is an ex-ante operational choice of banks, not just an outcome of an ex-post deterioration of banks' health.[15] One reason for the documented sorting pattern might be that investment banks are most active in the nonbank segment because they are specialized in transactional investment banking services such as IPOs, bond or loan underwriting. At the same time, these banks have less access to deposits and typically operate with low equity ratios. Ultimately, we leave it for future work to further investigate the reasons for the bank-nonbank matching.

4.2 A Decomposition of Bank-level Loan Originations

Next, we examine how exposure to nonbanks affected bank-level loan originations. Did banks with high pre-crisis nonbank dependence cut loan originations more or less during the GFC than banks with low nonbank dependence?

We answer this question with a simple accounting exercise. In particular, we decompose the change in loan originations by bank b into

$$\Delta \mathrm{L}_b = (1 - \mathrm{NBDep}_b) \cdot \Delta \mathrm{L}_b^B + \mathrm{NBDep}_b \cdot \Delta \mathrm{L}_b^{NB}, \tag{1}$$

where NBDep_b denotes the fraction of loans arranged by bank b through nonbank deals during the pre-crisis period, and $\Delta \mathrm{L}_b^B$, $\Delta \mathrm{L}_b^{NB}$ and $\Delta \mathrm{L}_b$ denote the change in the number of loans originated during the GFC relative to the pre-crisis period for loans originated through bank deals, nonbank deals or all deals, respectively. Dividing equation (1) by $\Delta \mathrm{L}_b$ yields the fraction of the lending decline attributable to bank deals (the first term) and nonbank deals

[15] We show in the appendix that the bank-nonbank sorting is mostly explained by bank fixed effects, instead of time fixed effects. Another way to put this is that we document a cross-sectional matching between weaker banks and nonbanks at a given point in time. The pattern we document is fundamentally different from the results shown in Irani, Iyer, Meisenzahl, and Peydro (2021) who document that the same bank sells more loans to nonbanks when reaches its regulatory limits (indicating a time-series relationship between bank health and nonbank activity).

(the second term)

$$1 = \frac{(1 - \text{NBDep}_b) \cdot \Delta \text{L}_b^B}{\Delta \text{L}_b} + \frac{\text{NBDep}_b \cdot \Delta \text{L}_b^{NB}}{\Delta \text{L}_b}. \tag{2}$$

Tables 2 shows this decomposition for the top 10 loan arrangers (measured by their pre-crisis market share) as well as for the aggregate loan market. As shown in column (2), there was a large and pervasive decline in originations of nonbank deals across all banks. The aggregate decline is 96%, the median decline across all banks is 95% and the minimum is 87% – implying that *all* arrangers essentially stopped originating nonbank deals during the crisis – irrespective of their health. In contrast, the aggregate decline in bank deals was less severe and much more dispersed as shown in column (4). Given an aggregate nonbank dependence of 50% in the pre-crisis period, this implies that the reduction in nonbank deals accounts for 71% of the aggregate lending decline, while bank deals account for only 29%.[16]

Because nonbank loan originations came to a halt during the GFC, banks which were most exposed to nonbanks were also the ones cutting their loan originations the most. The correlation between the decline in bank-level loan originations during the crisis and pre-crisis bank-level nonbank dependence is -76%. For example, the highly nonbank-exposed Goldman Sachs cut its origination by 92%, while the less nonbank-exposed Wells Fargo reduced its origination by only 32%. Figure 4 graphically illustrates the stark relationship between lending changes and nonbank dependence.[17]

4.3 Bank Health vs. Nonbank Dependence

The above results suggest that nonbank exposure was a key determinant of bank-level originations. This contrasts with the prior literature which emphasizes mostly bank health (Ivashina and Scharfstein 2010a, Santos 2010, Chodorow-Reich 2013). We therefore revisit the determinants of bank-level originations.

[16]These numbers reduce to 56% and 44% when we focus on corporate purpose loans. Generally, the numbers likely underestimate the contribution of nonbank lending to the credit crunch, since firms drew down their existing credit lines which are typically held by banks (Ivashina and Scharfstein 2010a) and nonbanks refused to roll over their outstanding loans (Irani, Iyer, Meisenzahl, and Peydro 2021).

[17]In contrast to Figure 3, we calculate the nonbank dependence based on loan originations from October 2005 to June 2007 to be consistent with Chodorow-Reich (2013). Similarly, we aggregate lenders to bank holding companies following Chodorow-Reich (2013). The results are robust to defining nonbank dependence only for 2006 and aggregating as in Schwert (2018).

Based on our previous results, we stipulate that the change in loans originated by bank b during the GFC relative to the pre-crisis is determined by

$$\Delta \mathrm{L}_b = \beta \cdot \text{Bank Health}_b + \text{NBDep}_b \cdot \psi^{NB}, \tag{3}$$

where β denotes the impact of bank health on total loan originations and ψ^{NB} denotes a *common* nonbank shock that affects bank-level originations based on their prior activity in the nonbank segment NBDep_b.[18]

Omitted variable bias. It is clear from equation (3) that in order to identify β, one either needs to control for nonbank dependence or use an instrument for bank health that is uncorrelated with nonbank dependence. Doing otherwise introduces an omitted variable bias equal to

$$\hat{\beta} - \beta = \psi^{NB} \cdot \frac{Cov(\text{Bank Health}_b, \text{NBDep}_b)}{Var(\text{Bank Health}_b)}, \tag{4}$$

which depends on (i) the magnitude of the nonbank supply shock ψ^{NB} as well as (ii) the covariance between bank health and nonbank dependence (i.e., on whether there is matching between banks and nonbanks).

We have shown above that (i) *all* banks reduced their loan originations by more than 87% (suggesting that ψ^{NB} was negative and large) and (ii) that banks with weaker health have a higher nonbank dependence. Based on equation (4), this suggests that there is a substantial omitted variable bias when we simply regress changes in bank-level loan originations on bank health measures. In other words, we overstate the relationship between bank health and lending change without taking into the influence of nonbanks on the primary loan market.

Updated results. We now revisit the determinants of bank-level originations following the specification of Chodorow-Reich (2013).[19] In particular, we are interested in how the

[18] We abstract from the role of credit demand in this analysis. To motivate this, we show in the Appendix that our results change only slightly when we additionally control for borrower characteristics as potential proxies for borrowers' credit demand.

[19] Contrary to Chodorow-Reich (2013) we include all loans. Chodorow-Reich (2013) focuses on corporate purpose loans because these seem to be the most relevant loans when studying real effects. Instead, we want to focus on the entire syndicated loan market. Nevertheless, the Appendix shows that our results hardly change when we focus on corporate purpose loans.

relationship between bank health and lending changes as we control for banks' nonbank dependence.

Table 3 presents the results. Columns 1 to 3 replicate the results in Chodorow-Reich (2013). They show that – without controlling for banks' nonbank dependence – there is a significant relationship between the decline in lending and bank health measures. Columns 4 to 6 add nonbank dependence. The R-squared rises on average by 27% across all specifications, implying that nonbank dependence has substantial explanatory power. Consistent with Table 2 discussed above, ψ^{NB} is 90% – suggesting a pervasive nonbank supply shock. By contrast, the bank health coefficients decrease in size and are no longer significant. This demonstrates that the estimates in columns 1 to 3 are biased upwards.

This perhaps surprising result indicates that bank health had a lower effect on the credit crunch than previously estimated, while the withdrawal of nonbanks had a substantial effect. Importantly, this does not imply that bank health is irrelevant. It only means that existing bank health proxies are not sufficient for identifying the impact of bank health on *total* new loans. Because *total* loan originations can be decomposed into bank and nonbank deals (following decomposition (1)), we can alternatively estimate the impact of bank health on *bank* and *nonbank* loan deals separately to overcome this issue. Column 7 shows that bank health measures have substantial explanatory power for the decline in *bank* deals. By contrast, they have no explanatory power for the decline in *nonbank* deals (column 8). This suggests that the health of originating banks – assuming that bank health proxies are able to capture bank health well – seem to have little influence on the origination of nonbank deals.

4.4 Revisiting the Employment Effects of the Credit Crunch

The ultimate goal of Chodorow-Reich (2013) is to examine how the "health of banks on Wallstreet affects economic outcomes on Main Street". To identify the effects of credit supply disruption on employment, Chodorow-Reich (2013) constructs borrower-level exposure to the credit crunch by measuring how much the pre-crisis syndicate members (in the last loan obtained by the borrower prior to the GFC) reduced their lending for all other borrowers. Our above results indicate that a large part of these borrower-level credit supply shocks are due to nonbanks withdrawing from the market. We, therefore, follow the analysis of Chodorow-Reich (2013), but distinguish between shocks originating from banks versus nonbanks. Unsurprisingly in light of our previous results, our estimates indicate that between 58% and 77% (the percentage varies with the overall importance of credit supply for the credit crunch) of the credit-induced employment losses can be traced back to the exit of nonbanks (see Table 4 for the results and Appendix Section A1.2.4 for more details). This suggests that the relationship between financial sector health and economic outcomes is more strongly influenced by the health of nonbanks rather than banks.

5 Banks vs. Nonbanks Over Multiple Credit Cycles

In the previous section, we established that nonbanks were responsible for the majority of the decline in lending and employment during the financial crisis. We now turn our focus to answering whether the sensitivity of nonbank lending to aggregate shocks was specific to the GFC or if, more broadly, nonbanks exhibit greater cyclicality compared to banks.

5.1 Aggregate Trends

We begin by exploring trends at an aggregate level. Specifically, we plot the relationship between the share of nonbank lending (the "nonbank share") and aggregate credit conditions, proxied with the EBP.[20]

We begin by plotting the time-series of monthly bank and nonbank loan origination volumes, from January 2000 to December 2020. Figure 5 reveals that lending by banks is remarkably stable, while lending by nonbanks appears highly cyclical. Nonbank lending falls sharply during periods of stress but also rises substantially during booms. When restricting the sample to loans that fund real investments (Panel B), the difference in lending cyclicality becomes even starker.

Figure 6 illustrates the relative cyclicality of bank and nonbank lending. Panel A shows

[20] The appendix presents results for alternate measures of credit conditions, including the GZ spread, the VIX, and the high yield bond spread. All results are robust to using these measures.

the tight inverse relation between the nonbank lending share and the EBP, while Panel B highlights that the difference between the average spread of nonbank and bank loans is highly positively correlated with the EBP. Interestingly, our figures highlight that nonbank lending shares and spreads vary even with small changes in EBP, and not just during large shocks such as the GFC or COVID-19.

To formally contrast bank and nonbank cyclicality, we estimate the sensitivity of bank and nonbank originations and spreads to the credit cycle:

$$\text{Lending Outcome}_{ft} = \beta_0 + \beta_1 \text{Credit Cycle}_{t-1} + \beta_2 \mathbb{I}_{f=\text{TermB}} + \beta_3 \text{Credit Cycle}_{t-1} \times \mathbb{I}_{f=\text{TermB}} + \epsilon_{ft}, \tag{5}$$

where the dependent variable Lending Outcome$_{ft}$ is either (a) the logarithm of the aggregate issuance volume of loans that are of type f in month t, or (b) the average (loan-amount-weighted) all-in-drawn spread of all newly originated loans of type f in month t. Loan type f separates bank and nonbank loans based on the classification described above. β_1 quantifies the sensitivity of bank loan outcomes to the credit cycle, while β_3 measures the differential sensitivity of nonbank loan outcomes relative to bank loan outcomes.

Table 5 presents the regression results. Column 1 shows that a one standard deviation increase in the EBP coincides with a 44.0% decrease in total loan originations (Panel A) and a 22.2 basis points increase in loan spreads (Panel B). This suggests that originations in the syndicated loan market strongly co-move with the credit cycle. Column 2 splits bank and nonbank loans (i.e., it follows the specification in equation (5)). The magnitude of β_1 (which now measures the cyclicality of bank originations) falls by half for both quantities and spreads, while $\beta_1 + \beta_3$ – which measures the cyclicality of nonbank originations – rises substantially (in absolute terms). A one standard deviation increase in the EBP is associated with a reduction in nonbank lending of 71.2%, compared to a reduction of only 16.9% for banks. Loan spreads exhibit a similar pattern (Panel B): the spreads of nonbank loans are nearly two and a half times as sensitive to the credit cycle as the spreads of bank loans (31.7 versus 12.7). Column 3 shows that these results are robust to including year-month fixed effects that control for macroeconomic conditions. In Appendix Table A8 we show that we draw similar conclusions when we focus on the extensive margin. We find that the number of deals originated reduces with the EBP, and that this reduction is concentrated exclusively in nonbank deals.

We also explore the aggregate evolution of several proxies for nonbank credit supply, which arise from the deal syndication process, proposed by the literature. Specifically, we consider (i) the time it takes for a loan to be syndicated to nonbanks (Ivashina and Sun 2011), (ii) the change in loan spreads during the syndication process (Bruche, Malherbe, and Meisenzahl 2020), and (iii) the discount at which the loan is first sold.[21] When there is a lot of demand from nonbank lenders for a particular deal, then (i) the deal closes more quickly, (ii) spreads are adjusted downwards which results (iii) in lower original issue discounts. On the other hand, when demand is low, it takes longer for deals to close and may require the lead arranger to adjust the spread upwards (or provide a larger discount at issuance) to illicit sufficient demand from investors. Figure A3 shows the strong correlation between nonbank shares and measures of credit supply proxied by time-on-market, changes in loan spreads during the syndication process, and original issue discount. This suggests that changes in nonbank share are correlated with changes in nonbanks' credit supply.

5.2 Demand vs. Supply

Our aggregate results show that nonbank lending varies to a greater extent than bank lending when economic conditions change. Additionally, the concurrent fall in originations and rise in spreads as well as features of the syndication process, when credit conditions tighten, are consistent with a stronger contraction in nonbank credit supply (rather than a reduction in credit demand).

However, the results could still arise because firms differ in their credit demand or credit risk. For example, the higher cyclicality may be the result of riskier firms, which rely more on nonbanks, exhibiting more cyclical credit demand or more volatile default risk than safer firms. We now take seriously the problem of disentangling credit supply from credit demand.

To address this identification challenge, we exploit the unique features of the syndicated loan market to obtain better identification of difference in credit supply from nonbanks and

[21] We obtain data on time-on-the-market, changes in loan spreads during the syndication process, and original issue discount from S&P Capital IQ's Leveraged Commentary & Data (LCD).

banks. As described in the introduction, individual loans in this market are originated as part of deals. About 18% of deals include both bank and nonbank loans which, as documented by Ivashina and Sun (2011), are claims to the same cash flows of a firm, are governed by the same contract, and have the same seniority. We, thus, study the cyclicality of bank vis-á-vis nonbank lending while controlling for deal-specific unobserved variables such as credit demand or borrower default risk through deal fixed effects, in a strategy reminiscent of Khwaja and Mian (2008) and Ivashina and Sun (2011).

We estimate

$$\text{Lending Outcome}_{idft} = \delta_{idt} + \beta_1 \mathbb{I}_{f=\text{TermB}} + \beta_2 \text{Credit Cycle}_{t-1} \times \mathbb{I}_{f=\text{TermB}} + \epsilon_{idft}, \quad (6)$$

where Lending Outcome_{idft} is either (a) the logarithm of the loan issuance volume, or (b) the all-in-drawn spread at origination for borrower i for deal d and facility type f in month t. As before, we use the EBP as the credit cycle variable. Given the inclusion of deal fixed effects δ_{idt}, β_2 measures the differential impact of nonbank lenders' credit supply on lending quantities and spreads when economy-wide credit conditions change. The coefficient is identified by comparing bank and nonbank facilities originated to the same borrower, at the same time, within the same deal. Importantly, deal fixed effects control for unobserved variables that are *common* across bank and nonbank facilities, such as time-varying borrower default risk and borrower credit demand.

Table 6 presents the regression results. Panel A focuses on lending volumes, and Panel B looks at loan spreads. Column 1 shows that a one standard deviation increase in EBP coincides with a reduction of 6.8% in total lending quantities for the same borrower. Splitting by loan type in column 2 shows that this effect is smaller for bank loans and larger for nonbank loans. A one standard deviation increase in the EBP decreases the size of nonbank loans by 12.5 percentage points more than that of bank loans for the same borrower. Again, this reduction is robust to including year-month fixed effects (column 3). After including deal fixed effects (column 4), nonbank lending to the same borrower in the same deal falls by 23.5 ppt more when EBP increases by one standard deviation.

To rule out the concern that firms which generally borrow more from nonbanks have higher credit demand when credit conditions ease and lower credit demand when credit conditions tighten, we include an additional borrower x facility-type fixed effect (column 5). A one standard deviation increase in EBP leads to a 13.9 percentage point difference in loan quantities between bank and nonbank facilities when comparing lending to the same borrower at the same time within the same deal. Comparing the regression coefficients in columns 2 and 5, we conclude that nonbanks' credit supply is more than three times as cyclical as banks' credit supply.[22]

Panel B of Table 6 presents similar results for loan spreads. Column 1 shows that a one standard deviation increase in the EBP coincides with an increase in loan spreads of 16 basis points. Column 2 interacts the EBP with the nonbank loan indicator. A one standard deviation increase in EBP leads to an increase in nonbank loan spreads of 33 basis points relative to bank loan spreads for the same borrower. The relative increase is robust to including year-month fixed effects (column 3), deal fixed effects (column 4), and borrower x facility-type fixed effects (column 5).[23]

Together, these results indicate that nonbank credit supply is more than three times as cyclical as bank credit supply. Nonbank facilities become smaller and more expensive relative to bank facilities when credit conditions tighten – even after controlling for time-varying borrower characteristics and demand.

5.3 Alternative Explanations

We now discuss a series of plausible explanations other than credit supply that could explain the stronger cyclicality in nonbank lending.

[22]Note that the coefficient on the EBP in Column 2, which reflects the cyclicality of bank lending, is not well identified - it captures the effect of credit demand, default risk, and credit supply. Because all forces would pull down lending volumes in bad times and drive up lending in good times, the coefficient essentially represents an upper bound for the credit supply cyclicality of banks. When comparing the coefficient in column 5, which is well identified, with this upper bound, we conclude that nonbank credit supply is *at least* 3.5 (=19.4/5.5 = (13.9 (Column 5) + 5.5 (Column 2))/ 5.5) times as cyclical as bank credit supply.

[23]The results also indicate that nonbank loans are relatively cheaper for firms in good times, while they became relatively more expensive in bad times. One potential reason why firms might borrow from both banks and nonbanks despite one being more expensive than the other is that lenders want to limit their exposure to a single group of lenders.

Bank health. In Section 4.1, we documented a matching pattern between banks and nonbanks and showed that nonbanks purchase more loans from banks with weaker health. This raises an alternate hypothesis - the observed cyclicality in nonbank lending could be due to the cyclical nature of the originating banks. Since banks originate all loans before selling some to nonbank lenders, bank balance sheets may affect originations of nonbank loans. In such a case, lead arrangers' health might influence the cyclicality of nonbank loans even if nonbank credit supply is stable. Our results on the GFC (Section 4) suggest that proxies for bank health commonly used in the literature do not explain declines in nonbank lending. However, those effects may be specific to the GFC or may suggest we need better measures of bank health.

To identify whether bank health and other unobserved bank characteristics affect nonbank cyclicality, we look at bank and nonbank loan origination by the same bank at the same point in time. For this, we aggregate bank and nonbank loans to the originating bank level. If bank capacity is the main determinant of loan origination, we would expect both bank and nonbank lending to vary with bank health. However, bank lending (that directly affects bank balance sheet capacity) would vary to a greater extent with bank health than nonbank lending (which only affects balance sheet capacity due to pipeline risk (Bruche, Malherbe, and Meisenzahl 2020).

The results, which are reported in Table 7, show that independent of syndicating banks' sensitivity to the credit cycle, nonbank loan originations fall by two to three times more than bank loan originations (for the same bank) when credit conditions tighten. We also take into account of whether the bank functions as a non-lead arranger in the syndicate which leaves our results unchanged. These results are in contrast to what we would expect if bank health was the main driver of cyclicality. Thus, our results suggest that nonbank credit supply varies over the cycle and affects lending, over and above, bank health.

Information asymmetry. A large literature argues that the lead bank is tasked with monitoring and screening syndicated loans (Sufi 2007, Ivashina 2009), which might give it an informational advantage over other lenders. Therefore, the lead bank is thought to retain part of the loan to (1) have incentives to engage in costly monitoring effort and (2) signal the quality of the loan. Ivashina and Scharfstein (2010b) argue that lead banks have to retain a larger share of a loan when credit conditions tighten because monitoring becomes more important and the information asymmetry widens. If lead arrangers need to have "skin-in-the-game" by retaining bank tranches, then this might explain the relative weaker decline in bank loan originations.

We conduct additional tests to address these concerns. First, instead of splitting nonbanks and banks to compare relative cyclicality over the credit cycle, we compare nonbanks separately to lead banks and non-lead participant banks. If monitoring becomes more valuable, or lead banks are forced to hold a greater share of the loan in a downturn, we expect to see lead bank lending increasing in a downturn relative to both participant banks and nonbanks. We report the results in Table 8. We find that indeed lead banks' lending is the least cyclical. However, we still find that nonbank lending is more cylical than lending by banks which do not have any special role in the syndicate. For instance, in the tightest specification which compares lending to the same borrower at the same time, we find that nonbanks reduce lending by 22.6 percentage points more than non-lead banks for a one standard deviation increase in the EBP. That is, not only are nonbanks more cyclical than lead banks, they are also more cyclical than participant banks in a syndicated deal.

Furthermore, since monitoring is particularly valuable for more opaque borrowers, we expect a greater shift from nonbank to bank loans for opaque borrowers under the alternative hypothesis. To test this, we repeat the exercise above but include interactions using asymmetric information measures. If asymmetric information is higher between lead banks and nonbanks relative to participant banks, we would expect that nonbank lending falls more than that of banks for firms that are more opaque. We use opaqueness measures from Sufi (2007) such as whether a borrower is young, small, or private. While we find that indeed nonbanks' lending cyclicality is larger for small firms, it does not vary significantly with the age of the firm, and is even lower for private firms (Table 9). We conclude that information asymmetry theories cannot fully explain the higher cyclicality of nonbank lending.

In addition, we look at whether banks that have served as a lead arranger in past deals (even if they are currently a participant in the syndicate) to control for any private information acquired through the past lead relationships. In Appendix Table A10, we interact the credit cycle measure, the excess bond premium, with an indicator for whether the bank has served as a lead arranger in any deal in the past three years.[24] We find, again, nonbank lending is more cyclical than lending by banks that did not function as a lead arranger for the borrower in the past three years. This result further suggests that any private information obtained through a lead arranger relationship does not explain the higher cyclicality of nonbanks.

Additional tests. While we control for time-constant borrower characteristics through borrower × facility-type fixed effects in the main specification, a remaining potential concern is that time variation in borrower characteristics is correlated with the EBP and, hence, with borrowers' suitability or preference for bank or nonbank lenders within the same deal. It is unlikely that worsening credit conditions reduce suitability for nonbank loans because, on average, nonbank borrowers are riskier.[25] Arguably, firms become riskier when the EBP is high and, therefore, one would expect more nonbank lending during crisis periods. This is exactly the opposite prediction relative to the empirical results we document. Nonetheless, changes in borrower characteristics may be correlated with the EBP. To test this, we regress the share of a loan funded by nonbanks, i.e., the Term B share of a deal, on borrower fixed effects, loan purpose fixed effects, and various time-varying borrower characteristics (the S&P rating of the borrower at a given point in time (from Compustat), the equity return volatility over the last three months (from CRSP), and the interest coverage ratio and the book leverage (from Compustat) in Appendix Table A11. We find that none of these controls significantly reduce the coefficient on the EBP, suggesting that time-varying borrower characteristics do not explain the higher cylicality of nonbank lending.

Overall, we conclude that the higher cyclicality of nonbank lending is likely explained by a difference in the cylicality of nonbanks' and banks' credit supply. Alternative explanations based on the special role of banks in loan syndications struggle to explain our results.

We also provide various other robustness checks in the appendix. First, we show that

[24] Results are not sensitive to the choice of time period.

[25] Nonbank lenders typically fund more risky loans (leveraged loans), while banks typically fund borrowers with higher creditworthiness (often investment-grade loans). See Table 1.

our results are unchanged when using only term loans (Table A12) or alternate credit cycle measures (Table A13). Second, our results also hold when we focus only on real investment loans (Table A14). This eliminates any concern that our results are driven by leveraged buyouts or refinancing activity. Our results are also robust to restricting the sample to private borrowers (Table A15). Thus, our findings are unlikely the result of borrowers switching between the loan and bond market. Finally, we show that our results are unchanged when we exclude the GFC (Table A16).

6 The Financing Frictions of Banks vs. Nonbanks

Why are nonbanks more cyclical than banks? The answer for short-term funded nonbanks such as open-end mutual funds seems clear. Their shares are redeemable daily which makes them susceptible to runs, potentially due to strategic complementarities.[26] The run risk of open-end bond and equity mutual funds has been shown in prior studies (Chen, Goldstein, and Jiang 2010, Goldstein, Jiang, and Ng 2017), and we confirm this also for loan mutual funds (Appendix Section A1.4.2). However, the answer is less obvious for long-term funded nonbanks, which constitute the vast majority of nonbank lending in the syndicated loan market.[27]

In the following, we provide a simple conceptual framework which can explain the higher cyclicality of levered, long-term financed nonbanks relative to banks. In particular, we argue and show that debt financing constraints are tighter for nonbanks than banks. To do so, we focus on CLOs, which are the main type of nonbanks in the syndicated loan market, providing about 60% of nonbank financing. We then show that a model with debt-constrained nonbanks and equity-constrained banks can explain the higher cyclicality of nonbank credit supply.

[26] Daily redeemability allows open-end funds to provide valuable liquidity services to their investors (Ma, Xiao, and Zeng 2022)

[27] Open-end mutual funds, and ETFs are the only significant short-term financed nonbanks in this market, and together they constitute less than 20% of nonbank lending. Long-term financed nonbanks includes CLOs and hedge funds.

6.1 Bank and Nonbank Frictions

CLOs are actively managed closed-end funds with maturities in excess of 7 years. Their liabilities are split into tranches of different seniority, and the debt tranches usually constitute 90% of their financing. Parts of the equity tranche are generally held by the CLO manager who structures and manages the CLO. In other words, they provide the initial capital necessary to issue the deal – and borrow the remaining amount from outside debt investors. The combination of inside equity, locked-in outside debt, and the manager's discretion in actively managing the portfolio leads to severe agency problems with debt investors which explains a large part of the strong cyclicality in CLO issuance (Fleckenstein 2022).[28] Thus, CLOs resemble debt-constrained intermediaries (Brunnermeier and Pedersen 2009, Adrian and Shin 2014) which need to delever and, thus, reduce lending in bad times because their debt constraint tightens.

For banks, the debt constraint is arguably much weaker. This is because banks enjoy implicit and explicit guarantees for their liabilities, such as deposit insurance (Gatev and Strahan 2006, Acharya and Mora 2015), ex-post bailouts of uninsured deposits (e.g., desposits at Silicon Valley Bank and others during the 2023 banking crisis), and through equity capital injections (e.g., TARP during the GFC[29]). However, we assume that banks are constrained in issuing outside equity – as are nonbanks – and thus correspond to the intermediaries modeled by He and Krishnamurthy (2012) as well as Brunnermeier and Sannikov (2014).[30]

We present evidence consistent with heterogeneous financing frictions for banks and nonbanks in Figure 7, which plots the dynamics of CLOs' and banks' equity ratio (Panel A), and debt financing costs (Panel B). Specifically, it reveals that CLOs' leverage is pro-cyclical, while, consistent with He, Kelly, and Manela (2017), banks' leverage is counter-cyclical. CLO leverage falls sharply during stress periods such as the GFC and 2015/2016 oil price shock

[28]In addition, as most other securitized and tranched products, CLOs are typically rated "at-the-edge" when issued – meaning that they maximize senior tranche sizes allowable by rating agency models (Griffin and Nickerson 2023).

[29]US banks received equity capital injections by the U.S. Treasury under the Troubled Asset Relief Program (TARP) during the GFC. Flanagan and Purnanandam (2020) find that this implied a $50 billion subsidy to banks. Such a subsidy (or the expectation therefore) can relax banks' debt constraint relative to that of nonbanks which typically do not enjoy these guarantees.

[30]A common micro-foundation for equity constraints is lax effort (He and Krishnamurthy 2012, Hébert 2018).

while bank leverage rose during these episodes, consistent with banks facing no, or at least a much weaker, debt constraints. For instance, during the GFC banks' average equity ratio was only slightly above 3%.

Additionally, CLOs' debt financing costs rise substantially more than those of banks during stress periods, consistent with CLOs facing a stronger tightening of debt constraints. Panel B shows that even for the safest (i.e., AAA-rated) CLO debt tranches, spreads relative to LIBOR (the wholesale funding rate for banks) rise in bad times.[31] Fleckenstein (2022) estimates that a large part of the rise in CLOs' financing costs relative to LIBOR can be attributed to rising agency problems with debt investors.

6.2 *Model Set-Up*

Motivated by this evidence, we propose a model in which debt-constrained nonbanks, as in Adrian and Shin (2014) and Brunnermeier and Pedersen (2009), and equity-constrained banks, as in He and Krishnamurthy (2012) and Brunnermeier and Sannikov (2014), lend to firms which have elastic demand for funds. We provide derivations in Appendix Section A2.

Let bank and nonbank wealth be denoted by w^j for $j \in \{B, NB\}$. Both intermediaries take on leverage to invest q^j in risky loans which have exogenous volatility σ and an endogenous expected return μ that depends on equilibrium credit supply and demand. We assume that the intermediaries can borrow at rate r^f. We model "good times" as times with a low fundamental volatility σ and "bad times" as times with high fundamental volatility. Denoting leverage by $\alpha^j = \frac{q^j}{w^j}$, portfolio j has expected return $\mathbb{E}\left[r^j\right] = \mathbb{E}\left[\frac{w^j_{t+1}}{w^j_t}\right] = r^f + \alpha^j\left(\mu - r^f\right)$ and variance $\mathrm{Var}(r^j) = (\alpha^j)^2\sigma^2$.

The representative nonbank is risk-neutral and faces a value-at-risk constraint. Adrian and Shin (2014) show that a value-at-risk constraint arises as the optimal financing contract under agency problems with debt investors and incomplete contracting, and thus represents a convenient way of modeling debt constraints. The nonbank chooses leverage α_{NB} to maximize

[31] In Appendix Section A1.4, we show that this is robust to using banks' bond yields as measure of banks' marginal funding rate.

expected wealth:

$$\max_{\alpha^{NB}} \mathbb{E}\left[w_{t+1}^{NB}\right] \qquad s.t. \quad \mathrm{Var}(r^{NB}) = (\alpha^{NB})^2\sigma^2 \leq \bar{\sigma}^2. \tag{7}$$

As long as the expected excess return is positive ($\mu > r^f$), optimal leverage is $\alpha^{NB*} = \frac{\bar{\sigma}}{\sigma}$, meaning that the nonbank chooses the maximum leverage possible that fulfills its portfolio volatility constraint, $\bar{\sigma}^2$. Total nonbank lending is then $q^{NB} = w^{NB}\frac{\bar{\sigma}}{\sigma}$.

The representative bank is risk-averse and has mean-variance preferences with an absolute risk aversion γ. This approximates the intermediaries in He and Krishnamurthy (2012) who face an equity issuance constraint that makes them effectively risk-averse.[32] The bank solves

$$\max_{\alpha^B} \mathbb{E}\left[w_{t+1}^B\right] - \frac{\gamma}{2}\mathrm{Var}\left(r^B\right), \tag{8}$$

which yields optimal leverage $\alpha^{*B} = \frac{\mu - r^f}{\gamma\sigma^2}$. Thus, bank leverage increases with equilibrium excess returns and decreases with risk aversion and volatility. Total bank lending is then $q^B = \frac{w^B}{\gamma\sigma^2}\left(\mu - r^f\right)$, which shows that $\frac{w^B}{\gamma\sigma^2}$ can be viewed as a measure of "bank lending capacity" for a given level of equilibrium excess returns, $\left(\mu - r^f\right)$.

The representative firm has downward-sloping demand for capital that depends on equilibrium excess returns

$$q = \bar{q} - \delta\left(\mu - r^f\right), \tag{9}$$

where $\delta \geq 0$ measures the demand elasticity and $\bar{q}$ the loan demand when the expected excess return is 0.

Last, the equilibrium excess return is pinned down by the market clearing condition, $q^{NB} + q^B = \bar{q} - \delta\left(\mu - r^f\right)$. Substituting the optimum for q^{NB} and q^B and solving for the excess return, we obtain:

$$\mu - r^f = \frac{\bar{q} - w^{NB}\frac{\bar{\sigma}}{\sigma}}{\frac{w^B}{\gamma\sigma^2} + \delta}, \tag{10}$$

[32] Another way to think about the risk-aversion of risk-neutral but equity-constrained intermediaries is that they fear bankruptcy and the associated costs (e.g., losing the right to continue the business and thus the ability to be a more productive manager of capital) in the spirit of Brunnermeier and Sannikov (2014). Thus, they require additional compensation to take on more leverage, in particular, when exogenous volatility is high.

which shows that the equilibrium excess returns increase with the residual credit demand (the credit demand that is not satisfied by nonbanks and therefore needs to be satisfied by banks), and decrease with bank lending capacity and firm demand elasticity.

6.3 Predictions for Bank and Nonbank Cyclicality

Let us now explore the model predictions for bank and nonbank lending cyclicality, i.e., their sensitivity to an increase in the exogenous asset volatility, σ.[33] In other words, we investigate how lending changes in "good" versus "bad times".

Bank, nonbank and aggregate lending semi-elasticities to changes in σ are:

$$\begin{aligned} \frac{d \log q^{NB}}{d\sigma} &= -\frac{1}{\sigma} < 0 \\ \frac{d \log q^{B}}{d\sigma} &= -\frac{2}{\sigma} + \frac{1}{(\mu - r^f)} \frac{d}{d\sigma}(\mu - r^f) \lesseqgtr 0 \\ \frac{d \log q}{d\sigma} &= \frac{-\delta}{q} \frac{d}{d\sigma}(\mu - r^f) \leq 0 \\ &\text{where} \quad \frac{d}{d\sigma}(\mu - r^f) = \frac{q^{NB} + 2q^B}{\sigma\left(\frac{w^B}{\gamma\sigma^2} + \delta\right)} > 0. \end{aligned} \tag{11}$$

The first line shows that nonbank lending falls with a rise in volatility since nonbank debt constraints tighten. For banks, the effect of a rise in volatility on lending is ambiguous. On the one side, banks also want to delever and thus reduce lending because of their risk aversion (the first term in the second line). On the other side, banks are willing to expand their lending because the risk premium rises (the second term in the second line). Which force prevails depends crucially on firms' loan demand elasticity, and hence their willingness to pay more on their loans when facing a credit supply contraction.

The third line states how aggregate lending moves with changes in the fundamental volatility. If demand is inelastic ($\delta = 0$) aggregate quantities are fixed and the setting reduces to an asset pricing setting (e.g. He, Kelly, and Manela 2017). Following the volatility-induced deleveraging by nonbanks, the bank takes on leverage to take over the nonbank's assets since

[33]For simplicity, we assume that $Cov(\sigma, w^j) = 0\, \forall j$, but as long as nonbank wealth is not less cyclical than bank wealth, this would strengthen the model predictions.

quantities are fixed (i.e., all assets must be held in equilibrium). The expected returns must rise to fully compensate the bank for the resulting increase in fundamental risk. This is exactly the pattern that He, Khang, and Krishnamurthy (2010) document for the secondary market of mortgage-backed securities during the GFC. However, to study lending markets (the primary market for syndicated loans in our case), we need to consider the case where credit demand is elastic ($\delta > 0$). In this case, bank lending can either fall or rise, depending on whether equilibrium loan returns rise sufficiently to compensate for the higher risk.

We, therefore, explore the model's predictions for the relative cyclicality of bank and nonbank lending when credit demand is elastic ($\delta > 0$). Nonbank credit supply falls more than bank credit supply under the following condition:

$$\frac{dlog(q^{NB})}{d\sigma} < \frac{dlog(q^{B})}{d\sigma} \quad \Leftrightarrow \quad \delta < \frac{\bar{q} \qquad \overbrace{\frac{w^B}{\gamma\sigma^2}}^{\text{bank lending capacity}}}{\bar{q} - 2 \qquad \underbrace{w^{NB}\frac{\overline{\sigma}}{\sigma}}_{\text{nonbank lending capacity}}} \equiv \bar{\delta}^C \tag{12}$$

This shows that nonbank credit supply falls relative to bank credit supply if firms' demand elasticity δ is below a cut-off value $\bar{\delta}^C$. Intuitively, while nonbanks are forced to delever when volatility rises (consistent with the evidence in Figure 7), whether and to what degree banks reduce (or even increase) their leverage (and thus lending) depends on how far they are from their equity constraint (i.e., the size of bank lending capacity), and how much loan returns rise to compensate them for taking on more risk. The latter depends on nonbanks' initial lending capacity and firms' demand elasticity.

Is firms' loan demand indeed sufficiently inelastic for the model to explain the higher cyclicality in nonbank lending? The empirical fact that bank leverage increases in bad times suggests so. Specifically, we show theoretically in Appendix Section A2 that bank leverage increases with volatility if firms' loan demand elasticity is below a certain threshold value (i.e., $\delta < \bar{\delta}^L$). We also show that this threshold is strictly smaller than the cut-off value for δ below which nonbank credit supply is more cyclical (i.e. $\bar{\delta}^L < \bar{\delta}^C$). Therefore, the fact that bank leverage increases in bad times in the data, as shown in Figure 7, suggests that firms' loan demand is sufficiently inelastic (i.e., $\delta < \bar{\delta}^L$) for the model to predict higher nonbank cyclicality (i.e., $\delta < \bar{\delta}^C$).

Therefore, this framework can rationalize our empirical findings that (1) nonbank credit supply is more cyclical than bank credit supply, (2) CLO leverage is pro-cyclical, and (3) bank leverage is counter-cyclical.

6.4 Discussion

We view the debt constraint also as a good representation of financing constraints for other levered nonbanks outside the syndicated loan market such as hedge funds and private debt funds, which typically have substantial leverage (Chernenko, Erel, and Prilmeier 2022, Block, Jang, Kaplan, and Schulze 2023). For instance, Ang, Gorovyy, and Van Inwegen (2011) find that across a wide range of hedge funds, including credit hedge funds, leverage is pro-cyclical, consistent with our argument that nonbanks' debt constraints tighten in bad times.

More generally, we regard government guarantees as the fundamental difference between banks and nonbanks, independent of whether a nonbank's main friction is run risk, or constraints on debt issuance as in the framework above. Banks' government guarantees reduce the run risk for bank liabilities, making them more stable than short-term funded nonbanks (such as open-end mutual funds), and they also relax banks' debt constraints which makes them more stable than levered nonbanks (such as CLOs). Interestingly, we find that the lending cyclicality of mutual funds and CLO is similar despite them being exposed to different underlying frictions (Appendix Table A18). This indicates that our simple model of nonbanks and banks captures the empirical regularities of all nonbanks active in the syndicated loan market.

Based on these arguments, we expect that the conclusions of our work also hold for other markets in which nonbanks and banks operate. Nonbank credit provisioning will be more volatile than bank credit provisioning. The evidence presented in He, Khang, and Krishnamurthy (2010) for the mortgage market supports this conclusion.

7 Conclusion

Our paper documents the impact of nonbanks on lending fluctuations. By contrast, prior work identifies bank health as a key driver of lending fluctuations. We show that not accounting for the importance of nonbanks for loan originations misattributes lending declines to bank health when it is instead the match between weak banks and nonbanks combined with the lack of nonbank demand for loans that drives lending changes. We document that nonbank lending is more cyclical than bank lending after accounting for borrower demand, bank balance sheet capacity, the special role of lead banks, lending relationships, and a multitude of other factors. Overall, our paper highlights the key role of nonbanks for aggregate credit supply in booms and busts.

Our paper has important implications for researchers and policymakers. First, our paper highlights that nonbanks are important for origination even if they do not directly participate in the primary market. Therefore, our results highlight the importance for policymakers to consider the independent role of nonbank credit supply when designing policies to stimulate lending during credit crunches.

Second, our results highlight how underlying frictions in financial markets amplify shocks. As market condition and composition changes with regulation and as the importance of nonbanks increases, it is important to account for heterogeneous intermediaries and their interactions in macro-finance models. One interesting angle for future work – something that our analysis does not take into account – is how the likely rise in aggregate cyclicality due to the growth of nonbank lending could have been offset by tighter bank regulation.

Third, our conceptual framework extends well beyond the syndicated loan market. With the universal rise of nonbanks, we may expect larger fluctuations in other financial markets that contain similar nonbanks.

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Figures

Figure 1: Example of a Syndicated Loan Deal

This figure provides an example of a syndicated loan deal (LPC Deal ID = "209819"). JP Morgan functioned as "admin agent" and all other syndicate banks functioned as "arrangers".

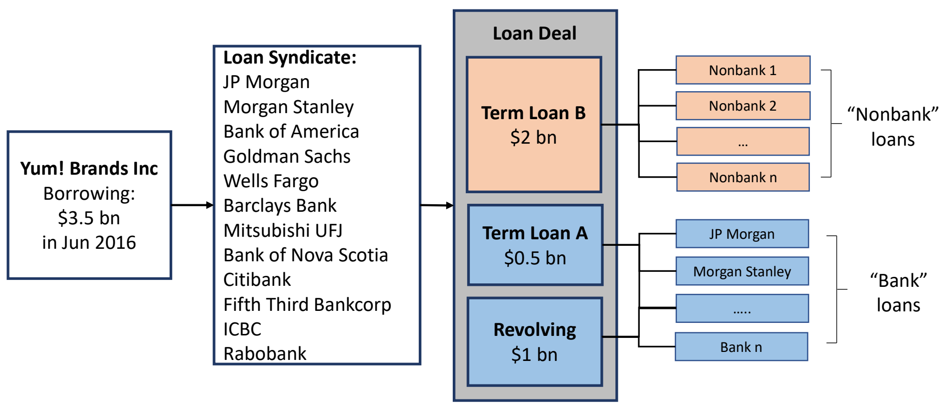


Figure 2: Composition of Nonbank Lenders

This figure shows the decomposition of nonbank lenders in the syndicated loan markets. The assets under management of collateralized loan obligations (CLOs) are obtained from Securities Industry and Financial Markets Association (SIFMA). The assets under management of loan mutual funds (open-end and closed-end), ETFs and separate accounts are obtained from Morningstar. The total nonbank holdings are from Shared National Credit (SNC) Reports, see https://www.occ.treas.gov/publications-and-resources/publications/shared-national-credit-report/index-shared-national-credit-report.html. Because of the reporting requirements, the SNC number represents a lower bound on the total nonbank loan holdings. This explains why the combined mutual fund and CLO holdings were higher than SNC-reported nonbank loan holdings in 2006. The sample period is from 2000-2020.

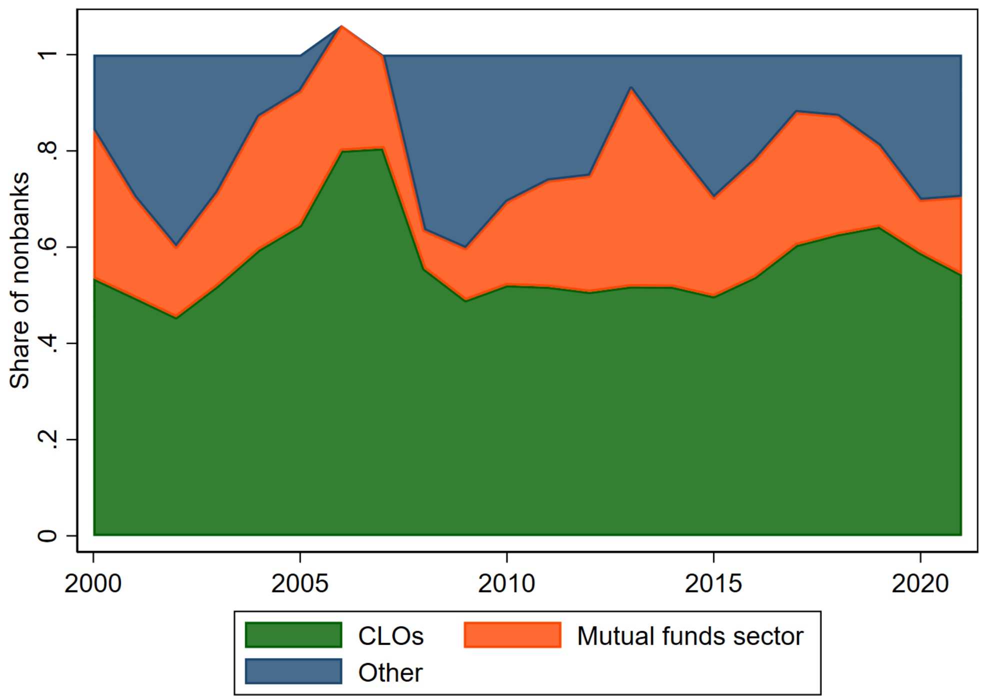


Figure 3: Bank-Nonbank Matching Pattern

This figure shows the sorting pattern between banks and nonbanks. It shows the relationship between a lead arranger's nonbank dependence in 2006 and (i) its business model (investment bank, universal bank or regional bank) and (ii) its capital ratio in 2006. Nonbank dependence is defined as the fraction of loans which are originated as part of nonbank deals. A nonbank deal is a loan deal which contains a nonbank tranche, e.g. Term Loan B. Each loan (deal) is scaled by the share of the lender in the syndicate following Chodorow-Reich (2013). The aggregation of Dealscan lender entities to bank holding companies follows Schwert (2018). Capital ratios are based on market equity relative to book liabilities and market equity obtained from Compustat following Schwert (2018). Only US banks are included. More information on the sample construction can be found in the Appendix Section A1.2.1.

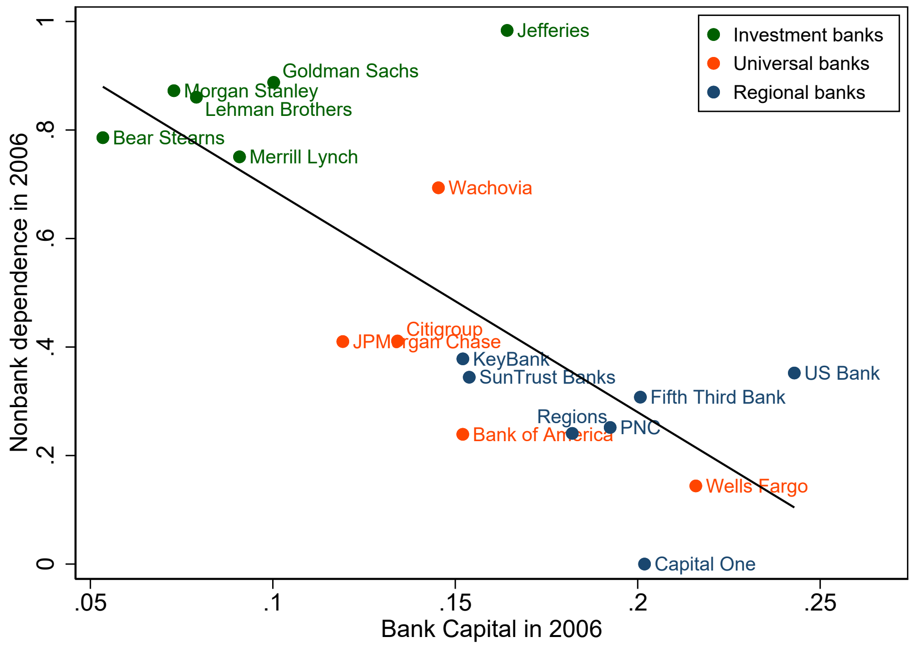


Figure 4: Bank-Nonbank Matching and Lending in the GFC

This figure documents the relationship between pre-crisis nonbank dependence and the decline in loan origination volume during the GFC. Nonbank dependence is defined as the fraction of loan volume that is originated as part of nonbank deals. A nonbank deal is a loan deal which contains a nonbank tranche, e.g. Term Loan B. Nonbank dependence is computed prior to the financial crisis for the period from October 2005 to June 2007. The lending change during the GFC is the volume change of loans originated by a bank between the period October 2005 to June 2007 and October 2008 to June 2009. The aggregation of Dealscan lender entities to bank holding companies follows Chodorow-Reich (2013). Each loan is scaled by the share of the lender in the syndicate following Chodorow-Reich (2013).

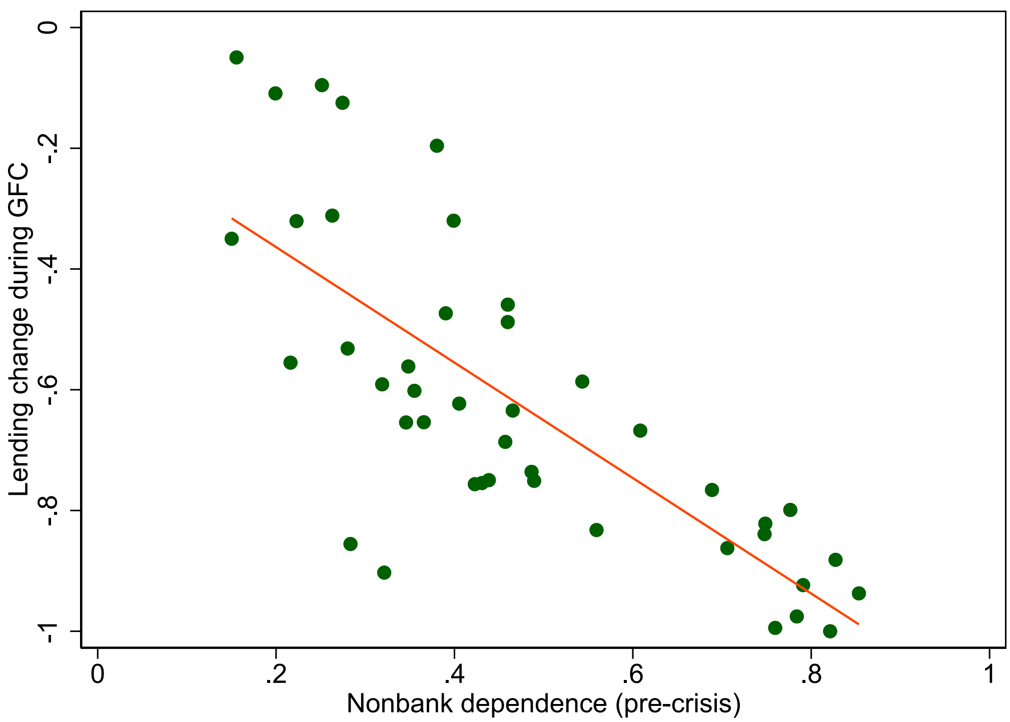
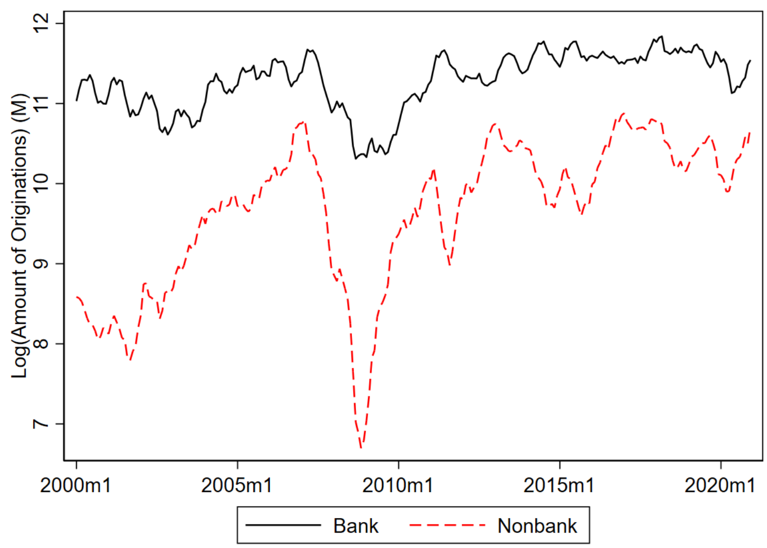


Figure 5: Cyclicality of Originations: Bank vs. Nonbank Lending

This figure shows new originations of bank and nonbank loans between January 2000 and December 2020. We plot a six-month (forward-looking) average of the logarithm of the total origination amount for bank and nonbank loans. Nonbank loans are loans classified as Term Loan B-K, while bank loans are all other loans, including credit lines, Term Loan As or undefined term loans, in Dealscan. Panel A contains all loans, while Panel B includes only real investment loans. Real investment loans are loans whose primary purpose is defined as "corporate purpose", "working capital", or "capital expenditure" according to Dealscan.

Panel A - All Loans



Panel B - Real Investment Loans

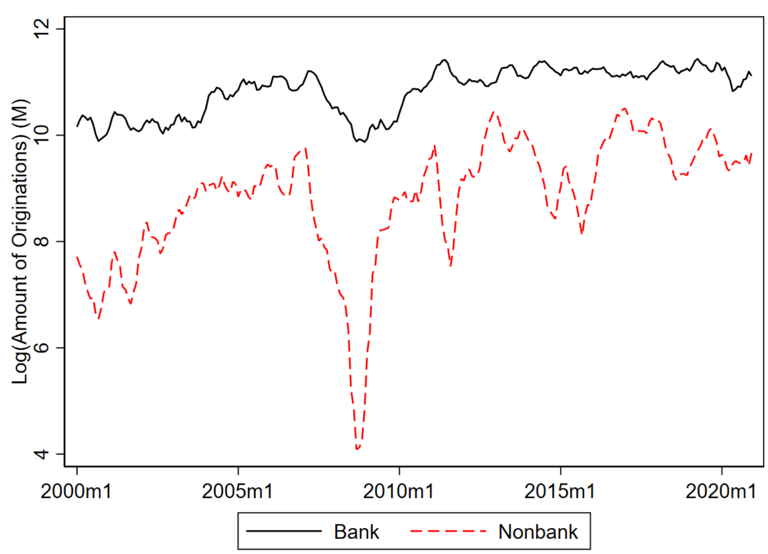
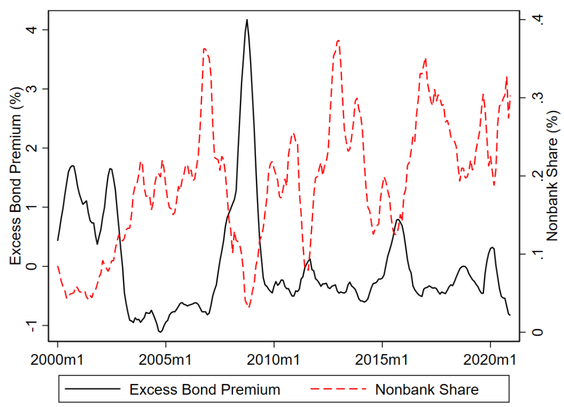


Figure 6: Sensitivity to Credit Cycle: Bank vs. Nonbank Lending

This figure shows how nonbank lending varies with aggregate credit conditions. Panel A shows the nonbank share of newly originated loans vs. the Excess Bond Premium from Gilchrist and Zakrajšek (2012) as a measure of the credit cycle. Panel B shows the difference in the all-in-drawn spread between nonbank and bank term loans, after controlling for loan maturity, seniority, loan purpose and borrower industry. All series are smoothed using a six-month (forward-looking) average. Nonbank loans are loans classified as Term Loan B-K, while bank loans are all other loans, including credit lines, Term Loan As or undefined term loans, in Dealscan. The sample period is from January 2000 to December 2020.

Panel A - Correlation Between Excess Bond Premium and Nonbank Lending Share



Panel B - Correlation Between Excess Bond Premium and Nonbank Loan Pricing

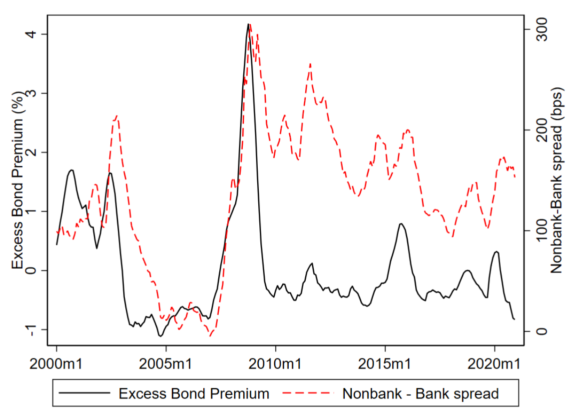
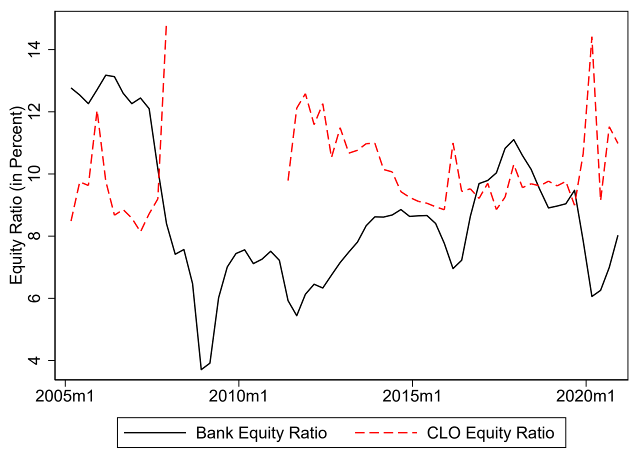


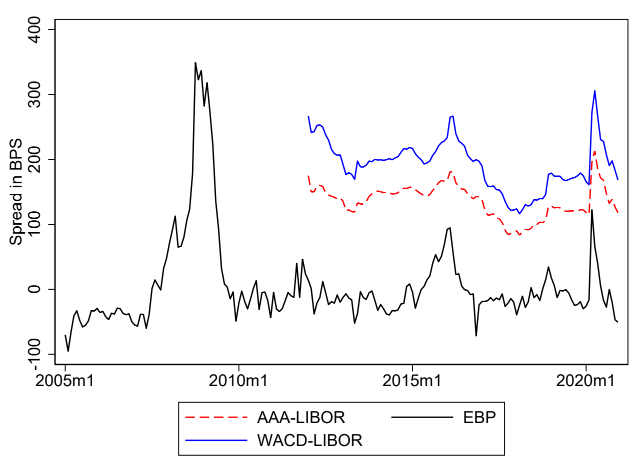
Figure 7: Banks vs. CLOs – Funding Costs and Leverage

This figure plots the average CLO and bank leverage (Panel A) as well as the difference between CLO and bank funding costs (Panel B). The spread between CLO and bank funding costs is defined as the discount margin of outstanding CLO debt relative to the three month USD LIBOR rate. CLO discount margins are obtained from Palmer Squares CLO Debt Indexes, available through Bloomberg. The weighted average cost of debt (WACD) weights each CLO debt tranche-level index by the tranche's share in the average CLO capital structure. The Excess Bond Premium (EBP) from Gilchrist and Zakrajšek (2012) is a measure of the credit cycle. CLO equity ratio is defined as the weighted average equity ratio of all newly issued CLOs in a month. CLO equity ratio is the size of the equity tranche relative to the combined notional value of CLO tranches at origination. We drop CLO equity ratio observations below and above the 2.5th and 97.5th percentile, respectively, which are likely data errors. We also require at least two CLOs for a month to be included to avoid results driven by outliers. We smooth the series by using the moving average of the current and next month. Bank equity ratio is defined as the weighted average $\frac{\text{market value of equity}}{\text{book value of assets + market value of equity - book value of equity}}$ of all bank holding companies in the Dealscan-Compustat link file from Schwert (2018) in a given quarter. We interpolate between quarters to obtain a monthly series. For the year 2020, in which no Dealscan-Compustat lender link file is available, we assume that the links from the prior year are still valid. Investment banks as classified in Dealscan are excluded, and each bank's equity ratio is weighted by its lending market share in Dealscan in the prior quarter. Each equity ratio series is smoothed by averaging over the current and lagged quarter. The sample period is January 2012 (when Palmer Square CLO debt indices become available) to December 2020 in Panel B, and January 2005 (when Creditflux starts covering a large part of the CLO market) to December 2020 in Panel A.

Panel A - Equity Ratio



Panel B - Funding Costs



Tables

Table 1: Summary Statistics

This table presents the summary statistics at the loan level for the loan-volume-weighted loan types (Panel A), general loan characteristics (Panel B), and the loan-volume-weighted loan purposes (Panel C). *Nonbank loans* are all loan facilities classified as Term Loan B-Term Loan K. *Bank Loan Volume* are all other loan types. *Volume* is the loan facility size. *Spread* is the all-in-drawn-spread of the facility. *Maturity* is the facility-level maturity. *Leveraged Loan* indicates whether the spread is above 225, following the leveraged loan definition of Lee, Li, Meisenzahl, and Sicilian (2019). *Part Nonbank Deal* indicates whether the loan facility is part of a loan deal that contains a nonbank loan facility. Loans are classified as *General Purpose* if the loan purpose variable in Dealscan contains “General Purpose”, *Working Capital* if the loan purpose contains “Working Capital”, and *LBO* if the loan purpose contains “Buyout”. The sample period is from January 2000 and December 2020.

Panel A - Loan Type

	Bank loans	Nonbank loans
	%	%
Term Loan A	15.54	0.00
Term Loan B	0.00	100.00
Credit Line & Other Loans	84.46	0.00
Observations	79198	14802

Panel B - General Loan Characteristics

	Bank loans		Nonbank loans	
	Mean	SD	Mean	SD
Volume (in Mill. USD)	277.29	807.30	380.99	624.45
Spread (in basis points)	274.75	165.63	389.67	139.85
Maturity (in months)	48.74	22.59	66.65	18.27
Leveraged Loan (in %)	52.08	49.96	87.02	33.61
Part Nonbank Deal (in %)	17.98	38.40	100.00	0.00
Observations	79217		14806	

Panel C - Loan Purpose

	Bank loans	Nonbank loans
	%	%
General Purpose	58.85	54.17
Working Capital	8.00	2.05
LBO	3.31	19.10
Other	29.84	24.68
Observations	79198	14802

Table 2: A Decomposition of the Credit Crunch during the GFC

This table uses equations (1) and (2) to decompose the change in the number of loans originated by a bank during the financial crisis. The lending change during the GFC is the change in the number of loans originated by a bank between the period October 2005 to June 2007 and October 2008 to June 2009. Nonbank dependence is defined as the fraction of loans that are originated as part of nonbank deals. A nonbank deal is a loan deal which contains a nonbank loan as defined in Section 2. Nonbank dependence is computed prior to the financial crisis for the period from October 2005 to June 2007. Each loan is scaled by the share of the lender in the syndicate following Chodorow-Reich (2013). The aggregation of Dealscan lender entities to bank holding companies follows Chodorow-Reich (2013). The table shows the lending changes of the top 10 banks by pre-crisis market share as well as the lending change of all banks (inside and outside of the top 10).

	Δ Loans in all deals	Δ Loans in nonbank deals	Nonbank depend.	Δ Loans in bank deals	Bank depend.	Nonbank contribution	Bank contribution	Market Share
	$(1) = (2) \cdot (3) + (4) \cdot (5)$	(2)	(3)	(4)	(5)	$= \frac{(2)\cdot(3)}{(1)}$	$= \frac{(4)\cdot(5)}{(1)}$	
Bank of America	-0.60	-0.94	0.36	-0.41	0.64	0.56	0.44	0.132
JPMorgan	-0.76	-0.98	0.42	-0.59	0.58	0.55	0.45	0.102
GE Capital	-0.82	-0.97	0.75	-0.39	0.25	0.88	0.12	0.075
Wachovia	-0.75	-0.99	0.43	-0.57	0.57	0.57	0.43	0.056
Wells Fargo	-0.32	-0.87	0.40	0.05	0.60	1.09	-0.09	0.052
Credit Suisse	-0.88	-0.95	0.83	-0.55	0.17	0.89	0.11	0.047
Citigroup	-0.74	-0.89	0.49	-0.59	0.51	0.59	0.41	0.046
CIT	-0.80	-0.94	0.78	-0.29	0.22	0.92	0.08	0.034
PNC	-0.31	-0.96	0.26	-0.08	0.74	0.81	0.19	0.028
Goldman Sachs	-0.92	-0.98	0.79	-0.69	0.21	0.84	0.16	0.027
All Banks	-0.68	-0.96	0.50	-0.40	0.50	0.71	0.29	1.000

Table 3: Bank Health vs. Nonbank Dependence during the GFC

This table reports regression results on lending changes during the GFC. The unit of observation is a bank. Columns (1)-(6) considers all loans, while Columns (7) and (8) include only bank and nonbank loan deals, respectively. The lending change is the change in the number loans originated by a bank between the period October 2005 to June 2007 and October 2008 to June 2009. Nonbank dependence is defined as the fraction of loans that are originated as part of nonbank deals. A nonbank deal is a loan deal which contains a nonbank loan (Term Loan B-K) as defined in Section 2. Nonbank dependence is computed prior to the financial crisis for the period from October 2005 to June 2007. Bank health measures are obtained from Chodorow-Reich (2013) and are normalized to have mean zero and standard deviation of one. Each loan is scaled by the importance of the lender in the loan syndicate computed as in Chodorow-Reich (2013). The observations are weighted by the number of pre-crisis borrowers to capture the economic importance of each bank. Robust standard errors are in parentheses. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

	Δ All Loans						Δ Bank	Δ Nonbank
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lehman exposure	−0.136***			0.029			−0.098	0.006
	(0.034)			(0.022)			(0.077)	(0.024)
ABX Exposure		−0.097*			−0.036		−0.061	−0.003
		(0.048)			(0.046)		(0.067)	(0.013)
07-08 Trading Rev/AT			0.061**			0.031	0.114***	−0.007
			(0.029)			(0.027)	(0.041)	(0.014)
RE CO flag			0.011			−0.057	−0.061	−0.010
			(0.049)			(0.046)	(0.055)	(0.015)
07-08 RE NCO/AT			−0.081*			−0.036	−0.061	−0.001
			(0.043)			(0.039)	(0.050)	(0.012)
07 Deposits/Assets			0.175***			0.068	0.101	0.015
			(0.054)			(0.059)	(0.083)	(0.024)
Nonbank Dependence				−0.964***	−0.830***	−0.901***		
				(0.176)	(0.150)	(0.243)		
Obs.	42	40	42	42	40	42	38	38
R^2	0.171	0.136	0.344	0.458	0.490	0.519	0.274	0.033

Table 4: Employment Effects of Bank and Nonbank Credit Availability

This table reports the fraction of employment losses due to *nonbank* and *bank* credit availability at small and medium firms. We follow the methodology and estimates in Chodorow-Reich (2013). Firm i's employment loss is computed as

$$\Delta E_i = \zeta_{1,i} \cdot \min\{\Delta L_{i,s} - \Delta L_{Q_\tau}, 0\},$$

where $\Delta L_{i,s}$ measures firm i's exposure to the credit crunch by looking at how much its pre-crisis syndicate members (in the last loan obtained by the firm i prior to the GFC) reduced their lending for all other borrowers. $\zeta_{1,i}$ measures the pass-through from credit to employment that depends on the size of firm i (smaller firms are more affected than medium-sized firms, large firms are not affected). τ refers to the percentile of the lending syndicate that is assumed to not have changed its credit supply or "lending function". Accordingly, ΔL_{Q_τ} states the threshold below which a lending change is ascribed to a decline in credit supply. We then use equation (1) to decompose $\Delta L_{i,s}$ into a *nonbank* component and a *bank* component. Summing across all small and medium firms and using the estimates for $\zeta_{1,i}$ from Chodorow-Reich (2013), we obtain the aggregate employment losses due to *nonbank* and *bank* credit availability. The methodology is described in detail in Appendix Section A1.2.4.

	Credit supply percentile		
	$\tau = 90$	$\tau = 95$	$\tau = 98$
	(1)	(2)	(3)
Total employment decline 2008:3 – 2009:3 (%)	7.0	7.0	7.0
Credit supply threshold L_{Q_τ} (%)	-29.7	-19.5	0.0
Share of losses due to credit availability (%)	36.8	49.8	77.2
thereof: Nonbank credit availability (%)	77.3	69.5	58.3
thereof: Bank credit availability (%)	22.7	30.5	41.7

Table 5: Nonbank Lending Cyclicality - Aggregate Results

This table reports results on aggregate monthly loan originations. The unit of observation is a Loan-type x Month pair. We report the results of

$$\text{Lending Outcome}_{ft} = \beta_0 + \beta_1 \text{Credit Cycle}_{t-1} + \beta_2 \mathbb{I}_{f=\text{TermB}} + \beta_3 \text{Credit Cycle}_{t-1} \times \mathbb{I}_{f=\text{TermB}} + \epsilon_{ft}$$

where Lending Outcome$_{f,t}$ is either the log of the total origination amount (Panel A) or the weighted average spread (Panel B) for all loans of facility type f originated in month t. $\mathbb{I}_{f=\text{Term B}}$ is a dummy variable that takes a value of 1 if the facility is a nonbank loan, as defined in Section 2. Credit Cycle is the Excess Bond Premium from Gilchrist and Zakrajšek (2012). Our sample includes all loans originated between January 2000 and December 2020. The Excess Bond Premium is standardized to have mean 0 and standard deviation of 1. Robust standard errors are presented. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Panel A - Loan Volumes

	Log(Facility Amount)		
	(1)	(2)	(3)
Excess Bond Premium	−0.440***	−0.169***	
	(0.042)	(0.037)	
Term B	−1.653***	−1.629***	−1.629***
	(0.059)	(0.054)	(0.038)
Excess Bond Premium x Term B		−0.543***	−0.543***
		(0.062)	(0.047)
Year-Month FE	N	N	Y
Obs.	504	504	504
R^2	0.665	0.721	0.930

Panel B - Loan Spreads

	All-in-drawn Spread		
	(1)	(2)	(3)
Excess Bond Premium	22.208***	12.672***	
	(4.449)	(4.480)	
Term B	185.024***	184.182***	184.182***
	(5.728)	(5.569)	(3.885)
Excess Bond Premium x Term B		19.072**	19.072**
		(8.969)	(7.864)
Year-Month FE	N	N	Y
Obs.	504	504	504
R^2	0.688	0.695	0.923

Table 6: Nonbank Lending Cyclicality - Within-Deal Results

This table reports results at the loan type $\times$ loan deal level. We estimate

$$\text{Lending Outcome}_{idft} = \delta_{idt} + \beta_1 \text{Credit Cycle}_{t-1} \times \mathbb{I}_{f=\text{TermB}} + \beta_2 \mathbb{I}_{f=\text{TermB}} + \epsilon_{idft}$$

where Lending Outcome$_{idft}$ is the logarithm of the loan issuance volume (Panel A), or the all-in-drawn spread (Panel B) at origination to borrower i for deal d, facility-type f, which is either a bank loan or nonbank loan as defined in Section 2, in month t. $\mathbb{I}_{f=\text{Term B}}$ is a dummy variable that takes a value of 1 if the facility is a nonbank loan, as defined in Section 2. Credit Cycle is the Excess Bond Premium from Gilchrist and Zakrajšek (2012). Our sample includes all loans originated between January 2000 and December 2020. The Excess Bond Premium is standardized to have mean 0 and standard deviation of 1. Standard errors are double clustered at the firm and month level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Panel A - Loan Volumes

	Log(Facility Amount)				
	(1)	(2)	(3)	(4)	(5)
Excess Bond Premium	−0.068***	−0.055***			
	(0.015)	(0.013)			
Term B	0.479***	0.445***	0.412***	0.585***	
	(0.027)	(0.029)	(0.028)	(0.038)	
Excess Bond Premium x Term B		−0.125***	−0.153***	−0.235***	−0.139***
		(0.032)	(0.029)	(0.050)	(0.029)
Borrower FE	Y	Y	Y	N	N
Year-Month FE	N	N	Y	N	N
Deal FE	N	N	N	Y	Y
Borrower x Facility-Type FE	N	N	N	N	Y
Obs.	59,881	59,881	59,881	18,166	11,978
R^2	0.722	0.723	0.758	0.815	0.930

Panel B - Loan Spreads

	All-in-drawn Spread				
	(1)	(2)	(3)	(4)	(5)
Excess Bond Premium	16.041***	12.332***			
	(2.380)	(2.492)			
Term B	27.161***	36.363***	37.966***	0.170	
	(3.057)	(2.665)	(2.659)	(2.782)	
Excess Bond Premium x Term B		32.979***	30.547***	25.240***	21.114***
		(3.292)	(2.656)	(2.967)	(2.811)
Borrower FE	Y	Y	Y	N	N
Year-Month FE	N	N	Y	N	N
Deal FE	N	N	N	Y	Y
Borrower x Facility-Type FE	N	N	N	N	Y
Obs.	53,452	53,452	53,452	16,576	10,882
R^2	0.678	0.680	0.719	0.786	0.904

Table 7: Within-bank Cyclicality

This table presents results on bank vs. nonbank loan originations at the bank level. Observations are at the Bank x Loan-type x Month level. We report results from the regression

$$\text{Lending Outcome}_{bft} = \delta_{bt} + \beta_1 \text{Credit Cycle}_{t-1} \times \mathbb{I}_{f=\text{TermB}} + \beta_2 \mathbb{I}_{f=\text{TermB}} + \epsilon_{bft}$$

where Lending $\text{Outcome}_{b,f,t}$ is either the log of total loan amount (Panel A) or the weighted average spread (Panel B) of all loans of facility type f originated by bank b in month t. We distribute loan amount across all syndicate members within a facility following Chodorow-Reich (2013).$\mathbb{I}_{f=\text{Term B}}$ is a dummy variable that takes a value of 1 if the facility is a nonbank loan, as defined in Section 2. Credit Cycle is the Excess Bond Premium from Gilchrist and Zakrajšek (2012). Our sample includes all loans originated between January 2000 and December 2020. Column (1)-(3) includes all loans the bank participantes in. Column (4) considers only loans where bank b was not a lead arranger. The Excess Bond Premium is standardized to have mean 0 and standard deviation of 1. Standard errors are clustered at the bank and month level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Panel A - Loan Volume

	Log(Amount)			
	(1)	(2)	(3)	(4)
Excess Bond Premium	−0.208***	−0.209***		
	(0.035)	(0.036)		
Term B	−1.547***	−1.764***	−1.841***	−1.887***
	(0.136)	(0.117)	(0.122)	(0.112)
Excess Bond Premium x Term B	−0.282***	−0.330***	−0.388***	−0.371***
	(0.058)	(0.055)	(0.047)	(0.051)
Bank FE	N	Y	N	N
Bank x Month FE	N	N	Y	Y
Role	All	All	All	Non-Lead
Obs.	17,521	17,521	15,014	14,568
R^2	0.255	0.560	0.840	0.836

Panel B - Loan Spread

	All-in-drawn-spread			
	(1)	(2)	(3)	(4)
Excess Bond Premium	11.988***	12.140***		
	(3.541)	(3.543)		
Term B	169.757***	168.331***	170.437***	169.986***
	(6.343)	(6.273)	(6.107)	(5.821)
Excess Bond Premium x Term B	15.547***	15.230***	18.126***	17.581***
	(5.108)	(4.927)	(4.765)	(4.897)
Bank FE	N	Y	N	N
Bank x Month FE	N	N	Y	Y
Role	All	All	All	Non-Lead
Obs.	17,521	17,521	15,014	14,568
R^2	0.456	0.514	0.811	0.813

Table 8: Cyclicality of Lead Banks, Non-lead Banks, and Nonbanks

This table presents results on new loan origiantions as in Table 6 but by lender role. We distribute loan amount across all syndicate members within a facility following Chodorow-Reich (2013). Lead Banks denotes the amount of the *bank loan* held by lead arrangers of the syndicate. Non-lead bank amounts are based on the amount of *bank loans* held by non-lead banks. Nonbank amount is nonbank loan volume. Bank and nonbank loans are classified as described in Section 2. Credit Cycle is the Excess Bond Premium from Gilchrist and Zakrajšek (2012), standardized to mean 0 and standard deviation 1. The lead bank is defined on the deal level and as by Sufi (2007) and Ivashina (2009). Non-lead banks are the ommitted group. Our sample includes all loans originated between January 2000 and December 2020.

	Log(Facility Amount)		
	(1)	(2)	(3)
EBP	−0.045***		
	(0.014)		
Lead Bank × EBP	0.015*	0.015*	0.010
	(0.008)	(0.008)	(0.008)
Nonbank × EBP	−0.141***	−0.164***	−0.226***
	(0.035)	(0.032)	(0.048)
Borrower FE	Y	Y	N
Year-Month FE	N	Y	N
Deal FE	N	N	Y
Lender-Role FE	Y	Y	Y
Obs.	114,781	114,781	107,033
R^2	0.688	0.715	0.855

Table 9: Cyclicality of Lead Banks, Non-lead Banks, and Nonbanks by Borrower Characteristics

This table presents results on new loan origiantions as in Table 6 but by lender role and borrower characteristics. We distribute the loan amount across all syndicate members within a facility following Chodorow-Reich (2013). We distribute loan amount across all syndicate members within a facility following Chodorow-Reich (2013). Lead Banks denotes the amount of the *bank loan* held by lead arrangers of the syndicate. Non-lead bank amounts are based on the amount of *bank loans* held by non-lead banks. Nonbank amount is nonbank loan volume. Bank and nonbank loans are classified as described in Section 2. Credit Cycle is the Excess Bond Premium from Gilchrist and Zakrajšek (2012), standardized to mean 0 and standard deviation 1. The lead bank is defined on the deal level and as by Sufi (2007) and Ivashina (2009). Non-lead participant banks are the ommitted group. *Small* indicates whether the borrower's total assets are below the median among all matched Dealscan-Compustat firms. *Young* indicates whether the borrower's time since the first filing in Compustat is below the median. *Young-DS* indicates whether the borrower's number of loan deals in Dealscan is below the median. *Public* indicates whether the borrower is in Compustat. Our sample includes all loans originated after 2000 in the matched Dealscan-Compustat sample, which ends in 2017Q1.

	Log(Facility Amount)			
	(1)	(2)	(3)	(4)
Lead Bank × EBP	0.068***	0.040***	0.009	−0.014*
	(0.013)	(0.012)	(0.009)	(0.008)
Nonbank × EBP	−0.168***	−0.239***	−0.254***	−0.158***
	(0.051)	(0.063)	(0.048)	(0.058)
Lead Bank × Small × EBP	−0.026*			
	(0.014)			
Nonbank × Small × EBP	−0.155***			
	(0.053)			
Lead Bank × Young × EBP		0.030**		
		(0.014)		
Nonbank × Young × EBP		−0.044		
		(0.066)		
Lead Bank × Young-DS × EBP			0.002	
			(0.010)	
Nonbank × Young-DS × EBP			0.066	
			(0.042)	
Lead Bank × Public × EBP				0.068***
				(0.012)
Nonbank × Public × EBP				−0.115**
				(0.051)
Borrower FE	N	N	N	N
Year-Month FE	N	N	N	N
Deal FE	Y	Y	Y	Y
Lender-Role FE	Y	Y	Y	Y
Obs.	44,489	44,489	107,033	91,137
R^2	0.874	0.858	0.855	0.867

Internet Appendix
Nonbank Lending and Credit Cyclicality

A1 Additional Empirical Results

A1.1 Institutional Setting

Table A1: Summary Statistics - Creditflux-DealScan Sample

This table presents the summary statistics at the loan facility level for general loan characteristics (Panel A), the CLO holding weighted loan types (Panel B) and the CLO holding weighted loan purposes (Panel C) for all loans in Dealscan that can be matched to the CLO holdings provided by Creditflux. *Nonbank loans* are all loan facilities classified as Term Loan B-Term Loan K. *Bank Loan Volume* are all other loan types. *Volume* is the loan facility size. *Spread* is the all-in-drawn-spread of the facility. *Maturity* is the facility-level maturity. *Leveraged Loan* indicates whether the spread is above 225, following the leveraged loan definition of Lee, Li, Meisenzahl, and Sicilian (2019). Loans are classified as *General Purpose* if the loan purpose variable in Dealscan contains "General Purpose", *Working Capital* if the loan purpose contains "Working Capital", and *LBO* if the loan purpose contains "buy out". The sample period goes from January 2000 to December 2020.

Panel A - General Loan Characteristics

	CLO Held Loans	
	Mean	SD
Volume (in Mill. USD)	507.66	829.85
Spread (in basis points)	397.70	163.88
Maturity (in months)	67.46	17.67
Leveraged Loan (in %)	82.13	38.31
Observations	8639	

Panel B - Loan Type

	CLO Held Loans
	%
Term Loan A	5.84
Term Loan B	86.13
Credit Line & Other Loans	8.02
Observations	8959

Panel C - Loan Purpose

	CLO Held Loans
	%
General Purpose	56.01
Working Capital	0.47
LBO	18.90
Other	24.62
Observations	8959

A1.2 Banks vs. Nonbanks During the Global Financial Crisis

A1.2.1 Bank-Nonbank Matching

In this section, we look at the interaction of banks originating loans and nonbank lenders providing funding for loans.[34] We ask which banks are have the highest nonbank dependence or, in other words, are the most active in the nonbank segment. From an institutional point of view, we would expect that banks who are specialized in intermediating between firms and investors originate a larger fraction of nonbank deals. This is exactly what we find. We show that "investment banks" and weaker capitalized banks in general originate a larger fraction of nonbank deals.

To document the bank-nonbank matching pattern, we relate a lead arranger's "nonbank dependence", defined as the fraction of loans originated through nonbank deals, to its business model and its capital ratio. To do so, we aggregate loan-level data to the lead arranger level, distinguishing between loans originated through bank deals and nonbank deals, i.e., loan deals that contain a nonbank tranche. We use the linking file from Schwert (2018) to match Dealscan lenders to the Compustat bank holding companies. The matching file is available for the period from 2000 to 2019 which represents our sample period for this analysis. We then define, for each lead arranger, the fraction of loans that is originated through nonbanks deals (nonbank dependence). For example, Goldman Sachs was the lead arranger on 209 loans in 2006 of which 183 loans were originated in nonbank deals. This implies that the fraction of loans originated through nonbank deals 87.5%. To get to the final nonbank dependence, we follow the prior literature and scale each loan by the importance of Goldman Sachs in the syndicate (i.e., the lead share) to follow the prior literature (Chodorow-Reich 2013, Schwert 2018). Adjusting for the loan shares, we obtain a nonbank dependence of 88.6% of Goldman Sachs for 2006.

We then examine which bank characteristics explain a lead arrangers' nonbank dependence. We test this formally with the regression

$$\text{Nonbank Dependence}_{tb} = \beta_0 + \beta_1 \text{Bank Type}_b + \beta_2 \text{Capital Ratio}_{tb} + \delta_t + \epsilon_{tb}, \qquad (13)$$

where Nonbank Dependence_{tb} is the fraction of loans originated by lead arranger b in year t through nonbank deals. BankType_b are dummies for whether a bank is an investment, a

[34] Technically, banks provide the funding for corporations and then enter into arrangements to sell their loan shares to nonbank lenders after deal closing. However, this two-step process occurs mostly due to tax incentives (Blickle, Fleckenstein, Hillenbrand, and Saunders 2020). Thus, we can think of nonbank lenders funding part of the original loan deal.

universal or a regional banks.[35] CapitalRatio$_{tb}$ is the capital ratio defined as the ratio of market capitalization relative to quasi-market assets computed Compustat data following Schwert (2018). We drop economically unimportant lead arrangers and focus on the top 43 lead arrangers over the past 20 years following Chodorow-Reich (2013). From the remaining list of arrangers, we also eliminate nonbanks and Bank of New York Mellon (because it is primarily a custodian bank). We also include year fixed effects δ_t to remove time trends. Thus, we are identifying the coefficients from the variation across banks at a given point in time. The coefficients β_1 and β_2 test the sorting patterns.

Figure 3 (which can be found in the main paper) relates lead arrangers' nonbank dependence to their capital ratio as well as their business model in 2006. The figure documents a strong negative relationship between a lead arranger's capital ratio and its nonbank dependence. Lead arrangers with a lower capital ratio collaborate more with nonbanks. There is strong overlap with a lead arranger's operating model: investment banks have the lowest capital ratios and collaborate the most with nonbank lenders, universal banks are in the middle, while regional banks have the highest capital ratios and collaborate the least with nonbank lenders.

Table A2 reports the regression estimates. Column (1) shows that investment banks originate a larger fraction of nonbanks than universal banks, while regional banks originate less. The R-squared of 78% indicates that a bank's business model explain most of the variation in the nonbank activity. Note that this comes almost entirely from thebank type dummies as the R-squared in a regression with only year fixed effect is only 10%. Thus, the sorting pattern is stark. Column (2) documents a negative relationship between a lead arranger's nonbank dependence and its capital ratio. The R-squared indicates that the capital ratio explains slightly less than a third of the variation in the nonbank dependence. We combine the variables in column (3). The R-squared rises only marginally relative to column (1) indicating that most of the explanatory power comes from a banks' business model. The coefficient on the capital ratio decreases relative to column (2). This makes sense given that investment banks typically operate with the lowest capital ratio, while regional banks have a much higher capital ratio (see also Figure 3). Column (4) documents that the relationships are similar when we focus on all loans for which a banks participates in the syndicate. Column (5) adds international banks and finds similar results.

[35] We classify Morgan Stanley, Jefferies, Goldman Sachs, Lehman Brothers, Bear Stearns, and Merrill Lynch as investment banks; JP Morgan Chase, Wachovia, Citigroup, Bank of America, Wells Fargo and BNY Mellon as universal banks; KeyBank, SunTrust Banks, US Bank, Regions Financial, Fifth Third Bank, Capital One, PNC Financial Services as regional banks.

Table A2: Bank-Nonbank Matching Pattern

This table tests the sorting pattern between banks and nonbanks by estimating regression (13). The table shows the relationship between a lead arranger's nonbank dependence and (i) its business model (ie., whether the bank is an investment bank, universal bank or regional bank) and (ii) its capital ratio. The unit of observation is a lead arranger x year observation. The dependent variable is a lead arranger's nonbank dependence. Nonbank dependence is defined as the fraction of loans that is originated as part of nonbank deals. A nonbank deal is a loan deal which contains a nonbank tranche, e.g. Term loan B tranche. Each loan (deal) is scaled by the share of the lender in the syndicate following Chodorow-Reich (2013). The aggregation of Dealscan lender entities to bank holding companies follows Schwert (2018). Capital ratios are based on market equity relative to book liabilities and market equity obtained from Compustat following Schwert (2018). Standard errors are clustered by year and by lead arranger. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

	Nonbank Dependence				
	(1)	(2)	(3)	(4)	(5)
Investment bank	0.455***		0.424***	0.365***	0.440***
	(0.050)		(0.049)	(0.042)	(0.035)
Regional bank	−0.104*		−0.081	−0.067	−0.068
	(0.053)		(0.050)	(0.042)	(0.044)
Capital ratio		−3.189***	−0.829**	−0.485*	−0.764**
		(0.572)	(0.300)	(0.262)	(0.360)
Observations	303	303	303	305	621
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.780	0.394	0.793	0.798	0.636
Bank Sample	US banks	US banks	US banks	US banks	All banks
Syndicate Role	Lead arranger	Lead arranger	Lead arranger	Any role	Lead arranger
R^2 with only Year FE	0.100	0.100	0.100	0.160	0.090
R^2 with Bank FE and Year FE	0.870	0.870	0.870	0.880	0.750

The bank-nonbank matching pattern has important implications. If the lending by nonbanks and banks varies over the business cycle, we need to make sure to look beyond a lead arranger's total originations to draw conclusions about the lending behavior of the lead arranger.

Table A3: Bank-Nonbank Matching Pattern prior to the GFC

This table reports regression results about nonbank dependence and bank health during the GFC. The unit of observation is a bank. It relates nonbank dependence to various bank health measures. Nonbank dependence is defined as the fraction of loans that are originated as part of nonbank deals. Bank health measures are obtained from Chodorow-Reich (2013) and are normalized to have mean zero and standard deviation of one. Each loan is scaled by the importance of the lender in the loan syndicate computed as in Chodorow-Reich (2013). The observations are weighted by the number of pre-crisis borrowers to capture the economic importance of each bank. Robust standard errors are in parentheses. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Panel A - All loans

	Nonbank Dependence		
	(1)	(2)	(3)
Lehman exposure	0.171***		
	(0.038)		
ABX Exposure		0.074**	
		(0.031)	
07-08 Trading Rev/AT			−0.034**
			(0.016)
RE CO flag			−0.075**
			(0.034)
07-08 RE NCO/AT			0.050***
			(0.015)
07 Deposits/Assets			−0.119***
			(0.032)
Obs.	42	40	42
R^2	0.468	0.133	0.626

Panel B - Corporate purpose loans

	Nonbank Dependence		
	(1)	(2)	(3)
Lehman exposure	0.169***		
	(0.039)		
ABX Exposure		0.064**	
		(0.028)	
07-08 Trading Rev/AT			−0.026
			(0.016)
RE CO flag			−0.064
			(0.038)
07-08 RE NCO/AT			0.045***
			(0.013)
07 Deposits/Assets			−0.116***
			(0.035)
Obs.	42	40	42
R^2	0.476	0.105	0.561

A1.2.2 A Decomposition of Bank-Level Loan Originations

We want to show the identity (1)

$$\Delta \mathrm{L}_b = \left(1 - \mathrm{NBDep}_{b,pre}\right) \times \Delta \mathrm{L}_b^B + \mathrm{NBDep}_{b,pre} \times \Delta \mathrm{L}_b^{NB}.$$

Let us start by decompose the number of loans originated by bank b, Count_b into the number of loans that are originated through bank deals, Count_b^B, and the number of loans that are originated through nonbank deals, Count_b^{NB}. We can do this decomposition for the period prior to the financial crisis

$$\mathrm{Count}_{b,pre} = \mathrm{Count}_{b,pre}^{NB} + \mathrm{Count}_{b,pre}^{B} \tag{14}$$

or during the financial crisis

$$\mathrm{Count}_{b,crisis} = \mathrm{Count}_{b,crisis}^{NB} + \mathrm{Count}_{b,crisis}^{B}. \tag{15}$$

We can then derive the identity by starting with the definition of the change in the number of loans originated by bank b, $\Delta \mathrm{L}_b$, and using equations (14) and (15)

$$\begin{aligned}
\Delta \mathrm{L}_b &\equiv \frac{\mathrm{Count}_{b,crisis} - \mathrm{Count}_{b,pre}}{\mathrm{Count}_{b,pre}} \\
&= \frac{\left(\mathrm{Count}_{b,pre}^{NB} + \mathrm{Count}_{b,pre}^{B}\right) - \left(\mathrm{Count}_{b,crisis}^{NB} - \mathrm{Count}_{b,crisis}^{B}\right)}{\mathrm{Count}_{b,pre}} \\
&= \frac{\mathrm{Count}_{b,pre}^{NB} - \mathrm{Count}_{b,crisis}^{NB}}{\mathrm{Count}_{b,pre}} + \frac{\mathrm{Count}_{b,pre}^{B} - \mathrm{Count}_{b,crisis}^{B}}{\mathrm{Count}_{b,pre}} \\
&= \frac{\mathrm{Count}_{b,pre}^{NB} - \mathrm{Count}_{b,crisis}^{NB}}{\mathrm{Count}_{b,pre}^{NB}} \cdot \frac{\mathrm{Count}_{b,pre}^{NB}}{\mathrm{Count}_{b,pre}} + \frac{\mathrm{Count}_{b,pre}^{B} - \mathrm{Count}_{b,crisis}^{B}}{\mathrm{Count}_{b,pre}^{B}} \cdot \frac{\mathrm{Count}_{b,pre}^{B}}{\mathrm{Count}_{b,pre}} \\
&= \Delta \mathrm{L}_b^{NB} \cdot \mathrm{NBDep}_{b,pre} + \Delta \mathrm{L}_b^{B} \cdot \left(1 - \mathrm{NBDep}_{b,pre}\right).
\end{aligned} \tag{16}$$

The same identity holds when we scale each loan by bank b's share in the syndicate. We can do the same decomposition for the aggregate loan market.

Table A4: Decomposition of lending - Corporate purpose loans

This table uses equations (1) and (2) to decompose the change in the number of real investment loans originated by a bank during the financial crisis. The lending change during the GFC is the change in the number of loans originated by a bank between the period October 2005 to June 2007 and October 2008 to June 2009. Nonbank dependence is defined as the fraction of loan volume that is originated as part of nonbank deals. A nonbank deal is a loan deal which contains a nonbank tranche, e.g. a Term B tranche. Nonbank dependence is computed prior to the financial crisis for the period from October 2005 to June 2007. Each loan is scaled by the share of the lender in the syndicate following Chodorow-Reich (2013). The aggregation of Dealscan lender entities to bank holding companies follows Chodorow-Reich (2013). The table shows the lending changes of the top 10 banks by pre-crisis market share as well as the lending change of all banks (inside and outside of the top 10).

	Δ Loans in all deals	Δ Loans in nonbank deals	Nonbank depend.	Δ Loans in bank deals	Bank depend.	Nonbank contribution	Bank contribution	Market Share
	$(1) = (2) \cdot (3) + (4) \cdot (5)$	(2)	(3)	(4)	(5)	$= \frac{(2)\cdot(3)}{(1)}$	$= \frac{(4)\cdot(5)}{(1)}$	
Bank of America	-0.56	-0.95	0.25	-0.43	0.75	0.42	0.58	0.151
JPMorgan	-0.71	-0.98	0.32	-0.58	0.68	0.45	0.55	0.121
Wachovia	-0.70	-1.00	0.32	-0.57	0.68	0.45	0.55	0.059
Wells Fargo	-0.22	-0.91	0.28	0.05	0.72	1.16	-0.16	0.056
GE Capital	-0.81	-0.98	0.66	-0.49	0.34	0.79	0.21	0.055
Citigroup	-0.64	-0.87	0.36	-0.51	0.64	0.49	0.51	0.046
PNC	-0.30	-0.96	0.22	-0.12	0.78	0.69	0.31	0.042
Credit Suisse	-0.86	-0.93	0.74	-0.66	0.26	0.80	0.20	0.031
National City	-0.70	-1.00	0.36	-0.53	0.64	0.52	0.48	0.029
CIT	-0.70	-0.87	0.63	-0.41	0.37	0.78	0.22	0.025
All Banks	-0.59	-0.95	0.35	-0.40	0.65	0.57	0.43	1.000

A1.2.3 Bank Health vs. Nonbank Dependence

Table A5: Bank Health vs. Nonbank Dependence – Firm Characteristics

This table reports regression results about lending changes during the GFC controlling for firm characteristics. The unit of observation is a bank. The lending change is the change in the number loans originated by a bank between the period October 2005 to June 2007 and October 2008 to June 2009. Nonbank dependence is defined as the fraction of loans that are originated as part of nonbank deals. A nonbank deal is a loan deal which contains a nonbank loan as defined in Section 2. Nonbank dependence is computed prior to the financial crisis for the period from October 2005 to June 2007. Bank health measures are obtained from Chodorow-Reich (2013) and are normalized to have mean zero and standard deviation of one. Each loan is scaled by the importance of the lender in the loan syndicate computed as in Chodorow-Reich (2013). The observations are weighted by the number of pre-crisis borrowers to capture the economic importance of each bank. Robust standard errors are in parentheses. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

	Δ All Loans					
	(1)	(2)	(3)	(4)	(5)	(6)
Nonbank Dependence	−0.964***	−0.830***	−0.901***	−0.888***	−0.713***	−0.727**
	(0.176)	(0.150)	(0.243)	(0.242)	(0.244)	(0.339)
Lehman exposure	0.029			0.059*		
	(0.022)			(0.032)		
ABX Exposure		−0.036			−0.011	
		(0.046)			(0.027)	
07-08 Trading Rev/AT			0.031			0.012
			(0.027)			(0.024)
RE CO flag			−0.057			−0.033
			(0.046)			(0.031)
07-08 RE NCO/AT			−0.036			−0.069**
			(0.039)			(0.030)
07 Deposits/Assets			0.068			0.065
			(0.059)			(0.059)
Share of private borrowers				−0.011	−0.012	−0.008
				(0.063)	(0.067)	(0.058)
Share of rated borrowers				−0.164**	−0.151**	−0.160**
				(0.068)	(0.069)	(0.070)
Sales of median borrower				0.085**	0.080**	0.084*
				(0.035)	(0.031)	(0.046)
Obs.	42	40	42	42	40	42
R^2	0.458	0.490	0.519	0.615	0.614	0.662

Table A6: Bank Health vs. Nonbank Dependence – Corporate Purpose Loans

This table reports regression results about lending changes during the GFC focusing on corporate purpose loans. The unit of observation is a bank. Columns (1)-(6) considers all loans, while Columns (7) and (8) include only bank and nonbank loan deals, respectively. The lending change is the change in the number loans originated by a bank between the period October 2005 to June 2007 and October 2008 to June 2009. Nonbank dependence is defined as the fraction of loans that are originated as part of nonbank deals. A nonbank deal is a loan deal which contains a nonbank loan as defined in Section 2. Nonbank dependence is computed prior to the financial crisis for the period from October 2005 to June 2007. Bank health measures are obtained from Chodorow-Reich (2013) and are normalized to have mean zero and standard deviation of one. Each loan is scaled by the importance of the lender in the loan syndicate computed as in Chodorow-Reich (2013). The observations are weighted by the number of pre-crisis borrowers to capture the economic importance of each bank. Robust standard errors are in parentheses. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

	Δ All Loans						Δ Bank	Δ Nonbank
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lehman exposure	−0.131***			0.036			−0.021	−0.017
	(0.037)			(0.027)			(0.078)	(0.026)
ABX Exposure		−0.090*			−0.027		−0.045	0.004
		(0.049)			(0.048)		(0.065)	(0.018)
07-08 Trading Rev/AT			0.050*			0.020	0.075*	−0.010
			(0.030)			(0.031)	(0.041)	(0.022)
RE CO flag			0.002			−0.067	−0.038	−0.033
			(0.053)			(0.051)	(0.055)	(0.027)
07-08 RE NCO/AT			−0.078*			−0.033	−0.067	0.014
			(0.046)			(0.045)	(0.053)	(0.027)
07 Deposits/Assets			0.183***			0.075	0.153*	0.002
			(0.060)			(0.071)	(0.084)	(0.035)
Nonbank Dependence				−0.978***	−0.849***	−0.911***		
				(0.172)	(0.153)	(0.262)		
Obs.	42	40	42	42	40	42	38	38
R^2	0.139	0.103	0.293	0.396	0.431	0.449	0.235	0.073

Table A7: The Effect of Bank Health on Bank and Nonbank Deals

This table reports regression results about lending changes during the GFC focusing on purely on *bank deals* in columns (1) to (3) and on *nonbank deals* in columns (4) to (6). The unit of observation is a bank. The lending change is the change in the number loans originated by a bank between the period October 2005 to June 2007 and October 2008 to June 2009. A nonbank deal is a loan deal which contains a nonbank loan as defined in Section 2. Nonbank dependence is computed prior to the financial crisis for the period from October 2005 to June 2007. Bank health measures are obtained from Chodorow-Reich (2013) and are normalized to have mean zero and standard deviation of one. Each loan is scaled by the importance of the lender in the loan syndicate computed as in Chodorow-Reich (2013). The observations are weighted by the number of pre-crisis borrowers to capture the economic importance of each bank. Robust standard errors are in parentheses. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Panel A - All loans

	Δ Bank Deals			Δ Nonbank Deals		
	(1)	(2)	(3)	(4)	(5)	(6)
Lehman exposure	−0.102***			−0.002		
	(0.035)			(0.009)		
ABX Exposure		−0.101			−0.006	
		(0.065)			(0.011)	
07-08 Trading Rev/AT			0.080*			−0.007
			(0.041)			(0.012)
RE CO flag			−0.032			−0.011
			(0.058)			(0.015)
07-08 RE NCO/AT			−0.075			−0.001
			(0.053)			(0.012)
07 Deposits/Assets			0.163**			0.015
			(0.076)			(0.017)
Obs.	42	40	42	42	40	42
R^2	0.067	0.102	0.186	0.000	0.010	0.032

Panel B - Corporate purpose loans

	Δ Bank Deals			Δ Nonbank Deals		
	(1)	(2)	(3)	(4)	(5)	(6)
Lehman exposure	−0.089**			−0.001		
	(0.040)			(0.009)		
ABX Exposure		−0.094			0.005	
		(0.057)			(0.016)	
07-08 Trading Rev/AT			0.061*			−0.015
			(0.036)			(0.016)
RE CO flag			−0.027			−0.028
			(0.056)			(0.023)
07-08 RE NCO/AT			−0.073			0.012
			(0.053)			(0.025)
07 Deposits/Assets			0.171**			0.010
			(0.072)			(0.025)
Obs.	42	40	42	42	40	42
R^2	0.052	0.092	0.184	0.000	0.002	0.060

A1.2.4 A Decomposition of the Employment Losses due to Credit Supply

We perform a back-of-the-envelope estimation of the contribution of nonbank supply for employment. To do so, we borrow the methodology and estimates of Chodorow-Reich (2013). Specifically, denote the aggregate employment loss as

$$\begin{aligned}\Delta E &= \sum_i \omega_i \cdot \zeta_{1,i} \cdot \Delta L_{i,s}, \\ \text{where} \quad \Delta L_{i,s} &= \sum_{b \in s} \alpha_{i,b} \cdot \Delta \mathrm{L}_{-i,b},\end{aligned} \tag{17}$$

where ΔE is the change in aggregate employment of firms in the sample, ω_i is the employment share of firm i, $\zeta_{1,i}$ is the sensitivity of employment to credit supply, and $\Delta L_{i,s}$ is the credit supply shock faced by firm i. This credit supply closely mirrors ΔL_b, but is instead constructed in a Bartik-style by multiplying the lending reduction of each pre-crisis lender b with their share $\alpha_{i,b}$ in the last pre-crisis loan syndicate s of borrower i. To obtain the parameter $\zeta_{1,i}$, Chodorow-Reich (2013) regresses employment growth of firm i during the GFC on $\Delta L_{i,s}$.

Using equation (1), we can decompose $L_{i,s}$ into

$$\begin{aligned}\Delta L_{i,s} &= \sum_{b \in s} \alpha_{i,b} \cdot \left(1 - \mathrm{NBDep}_{-i,b}\right) \cdot \Delta \mathrm{L}^{B}_{-i,b} + \sum_{b \in s} \alpha_{i,b} \cdot \mathrm{NBDep}_{-i,b} \cdot \Delta \mathrm{L}^{NB}_{-i,b} \\ &= \Delta L^{B}_{i,s} + \Delta L^{NB}_{i,s}.\end{aligned} \tag{18}$$

which assumes that nonbank supply shocks have the same sensitivity to employment as bank supply shocks.

Aggregate employment losses are then given by

$$\Delta E = \sum_i \omega_i \cdot \zeta_{1,i} \cdot \Delta L^{B}_{i,s} + \sum_i \omega_i \cdot \zeta_{1,i} \cdot \Delta L^{NB}_{i,s} \tag{19}$$

Dividing this equation by ΔE gives the fraction of employment losses due to banks and nonbanks exiting the syndicated loan market.

This framework takes into account that the sensitivity of employment to credit supply shocks in the syndicated loan market can differ across firms. For example, large firms might be able to switch to the bond market when the loan market dried up. Therefore, if nonbanks were to provide financing mostly to large (small) firms, then the contribution of the nonbank credit supply to employment losses might be less (more) than what is implied our decomposition of lending quantities.

We implement the decomposition (19) focusing on corporate purpose loans and using the estimates $\hat{\zeta}_{1,i}$ from Chodorow-Reich (2013) (i.e., we use $\hat{\zeta}_{1,small} = 2.16$ for firms with 1-250 employees, $\hat{\zeta}_{1,medium} = 1.84$ for firms with 251-999 employees, and $\hat{\zeta}_{1,large} = 0$ for firms with more than 1000+ employees).[36,37]

Assuming all lending declines arose due to credit supply (instead of firms' credit demand), we find that nonbanks were responsible for 58% of the employment losses arising from reduced credit supply (Table 4). As we decrease the importance of credit supply versus credit demand to the overall lending decline (by imposing a "credit supply threshold" following Chodorow-Reich (2013) such that firm i only faces a credit supply shock when $\Delta L_{i,s}$ is smaller than a threshold), the contribution of nonbanks becomes larger. Intuitively, this is the case because many bank syndicate members did not reduce lending by much and therefore are above this threshold. Assuming that only a lending decline of more than 30% can be attributed to credit supply, we find that the nonbank contribution to aggregate employment losses increases to 77%.

We conclude that bank health, while it was important, seems to have played a less critical role for the credit crunch during the GFC than previously emphasized.[38] On the contrary side, we find that the reduction in nonbank activity explains the majority of the credit crunch during the GFC. This is an important finding since it suggests that supporting banks is not enough to restart the flow of syndicated credit during periods of stress.

Not of all the changes in $\Delta \mathrm{L}_{i,s}$ might reflect credit supply, but also credit demand. To get at this issue, Chodorow-Reich (2013) assumes that the syndicate at the τ percentile did not change its lending function. Let us denote lending of the τ-percentile syndicate by ΔL_{Q_τ}. Intuitively, if $\Delta L_{i,s} < \Delta L_{Q_\tau}$, then firm i faced a credit supply shock. Vice versa, if $\Delta L_{i,s} > \Delta L_{Q_\tau}$, then firm i cut its credit demand (while facing unconstrained credit supply). Under these assumptions, the total employment losses due to credit supply are

$$\Delta E = \sum_{\Delta L_{i,s} < \Delta L_{Q_\tau}} \omega_i \cdot \zeta_{1,i} \cdot \left(\Delta L_{i,s} - \Delta L_{Q_\tau}\right). \tag{20}$$

Using equation (18), we can decompose the employment losses due to nonbank and bank

[36]Note that our decomposition is somewhat independent of the average magnitude of the estimates $\hat{\zeta}_{1,i}$ (and therefore also to whether the identification assumptions holds), since both nonbank and bank credit supply shocks get multiplied by the same estimates (see equation (19)).

[37]To determine the firm size, we first use pre-crisis employment as observed in Compustat. If missing, we use sales reported in Dealscan to impute missing employment. For the firms that are still unclassified, we classify firms as "large" if they have publicly-trading equity and otherwise classify them as small firms. We are able to closely replicate the results obtained in Chodorow-Reich (2013) despite a potentially different firms splits due to our reliance on Compustat data to estimate firm sizes.

[38]See, for example, Ivashina and Scharfstein (2010a), Santos (2010), Chodorow-Reich (2013), Adrian, Colla, and Song Shin (2013), Becker and Ivashina (2014).

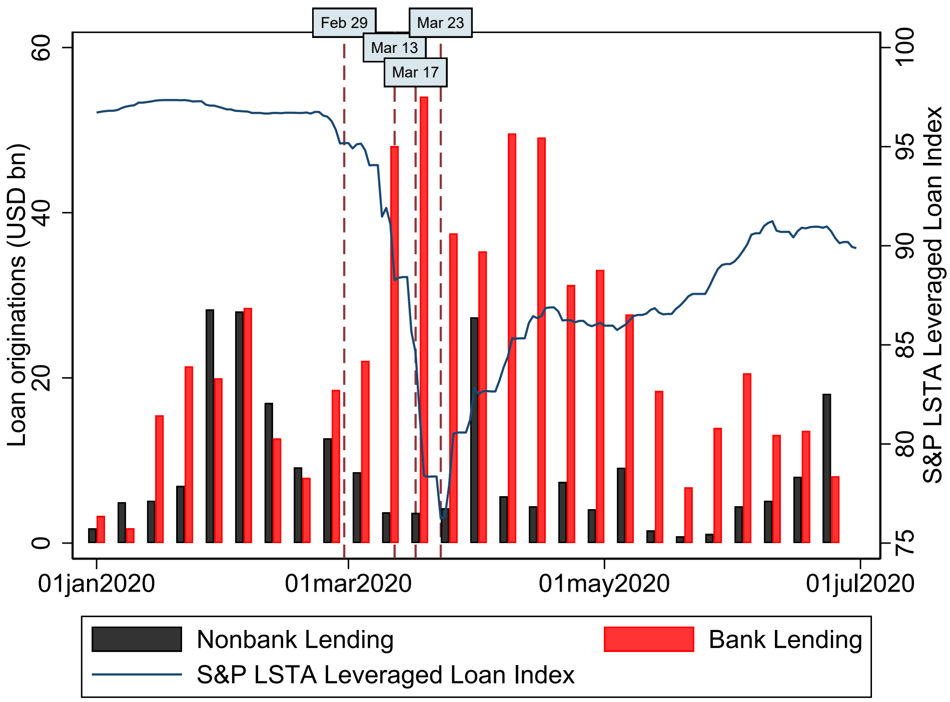
credit supply into

$$\Delta E = \sum_{\Delta L_{i,s} < \Delta L_{Q_\tau}} \omega_i \cdot \zeta_{1,i} \cdot \left(\Delta L_{i,s}^{B} - \Delta L_{Q_\tau}\right) + \sum_{\Delta L_{i,s} < \Delta L_{Q_\tau}} \omega_i \cdot \zeta_{1,i} \cdot \left(\Delta L_{i,s}^{NB} - \Delta L_{Q_\tau}\right). \quad (21)$$

A1.2.5 Bank and Nonbank Lending during the COVID-19 Crisis

Figure A1: Lending during the COVID-19 Crisis

The figure plots the weekly aggregate issuance of nonbank deals and bank deals, and the daily S&P LSTA Leveraged Loan Index from January 2020 to June 2020. Nonbank deals are defined as syndicated loan deals that include at least one nonbank tranche. The dashed vertical lines indicate the following four events: (1) the first COVID-19 related death in the U.S. (February 29), (2) the declaration of a national emergency in the U.S. (March 13), (3) the Fed's announcement of its Primary Dealer Credit Facility and its Commercial Paper Funding Facility (March 17), (4) the Fed's announcement of its Primary Market Corporate Credit Facility, Secondary Market Corporate Credit Facility, and Term Asset-Backed Securities Loan Facility (March 23).



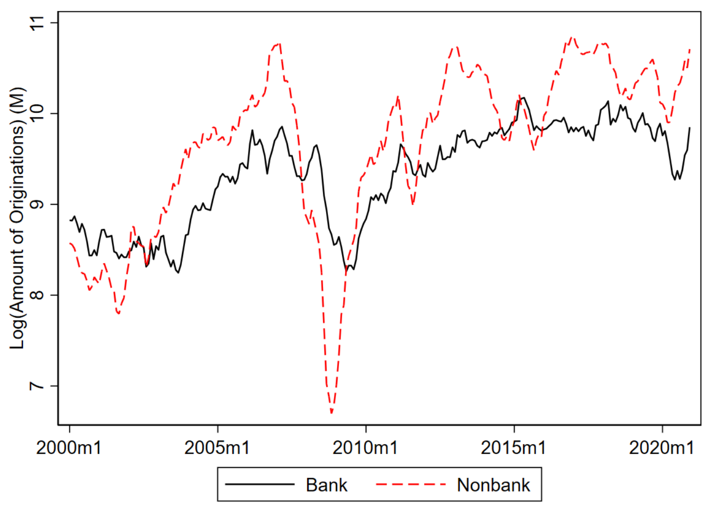
A1.3 Banks vs. Nonbanks Over Multiple Credit Cycles

A1.3.1 Aggregate Results

Figure A2: Cyclicality of Originations: Term Lending

This figure shows new originations of bank and nonbank **term** loans between January 2000 and December 2020. We plot a six-month (forward-looking) average of the logarithm of the total origination amount for bank and nonbank loans. Nonbank loans are loans classified as Term Loan B-Term Loan K, while bank loans are loans classified as Term Loan A or Term Loan in Dealscan. Panel A contains all term loans, while Panel B includes only real investment term loans. Real investment loans are loans whose primary purpose is "corporate purpose", "working capital", or "capital expenditure" according to Dealscan.

Panel A - All Term Loans



Panel B - Real Investment Term Loans

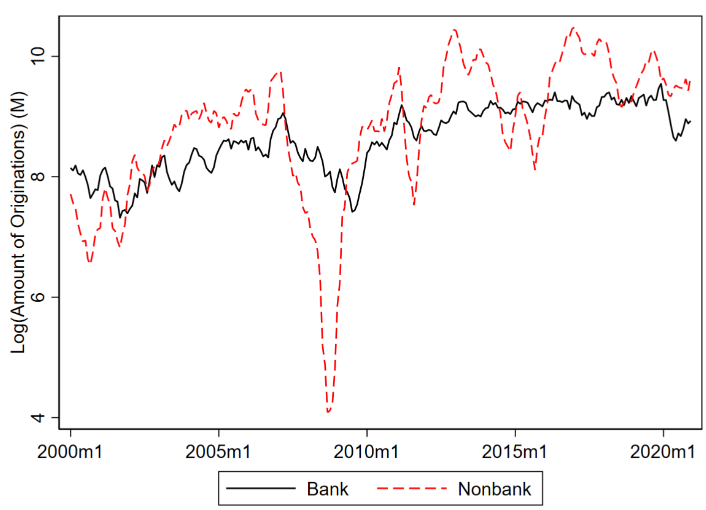


Table A8: Nonbank Lending Cyclicality - Extensive Margin

This table reports results on aggregate monthly loan originations. The unit of observation is a deal-type x month pair. We report the results of

$$\text{Lending Outcome}_{dt} = \beta_0 + \beta_1 \text{Credit Cycle}_{t-1} + \beta_2 \mathbb{I}_{d=\text{NonbankDeal}} + \beta_3 \text{Credit Cycle}_{t-1} \times \mathbb{I}_{d=\text{NonbankDeal}} + \epsilon_{dt}$$

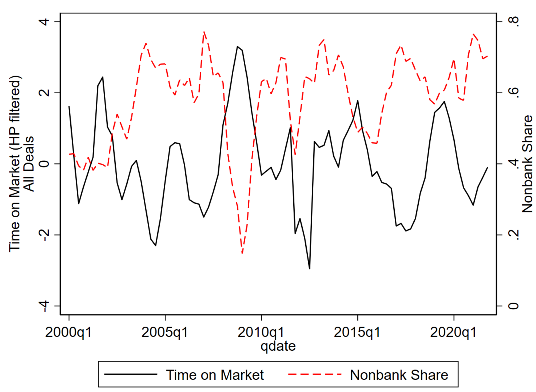
where Lending Outcome_{dt} is the log number of deals (where d is either a "bank deal" if the deal does not contain any Term Loan B or a "nonbank deal" if it includes a term loan B) originated in month t. Therefore, $\mathbb{I}_{d=\text{NonbankDeal}}$ is a dummy variable that takes a value of 1 if the deal includes a Term Loan B. Credit Cycle is the Excess Bond Premium from Gilchrist and Zakrajšek (2012). Our sample includes all loans originated between January 2000 and December 2020. The Excess Bond Premium is standardized to have mean 0 and standard deviation of 1. Robust standard errors are presented. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

	Log(Number of Deals)		
	(1)	(2)	(3)
Excess Bond Premium	−0.256***	−0.016	
	(0.038)	(0.022)	
Term B	−1.453***	−1.435***	−1.437***
	(0.045)	(0.039)	(0.027)
Excess Bond Premium x Term B		−0.494***	−0.500***
		(0.042)	(0.030)
Year-Month FE	N	N	Y
Obs.	503	503	502
R^2	0.703	0.774	0.944

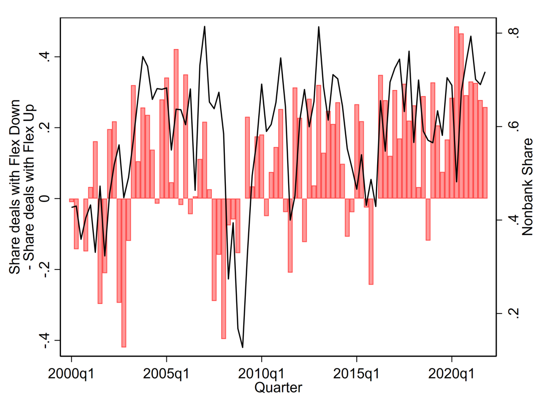
Figure A3: Syndication Process and Nonbank Share

This figure plots the relationship between nonbank share and time-on-market, loan flex, original issue discount. Time-on-market is the time between the start of the syndication process and the close of the deal. Higher time-on-market suggests lower demand from institutional investors. We measure the direction of loan flex as the share of deals in each period that see a decrease in loan spreads (flex down) compared to loans with an increase in loan spreads (flex up) during the syndication process. When loans are flexed up it suggests institutional investors require higher returns to participate in the deal and is a measure of lower institutional demand. Original Issue Discount (OID) is the discount in price from a loan's face value at the time a loan is issued. Larger discounts imply lower demand from institutional investors. Nonbank share is the share of term loans origianted by nonbanks (Term Loans B-K are classified as nonbank loans). The sample period is from January 2000 to December 2020.

Panel A - Correlation between Time-on-Market and Nonbank Share



Panel B - Correlation between Loan Flex and Nonbank Share



Panel C - Correlation between OID and Nonbank Share

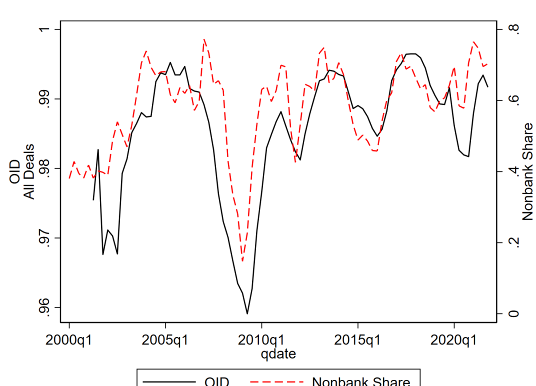


Table A9: Nonbank Credit Supply Measures

This table shows the correlation between supply from institutional investors and the Excess Bond Premium (EBP). Time-on-market is the time between the start of the syndication process and the close of the deal. Higher time-on-market suggests lower demand from institutional investors. We measure the direction of loan flex as the share of deals in each period that see a decrease in loan spreads (flex down) compared to loans with an increase in loan spreads (flex up) during the syndication process. When loans are flexed up it suggests institutional investors require higher returns to participate in the deal and is a measure of lower institutional demand. Original Issue Discount (OID) is the discount in price from a loan's face value at the time a loan is issued. Larger discounts imply lower demand from institutional investors. The Excess Bond Premium from Gilchrist and Zakrajšek (2012) is a measure of the credit cycle. The sample period is from January 2000 to December 2020.

	Time on Market		Loan Flex			OID		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EBP	0.193***	0.173***	−0.758***	−0.783***		0.241***	0.253***	
	(0.029)	(0.030)	(0.051)	(0.051)		(0.027)	(0.029)	
Time on Market					−0.193***			0.104***
					(0.016)			(0.013)
Borrower FE	Y	Y	Y	Y	Y	Y	Y	Y
Lender FE	N	Y	N	Y	Y	N	Y	Y
Obs.	9,980	9,915	7,891	7,862	8,007	9,980	9,915	10,059
R^2	0.379	0.409	0.388	0.397	0.354	0.287	0.292	0.289

A1.3.2 Alternative Explanations

Table A10: Cyclicality of Lead Banks, Non-lead Banks, and Nonbanks - Including Past Lead Lender Relationship

This table presents results on new loan origiantions as in Table 6 split by lender role. We distribute loan amount across all syndicate members within a facility following Chodorow-Reich (2013). Lead Banks denotes the amount of the *bank loan* held by lead arrangers of the syndicate or participant banks that acted as lead arranger to the borrower within the prior three years. Non-lead bank amounts are based on the amount of *bank loans* held by all other banks in the syndicate. Nonbank amount is nonbank loan volume. Bank and nonbank loans are classified as described in Section 2. Credit Cycle is the Excess Bond Premium from Gilchrist and Zakrajšek (2012), standardized to mean 0 and standard deviation 1. The lead bank is defined on the deal level and as by Sufi (2007) and Ivashina (2009). Non-lead participant banks are the ommitted group. Our sample includes all loans originated between January 2000 and December 2020.

	Log(Facility Amount)		
	(1)	(2)	(3)
Excess Bond Premium	−0.040***		
	(0.014)		
Lead Bank - Past 3 years × Excess Bond Premium	0.006	0.008	0.006
	(0.010)	(0.010)	(0.010)
Nonbank × Excess Bond Premium	−0.142***	−0.165***	−0.226***
	(0.035)	(0.031)	(0.049)
Borrower FE	Y	Y	N
Year-Month FE	N	Y	N
Deal FE	N	N	Y
Lender-Role FE	Y	Y	Y
Obs.	111,462	111,462	101,776
R^2	0.690	0.717	0.848

Table A11: Time-varying Borrower Characteristics

For each loan deal d, we compute the share that is funded by nonbanks according to

$$\text{TLBShare}_d = \frac{\text{Term B Amount}_d}{\text{Total Loan Amount}_d}.$$

Accordingly, the TLBShare is 0 if a loan deal is fully funded by banks, 1 if it is fully funded by nonbanks, and between 0 and 1 if it contains both a Term B and a bank loan facility. We then run the following regression

$$\text{TLBShare}_{dit} = \beta_0 + \beta_1 \text{Credit Cycle}_{t-1} + \text{BorrowerControls}_{it} + \epsilon_{dit}.$$

The unit of observation is a loan deal. The time-varying borrower characteristics that we include are the S&P rating of the borrower at a given point in time (from Compustat), the equity return volatility over the last three months (from CRSP), and the interest coverage ratio and the book leverage (from Compustat). Our sample includes all loans originated between 2000Q1 and 2020Q4. Credit Cycle is the Excess Bond Premium from Gilchrist and Zakrajšek (2012). The Excess Bond Premium and all other regressors are standardized to have mean 0 and standard deviation of 1. Standard errors are double clustered at the firm and month level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

	TLB Share					
	(1)	(2)	(3)	(4)	(5)	(6)
Excess Bond Premium	-0.155***	-0.073***	-0.077***	-0.102***	-0.149***	-0.125***
	(0.012)	(0.006)	(0.022)	(0.033)	(0.051)	(0.026)
3-Month Equity Return Volatility					0.063	
					(0.058)	
3-Month Equity Return					0.099**	
					(0.044)	
Book Leverage						0.045*
						(0.027)
Interest Coverage Ratio						-0.056
						(0.045)
Sample	All	All	DealPurpose	Rating	CRSP	Compustat
Borrower FE	N	Y	Y	Y	Y	Y
DealPurpose FE	N	N	Y	N	N	N
Rating FE	N	N	N	Y	N	N
Coefficient with Borrower FE only			-0.097	-0.109	-0.119	-0.126
Obs.	57,789	48,250	9,558	2,233	802	3,763
R^2	0.019	0.598	0.555	0.488	0.559	0.512

A1.3.3 Sample Robustness

Table A12: Nonbank Lending Cyclicality - Within-Deal Results - Only Term Loans

This table reports results at the loan type × loan deal level. We estimate

$$\text{Lending Outcome}_{idft} = \delta_{idt} + \beta_1 \text{Credit Cycle}_{t-1} \times \mathbb{I}_{f=\text{TermB}} + \beta_2 \mathbb{I}_{f=\text{TermB}} + \epsilon_{idft}$$

where Lending Outcome$_{idft}$ is the logarithm of the loan issuance volume (Panel A), or the all-in-drawn spread (Panel B) at origination to borrower i for deal d, facility-type f, which is either a bank loan or nonbank loan as defined in Section 2, in month t. $\mathbb{I}_{f=\text{Term B}}$ is a dummy variable that takes a value of 1 if the facility is a nonbank loan, as defined in Section 2. Credit Cycle is the Excess Bond Premium from Gilchrist and Zakrajšek (2012). Our sample includes all term loans originated between January 2000 and December 2020. The Excess Bond Premium is standardized to have mean 0 and standard deviation of 1. Standard errors are double clustered at the firm and month level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Panel A - Loan Volumes

	Log(Facility Amount)				
	(1)	(2)	(3)	(4)	(5)
Excess Bond Premium	−0.077***	−0.043***			
	(0.017)	(0.013)			
Term B	0.503***	0.479***	0.455***	0.432***	
	(0.019)	(0.020)	(0.019)	(0.025)	
Excess Bond Premium x Term B		−0.104***	−0.117***	−0.148***	−0.095***
		(0.020)	(0.017)	(0.029)	(0.033)
Borrower FE	Y	Y	Y	N	N
Year-Month FE	N	N	Y	N	N
Deal FE	N	N	N	Y	Y
Borrower x Facility-Type FE	N	N	N	N	Y
Obs.	25,795	25,795	25,795	7,580	3,976
R^2	0.779	0.779	0.811	0.900	0.966

Panel B - Loan Spreads

	All-in-drawn Spread				
	(1)	(2)	(3)	(4)	(5)
Excess Bond Premium	17.568***	0.784			
	(2.549)	(3.220)			
Term B	−44.359***	−33.134***	−29.779***	−78.370***	
	(5.654)	(4.778)	(4.830)	(7.201)	
Excess Bond Premium x Term B		47.815***	46.338***	64.362***	38.186***
		(4.659)	(4.074)	(7.683)	(6.704)
Borrower FE	Y	Y	Y	N	N
Year-Month FE	N	N	Y	N	N
Deal FE	N	N	N	Y	Y
Borrower x Facility-Type FE	N	N	N	N	Y
Obs.	23,540	23,540	23,540	6,932	3,596
R^2	0.619	0.627	0.663	0.713	0.933

Table A13: Robustness: Alternate Credit Cycle Measures - Within-Deal Results

This table reports results at the loan type × loan deal level. We estimate

$$\text{Lending Outcome}_{idft} = \delta_{idt} + \beta_1 \text{Credit Cycle}_{t-1} \times \mathbb{I}_{f=\text{TermB}} + \beta_2 \mathbb{I}_{f=\text{TermB}} + \epsilon_{idft}$$

where Lending Outcome$_{idft}$ is the logarithm of the loan issuance volume (Panel A), or the all-in-drawn spread (Panel B) at origination to borrower i for deal d, facility-type f, which is either a bank loan or nonbank loan as defined in Section 2, in month t. $\mathbb{I}_{f=\text{Term B}}$ is a dummy variable that takes value of 1 if the loan is a Term B loan and 0 otherwise. Credit Cycle is measured by the VIX (Panel A), the High Yield Spread (Panel B), and the GZ Spread (Gilchrist and Zakrajšek (2012)) (Panel C). Our sample includes all loans originated between January 2000 and December 2020. The Credit Cycle variables are standardized to have mean 0 and standard deviation of 1. Standard errors are double clustered at the firm and month level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Panel A - VIX

	Log(Facility Amount)			All-in-drawn Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
VIX	−0.099***			17.972***		
	(0.019)			(2.311)		
Term B	0.475***	0.418***		52.490***	62.815***	
	(0.027)	(0.029)		(3.040)	(2.793)	
VIX x TermB		−0.108***	−0.096***		26.443***	20.681***
		(0.029)	(0.025)		(3.171)	(3.619)
Borrower FE	Y	Y	N	Y	Y	N
Year-Month FE	N	Y	N	N	Y	N
Deal FE	N	N	Y	N	N	Y
Borrower x Facility-Type FE	N	N	Y	N	N	Y
Obs.	59,881	59,881	11,978	59,881	59,881	11,978
R^2	0.724	0.758	0.930	0.616	0.642	0.862

Robustness: Alternate Credit Cycle Measures - Within-Deal Results - Continued

Panel B - High Yield spread

	Log(Facility Amount)			All-in-drawn Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
High Yield Spread	−0.132***			26.878***		
	(0.016)			(1.871)		
Term B	0.469***	0.402***		53.846***	66.403***	
	(0.026)	(0.029)		(3.028)	(2.712)	
High Yield Spread x TermB		−0.161***	−0.120***		38.541***	27.911***
		(0.028)	(0.030)		(3.675)	(4.432)
Borrower FE	Y	Y	N	Y	Y	N
Year-Month FE	N	Y	N	N	Y	N
Deal FE	N	N	Y	N	N	Y
Borrower x Facility-Type FE	N	N	Y	N	N	Y
Obs.	59,881	59,881	11,978	59,881	59,881	11,978
R^2	0.725	0.758	0.930	0.621	0.643	0.862

Panel C - Gilchrist-Zakrajsek Spread

	Log(Facility Amount)			All-in-drawn Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
GZ Spread	−0.147***			22.601***		
	(0.018)			(2.060)		
Term B	0.468***	0.393***		53.238***	64.371***	
	(0.026)	(0.027)		(3.037)	(2.716)	
GZ Spread x TermB		−0.215***	−0.147***		36.552***	27.224***
		(0.030)	(0.032)		(3.740)	(4.547)
Borrower FE	Y	Y	N	Y	Y	N
Year-Month FE	N	Y	N	N	Y	N
Deal FE	N	N	Y	N	N	Y
Borrower x Facility-Type FE	N	N	Y	N	N	Y
Obs.	59,881	59,881	11,978	59,881	59,881	11,978
R^2	0.726	0.758	0.930	0.617	0.643	0.862

Table A14: Robustness: Real Investment Loans - Within-Deal Results

This table reports results at the loan type $\times$ loan deal level. We estimate

$$\text{Lending Outcome}_{idft} = \delta_{idt} + \beta_1 \text{Credit Cycle}_{t-1} \times \mathbb{I}_{f=\text{TermB}} + \beta_2 \mathbb{I}_{f=\text{TermB}} + \epsilon_{idft}$$

where Lending Outcome$_{idft}$ is the logarithm of the loan issuance volume (Panel A), or the all-in-drawn spread (Panel B) at origination to borrower i for deal d, facility-type f, which is either a bank loan or nonbank loan as defined in Section 2, in month t. $\mathbb{I}_{f=\text{Term B}}$ is a dummy variable that takes value of 1 if the loan is a Term Loan B-K and 0 otherwise. Credit Cycle is the Excess Bond Premium from Gilchrist and Zakrajšek (2012). Our sample includes all *real investment* originated between January 2000 and December 2020. Real investment loans are loans whose primary purpose is "corporate purpose", "working capital", "capital expenditure" according to Dealscan. The Excess Bond Premium is standardized to have mean 0 and standard deviation of 1. Standard errors are double clustered at the firm and month level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Panel A - Loan Volumes

	Log(Facility Amount)				
	(1)	(2)	(3)	(4)	(5)
Excess Bond Premium	−0.074***	−0.065***			
	(0.015)	(0.013)			
Term B	0.369***	0.331***	0.299***	0.440***	
	(0.036)	(0.038)	(0.036)	(0.047)	
Excess Bond Premium x Term B		−0.131***	−0.153***	−0.258***	−0.154***
		(0.038)	(0.033)	(0.056)	(0.037)
Borrower FE	Y	Y	Y	N	N
Year-Month FE	N	N	Y	N	N
Deal FE	N	N	N	Y	Y
Borrower x Facility-Type FE	N	N	N	N	Y
Obs.	37,981	37,981	37,981	7,482	4,146
R^2	0.751	0.752	0.790	0.793	0.949

Panel B - Loan Spreads

	All-in-drawn Spread				
	(1)	(2)	(3)	(4)	(5)
Excess Bond Premium	17.284***	14.909***			
	(2.304)	(2.357)			
Term B	57.407***	66.548***	67.958***	23.472***	
	(3.528)	(3.398)	(3.284)	(2.916)	
Excess Bond Premium x Term B		30.743***	28.528***	21.287***	14.963***
		(4.296)	(3.653)	(3.011)	(4.003)
Borrower FE	Y	Y	Y	N	N
Year-Month FE	N	N	Y	N	N
Deal FE	N	N	N	Y	Y
Borrower x Facility-Type FE	N	N	N	N	Y
Obs.	33,491	33,491	33,491	6,726	3,704
R^2	0.690	0.692	0.737	0.824	0.934

Table A15: Robustness: Private Borrowers - Within-Deal Results

This table reports results at the loan type × loan deal level. We estimate

$$\text{Lending Outcome}_{idft} = \delta_{idt} + \beta_1 \text{Credit Cycle}_{t-1} \times \mathbb{I}_{f=\text{TermB}} + \beta_2 \mathbb{I}_{f=\text{TermB}} + \epsilon_{idft}$$

where Lending Outcome_{idft} is the logarithm of the loan issuance volume (Panel A), or the all-in-drawn spread (Panel B) at origination to borrower i for deal d, facility-type f, which is either a bank loan or nonbank loan as defined in Section 2, in month t. $\mathbb{I}_{f=\text{Term B}}$ is a dummy variable that takes value of 1 if the loan is a Term B loan and 0 otherwise. Credit Cycle is the Excess Bond Premium from Gilchrist and Zakrajšek (2012). Our sample includes all loans originated between 2000Q1 and 2017Q2 (when the Dealscan-Compustat link file ends) for *non-publicly traded firms*, i.e., firms not matched to Compustat. The Excess Bond Premium is standardized to have mean 0 and standard deviation of 1. Standard errors are double clustered at the firm and month level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Panel A - Loan Volume

	Log(Facility Amount)				
	(1)	(2)	(3)	(4)	(5)
Excess Bond Premium	−0.012	0.000			
	(0.011)	(0.010)			
Term B	0.408***	0.372***	0.361***	0.530***	
	(0.036)	(0.039)	(0.038)	(0.049)	
Excess Bond Premium x Term B		−0.124***	−0.158***	−0.171***	−0.111**
		(0.041)	(0.039)	(0.060)	(0.050)
Borrower FE	Y	Y	Y	N	N
Year-Month FE	N	N	Y	N	N
Deal FE	N	N	N	Y	Y
Borrower x Facility-Type FE	N	N	N	N	Y
Obs.	22,450	22,450	22,450	8,078	4,456
R^2	0.721	0.721	0.746	0.766	0.917

Panel B - Loan Spreads

	All-in-drawn Spread				
	(1)	(2)	(3)	(4)	(5)
Excess Bond Premium	10.229***	7.929***			
	(1.851)	(1.833)			
Term B	29.557***	36.376***	38.809***	16.552***	
	(4.039)	(3.736)	(3.791)	(3.584)	
Excess Bond Premium x Term B		23.435***	21.363***	19.613***	15.308**
		(4.485)	(4.182)	(4.183)	(7.251)
Borrower FE	Y	Y	Y	N	N
Year-Month FE	N	N	Y	N	N
Deal FE	N	N	N	Y	Y
Borrower x Facility-Type FE	N	N	N	N	Y
Obs.	22,450	22,450	22,450	8,078	4,456
R^2	0.667	0.668	0.689	0.749	0.870

Table A16: Robustness: Excluding Great Recession - Within-Deal Results

This table reports results at the loan type × loan deal level. We estimate

$$\text{Lending Outcome}_{idft} = \delta_{idt} + \beta_1 \text{Credit Cycle}_{t-1} \times \mathbb{I}_{f=\text{TermB}} + \beta_2 \mathbb{I}_{f=\text{TermB}} + \epsilon_{idft}$$

where $\text{Lending Outcome}_{idft}$ is the logarithm of the loan issuance volume (Panel A), or the all-in-drawn spread (Panel B) at origination to borrower i for deal d, facility-type f, which is either a bank loan or nonbank loan as defined in Section 2, in month t. $\mathbb{I}_{f=\text{Term B}}$ is a dummy variable that takes value of 1 if the loan is a Term B loan and 0 otherwise. Credit Cycle is the Excess Bond Premium from Gilchrist and Zakrajšek (2012). Our sample includes all loans originated between January 2000 and December 2020 excluding the years 2008, 2009 and 2010. The Excess Bond Premium is standardized to have mean 0 and standard deviation of 1. Standard errors are double clustered at the firm and month level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Panel A - Loan Volume

	Log(Facility Amount)				
	(1)	(2)	(3)	(4)	(5)
Excess Bond Premium	−0.079***	−0.058***			
	(0.024)	(0.021)			
Term B	0.472***	0.424***	0.389***	0.545***	
	(0.027)	(0.031)	(0.030)	(0.041)	
Excess Bond Premium x Term B		−0.152***	−0.190***	−0.281***	−0.179***
		(0.037)	(0.035)	(0.056)	(0.032)
Borrower FE	Y	Y	Y	N	N
Year-Month FE	N	N	Y	N	N
Deal FE	N	N	N	Y	Y
Borrower x Facility-Type FE	N	N	N	N	Y
Obs.	53,695	53,695	53,695	17,096	11,028
R^2	0.723	0.724	0.760	0.814	0.932

Panel B - Loan Spreads

	All-in-drawn Spread				
	(1)	(2)	(3)	(4)	(5)
Excess Bond Premium	7.095***	2.822*			
	(2.064)	(1.706)			
Term B	51.905***	61.757***	61.087***	26.110***	
	(3.144)	(2.873)	(2.891)	(2.885)	
Excess Bond Premium x Term B		31.423***	26.179***	21.014***	22.900***
		(3.922)	(3.658)	(3.356)	(4.072)
Borrower FE	Y	Y	Y	N	N
Year-Month FE	N	N	Y	N	N
Deal FE	N	N	N	Y	Y
Borrower x Facility-Type FE	N	N	N	N	Y
Obs.	53,695	53,695	53,695	17,096	11,028
R^2	0.627	0.629	0.646	0.743	0.862

A1.4 The Financing Frictions of Banks vs. Nonbanks

A1.4.1 Bank and Nonbank Frictions

Table A17: CLO vs. Bank Funding Cyclicality

This table reports results from a regression of the difference between average CLO and bank equity ratios (Panel A) and average CLO and bank funding costs (Panel B) on the excess bond premium (EBP) from Gilchrist and Zakrajšek (2012). Bank equity ratio is defined as the quarterly weighted average $\frac{\text{market value of equity}}{\text{book value of assets + market value of equity - book value of equity}}$ of all bank holding companies in the Dealscan-Compustat link file from Schwert (2018). Investment banks as classified in Dealscan are excluded, and each bank's equity ratio is weighted by its lending market share in Dealscan in the prior quarter. CLO equity ratio is defined as the weighted average equity ratio of all newly issued CLOs in a month. The spread between CLO and bank funding costs is defined as the discount margin of outstanding CLO debt relative to the three month USD LIBOR rate. CLO discount margins are obtained from monthly Palmer Square CLO Debt Indexes (available through Bloomberg) and measured in basis points. The weighted average cost of debt (WACD) weights each CLO debt tranche-level index by the tranche's share in the average CLO capital structure. The sample period is January 2012 (when Palmer Square CLO debt indices become available) to December 2020 in Panel A, and January 2005 (when Creditflux starts covering a large part of the CLO market) to December 2020 in Panel B. The table reports Newey and West (1987) standard errors. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Panel A - Equity Ratio

	CLO Equity Ratio	Bank Equity Ratio
	(1)	(2)
EBP	0.94**	−1.29***
	(0.44)	(0.26)
Constant	10.98***	9.08***
	(0.40)	(0.37)
Obs.	173	68
R^2	0.035	0.340

Panel B - Funding Costs

	CLO AAA-LIBOR	CLO WACD-LIBOR
	(1)	(2)
EBP	24.78***	34.08***
	(3.11)	(4.70)
Constant	140.26***	198.37***
	(2.71)	(4.28)
Obs.	124	124
R^2	0.335	0.294

Table A18: Robustness: CLOs vs. Banks – Funding Costs and Leverage

This table reports results from a regression of the difference between CLO and bank funding costs on the excess bond premium (EBP) from Gilchrist and Zakrajšek (2012). Column (1) uses the spread between CLOs' primary market AAA-rated tranche yields and LIBOR, Column (2) the spread between CLOs' primary market weighted average costs of debt yields and LIBOR, Column (3) the spread between CLOs' secondary market A-rated tranche yields and A-rated bank bond yields, and Column (4) the spread between CLOs' secondary market BBB-rated tranche yields and BBB-rated bank bond yields. The weighted average cost of debt (WACD) weights each CLO debt tranche-level index by the tranche's share in the average CLO capital structure. To compare CLO and bank yields, we convert bank yields into spreads relative to LIBOR using LIBOR forward curves, which are matched based on the same integer remaining maturity. Bank yields are aggregated to a time-series by weighting each bond by its outstanding amount. The table reports Newey and West (1987) standard errors. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

	AAA-LIBOR	WACD-LIBOR	A-Bank Bond Spread	BBB-Bank Bond Spread
	(1)	(2)	(3)	(4)
EBP	11.97*	15.66*	10.72	29.24***
	(6.48)	(8.80)	(6.50)	(10.99)
Constant	100.77***	143.38***	208.33***	326.27***
	(4.97)	(6.50)	(5.71)	(10.37)
Obs.	198	198	124	124
R^2	0.041	0.043	0.023	0.056

Table A19: Cyclicality of Flows into CLOs and Open-end Mutual Funds

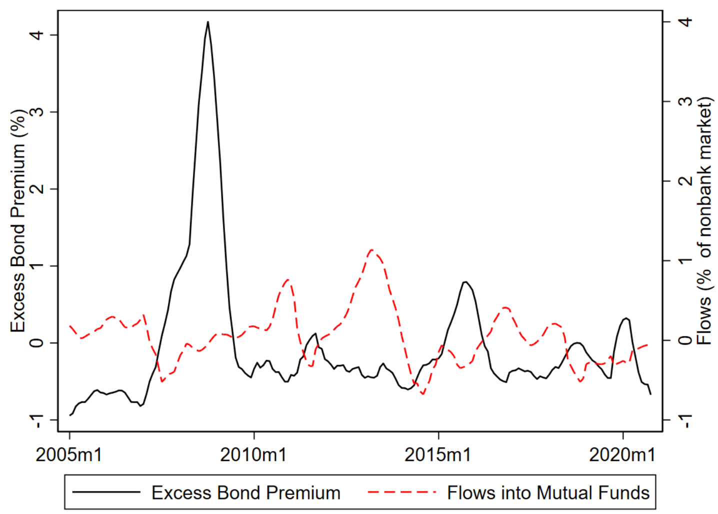
This table reports results from a regression of flows into CLOs and open-end loan mutual funds on the excess bond premium (EBP) from Gilchrist and Zakrajšek (2012). The dependent variables are the monthly flows into CLOs or mutual funds relative to the respective assets under management in columns (1) and (2) or the size of the nonbank loan market in columns (3) and (4). Flows into mutual funds are obtained from Morningstar and include all open-end loan mutual funds. Flows into CLOs are computed from changes in the assets under management (based on book values) of CLOs obtained from Creditflux. The size of the nonbank loan market is based on the committed nonbank loan amount in the previous year obained from SNC. The regression is estimated on a monthly frequency from January 2005 (when Creditflux starts covering close to the entire CLO market) to October 2020 (after which Creditflux CLO issuance coverage for our sample deteriorates). The Excess Bond Premium is standardized to have mean 0 and standard deviation of 1. The table reports Newey and West (1987) standard errors. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

	Flows rel. to AUM (%)		Flows rel. to nonbank market (%)	
	(1) CLOs	(2) Mutual funds	(3) CLOs	(4) Mutual funds
EBP	−0.78***	−0.93**	−0.38***	−0.10***
	(0.19)	(0.38)	(0.09)	(0.03)
Constant	1.37***	0.40	0.72***	0.04
	(0.18)	(0.33)	(0.10)	(0.04)
Obs.	190	190	190	190
R^2	0.125	0.066	0.102	0.056

Figure A4: Cyclicality of Flows into CLOs and Open-End Mutual Funds

This figure shows the cyclicality of flows into open-end loan mutual funds and CLOs, relative to the size of the nonbank market. Flows into open-end mutual funds are obtained from Morningstar. Flows into CLOs are computed from changes in the assets under management (based on book values) of CLOs obtained from Creditflux. The size of the nonbank loan market is based on the committed nonbank loan amount in the previous year obtained from SNC. The graph shows a six-month moving average of flows. The data is from January 2005 to October 2020.

Panel A - Flows into Open-end Mutual Funds



Panel B - Flows into CLOs

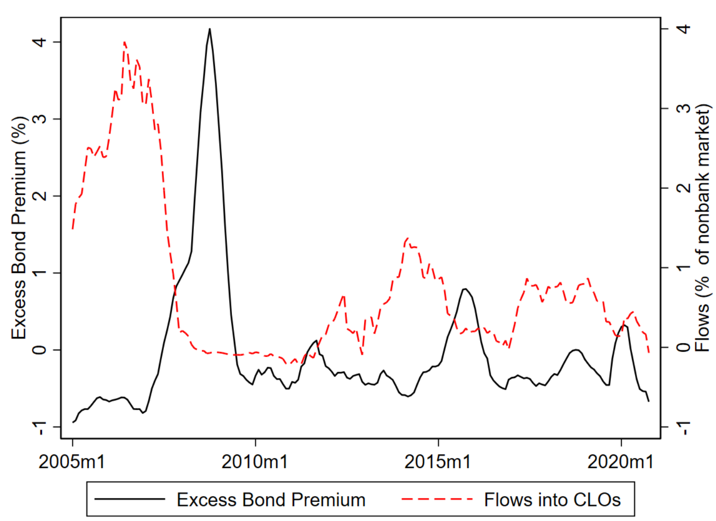
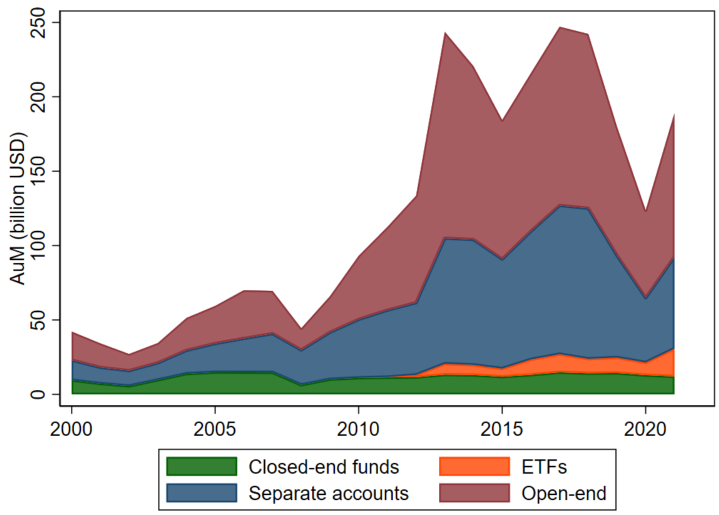


Figure A5: Decomposition of Assets under Management of Loan Mutual Fund Sector

The figure shows the assets under management of closed-end mutual funds, ETFs, separate accounts, and open-end mutual funds that invest into loans. The data is obtained from Morningstar.



A1.4.2 Fragility of Open-End Loan Mutual Funds

In this section, we provide evidence for the fragility and run risk of open-end loan mutual funds.

While the capital in a CLO is typically locked in for several years, investors in open-end loan mutual funds have the option to deposit or withdraw funds daily.[39] Specifically, shares of open-end mutual funds can be purchased or redeemed at the net asset value at the end of each trading day, and these redemptions are usually settled on the following business day. Changes in investor preferences and beliefs, therefore, may lead to drastic outflows during periods of stress.

Institutional details might further exacerbate the cyclicality of fund flows. Syndicated loans have a target settlement period of T+7, yet the average settlement time is often longer.[40] This introduces a significant liquidity mismatch between the assets and liabilities of open-end mutual funds. Furthermore, loans usually have high bid-ask spreads – especially during periods of stress – making it expensive for mutual funds to fulfill redemptions with loan sales.[41] As such, investor redemptions might impose costs on the remaining investors, and this might give investors an incentive to "run". Theoretical research has highlighted this fragility, which is also supported by recent evidence for corporate bond funds (Morris, Shim, and Shin (2017), Goldstein, Jiang, and Ng (2017)) and money-market funds (Kacperczyk and Schnabl (2013)).

We test for the fragility of open-end mutual funds by estimating the flow-performance relationship on the individual fund level. We gather assets-under-management (AuM), flows, returns, and fund age (in years) from Morningstar, and follow Goldstein, Jiang, and Ng (2017) in estimating

$$\text{Flows}_{ft} = \beta_0 + \beta_1 \alpha_{ft-1} + \beta_2 \alpha_{ft-1} \mathbb{I}_{\alpha_{ft-1}<0} + \text{Fund Controls}_{ft-1} + \gamma_t + \varepsilon_{ft} \tag{22}$$

where Flows_{ft} are the flows of fund f in month t relative to the fund's AuM in the previous month. Our main explanatory variable α_{ft-1} measures either the fund's return over the past

[39] We ignore closed-end mutual funds and ETFs because they are relatively unimportant in terms of their size. We focus our analysis on open-end mutual funds and leave out separate accounts because concerns have been raised about the stability of open-end mutual funds. See, for example, the *Investment Company Liquidity Risk Management Program Rules* implemented by the SEC. Link: `https://www.sec.gov/divisions/investment/guidance/secg-liquidity.htm`.

[40] It took on average 19.3 days to settle loan transactions in 2016Q1 (see `https://www.reuters.com/article/us-loan-settlement/lpc-loan-market-pushes-forward-to-cut-settlement-times-idUSKCN0Y323Y`)

[41] The average bid-ask spread for traded syndicated loans was 0.76% between 2002-07, while it rose to 5.5% at the peak of the Great Recession. These numbers are based on dealer quotes in the LSTA data.

month or the fund's relative performance (alpha) measured over the last 12 months.[42] We interact alpha with the dummy variable $\mathbb{I}_{\alpha_{ft-1}<0}$ which is equal to one if the alpha measured over the past year is negative and zero otherwise. The regression coefficient β_2 indicates whether the flow-performance relationship is concave. We include lagged flows, lagged AuM, lagged age, and month fixed effect as controls.

The results of our analysis, reported in Table A20, show that fund flows react strongly to fund performance. Column 1 shows that a -10% return in the past month leads to outflows of 2.6% (in terms of past AuM), on average, suggesting that changes in investor preferences lead to a strong reduction in available funds during periods of stress. Column 2 adds year-month fixed effects in order to compare outflows across funds. It shows that investors pull their investment more strongly from underperforming funds. This result is confirmed when we use alpha as the performance measure in Column 3. Column 4 follows Equation 22 and tests whether the flow-performance relationship is stronger when the fund underperforms. We find a positive and significant coefficient, implying that the relationship between flows and performance is concave. This means that fund flows are more sensitive to performance when fund performance is weak. We interpret this as suggestive evidence for the financial fragility and the risk of runs for open-end loan mutual funds.

[42] We obtain the fund alpha by regressing fund returns over the last 12 months on returns of the most widely-used benchmark in the loan market: the S&P/LSTA Leveraged Loan Index.

Table A20: Flow-Performance Relationship for Open-End Loan Mutual Funds

This table reports results on the flow-performance relationship at the individual fund level. A unit of observation is a Fund x Month pair. We estimate

$$\text{Flows}_{ft} = \beta_0 + \beta_1 \alpha_{ft-1} + \beta_2 \alpha_{ft-1} \mathbb{I}_{\alpha_{ft-1}<0} + \text{Fund Controls}_{ft-1} + \gamma_t + \varepsilon_{ft}$$

where Flows_{ft} are the flows of fund f in month t relative to the fund's AuM in the previous month. The explanatory variable α_{ft-1} measures either the fund's return over the past month or the relative performance (alpha). We obtain the fund alpha by regressing the fund returns over the last 12 months on returns of the most widely-used benchmark in the loan market: the S&P/LSTA Leveraged Loan Index. We interact alpha with the dummy variable $\mathbb{I}_{\alpha_{ft-1}<0}$ which is equal to one if the fund's alpha is negative and zero otherwise. We include lagged flows, AuM and age (in years) as controls. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

	Fund Flows			
	(1)	(2)	(3)	(4)
Lagged Return	0.256***	0.424***		
	(0.087)	(0.145)		
Alpha			2.155***	0.284
			(0.767)	(1.102)
Alpha * (Alpha < 0)				1.820**
				(0.765)
Lagged Flows	0.510***	0.401***	0.316***	0.294***
	(0.048)	(0.049)	(0.047)	(0.047)
Log(Fund Age)	−0.628***	−0.820***	−0.560***	−0.492**
	(0.146)	(0.199)	(0.209)	(0.201)
Log(Lagged Fund Size)	−0.022	0.003	0.131	0.141
	(0.070)	(0.089)	(0.093)	(0.091)
(Alpha < 0)				−0.501***
				(0.170)
Year-Month FE	N	Y	Y	Y
Obs.	6,090	6,090	5,433	5,433
R^2	0.306	0.448	0.405	0.414

A2 Model Derivations

A2.1 Main Derivation

Nonbank Problem:

$$\max_{\alpha_t^{NB}} \mathbb{E}\left[w_{t+1}^{NB}\right] \qquad s.t. \quad Var(r_{t+1}^{NB}) \leq \bar{\sigma}^2.$$

with: $\mathbb{E}\left[w_{t+1}^{NB}\right] = w_t^{NB} \cdot \mathbb{E}\left[r_{t+1}^{NB}\right], \mathbb{E}\left[r_{t+1}^{NB}\right] = \alpha_t^{NB}\mu_t + (1-\alpha_t^{NB})r^f, \mathrm{Var}\left(r_{t+1}^{NB}\right) = (\alpha_t^{NB})^2\sigma_t^2$, and $\mu_t > r^f$

We drop the time subscript because agents' decisions and equilibrium outcomes depend only on current period values.

$$\Rightarrow \text{optimal leverage: } \alpha^{NB*} = \frac{\bar{\sigma}}{\sigma}$$

Bank Problem:

$$\max_{\alpha_t^{B}} \mathbb{E}\left[w_{t+1}^{B}\right] - \frac{\gamma}{2}\mathrm{Var}\left(r_{t+1}^{B}\right)$$

with: $\mathbb{E}\left[w_{t+1}^{B}\right] = w_t^{B} \cdot \mathbb{E}\left[r_{t+1}^{B}\right], \mathbb{E}\left[r_{t+1}^{B}\right] = \alpha_t^{B}\mu_t + (1-\alpha_t^{B})r^f$, and $\mathrm{Var}\left(r_{t+1}^{B}\right) = (\alpha_t^{B})^2\sigma_t^2$

Again, we can drop the time-subscripts.

$$\Rightarrow \text{optimal leverage: } \alpha^{B*} = \frac{\mu - r^f}{\gamma\sigma^2}$$

Firm's loan demand:

$$q = \bar{q} - \delta\left(\mu - r^f\right)$$

We first derive $\mu - r^f$ in equilibrium:

$$\begin{aligned}
\overbrace{w^{NB}\alpha^{NB*}}^{q^{NB}} + \overbrace{w^{B}\alpha^{B*}}^{q^{B}} &= \bar{q} - \delta\left(\mu - r^f\right) \qquad \text{[Market Clearing]} \\
w^{NB}\frac{\bar{\sigma}}{\sigma} + w^B \cdot \frac{\mu - r^f}{\gamma\sigma^2} &= \bar{q} - \delta\left(\mu - r^f\right) \qquad \text{[Adding FOCs]} \\
\Rightarrow \left(\mu - r^f\right) \cdot \left(\frac{w^B}{\gamma\sigma^2} + \delta\right) &= \bar{q} - w^{NB}\frac{\bar{\sigma}}{\sigma} \\
\Rightarrow \mu - r^f &= \frac{\bar{q} - w^{NB}\frac{\bar{\sigma}}{\sigma}}{\frac{w^B}{\gamma\sigma^2} + \delta}
\end{aligned}$$

Taking the derivative wrt. volatility:

$$\frac{d\left(\mu - r^f\right)}{d\sigma} = \frac{w^{NB}\frac{\bar{\sigma}}{\sigma^2}\left(\frac{w^B}{\gamma\sigma^2} + \delta\right) - \left(\bar{q} - w^{NB}\frac{\bar{\sigma}}{\sigma}\right)\left(-2\frac{w^B}{\gamma\sigma^3}\right)}{\left(\frac{w^B}{\gamma\sigma^2} + \delta\right)^2}$$

$$= \frac{\frac{q^{NB}}{\sigma}}{\frac{w^B}{\gamma\sigma^2} + \delta} + \frac{2\frac{w^B}{\gamma\sigma^3}\left(\bar{q} - q^{NB}\right)}{\left(\frac{w^B}{\gamma\sigma^2} + \delta\right)^2}$$

$$= \frac{\frac{q^{NB}}{\sigma}}{\frac{w^B}{\gamma\sigma^2} + \delta} + \frac{2w^B}{\gamma\sigma^3}\frac{\mu - r^f}{\frac{w^B}{\gamma\sigma^2} + \delta}$$

$$= \frac{1}{\sigma\left(\frac{w^B}{\gamma\sigma^2} + \delta\right)}\left[q^{NB} + \frac{2w^B}{\gamma\sigma^2}\left(\mu - r^f\right)\right]$$

$$= \frac{1}{\sigma\left(\frac{w^B}{\gamma\sigma^2} + \delta\right)}\left[q^{NB} + 2q^B\right]$$

Now, one can derive the condition under which nonbank lending is more cyclical:

$$\frac{dlog(q^{NB})}{d\sigma} - \frac{dlog(q^B)}{d\sigma} =$$

$$= -\frac{1}{\sigma} + \frac{2}{\sigma} - \frac{1}{\mu - r^f}\frac{d\left(\mu - r^f\right)}{d\sigma}$$

$$= \frac{1}{\sigma} - \frac{\frac{w^B}{\gamma\sigma^2} + \delta}{\bar{q} - w^{NB}\frac{\bar{\sigma}}{\sigma}}\frac{1}{\sigma\left(\frac{w^B}{\gamma\sigma^2} + \delta\right)}\left[q^{NB} + 2q^B\right]$$

This is < 0 iff:

$$\bar{q} - w^{NB}\frac{\bar{\sigma}}{\sigma} < q^{NB} + 2q^B$$

$$\bar{q} - 2w^{NB}\frac{\bar{\sigma}}{\sigma} < 2\frac{w^B}{\gamma\sigma^2}\frac{\bar{q} - w^{NB}\frac{\bar{\sigma}}{\sigma}}{\frac{w^B}{\gamma\sigma^2} + \delta}$$

$$\left(\bar{q} - 2w^{NB}\frac{\bar{\sigma}}{\sigma}\right)\left(\frac{w^B}{\gamma\sigma^2} + \delta\right) < 2\frac{w^B}{\gamma\sigma^2}\left(\bar{q} - w^{NB}\frac{\bar{\sigma}}{\sigma}\right)$$

$$\left(\bar{q} - 2w^{NB}\frac{\bar{\sigma}}{\sigma}\right)\delta < \frac{w^B}{\gamma\sigma^2}\bar{q}$$

$$\delta < \frac{\bar{q}\frac{w^B}{\gamma\sigma^2}}{\bar{q} - 2w^{NB}\frac{\bar{\sigma}}{\sigma}} \equiv \bar{\delta}^C$$

One can also derive the condition under which bank leverage rises with volatility.

$$\alpha^B = \frac{\mu - r^f}{\gamma\sigma^2} \quad , \mu - r^f = \frac{\bar{q} - w^{NB}\frac{\bar{\sigma}}{\sigma}}{\frac{w^B}{\gamma\sigma^2} + \delta}$$

$$\Rightarrow \quad \alpha^B = \frac{\bar{q} - w^{NB}\frac{\bar{\sigma}}{\sigma}}{w^B + \delta\gamma\sigma^2}$$

$$\log\left(\alpha^B\right) = \log\left(\bar{q} - w^{NB}\frac{\bar{\sigma}}{\sigma}\right) - \log\left(w^B + \delta\gamma\sigma^2\right)$$

$$\frac{d\log\left(\alpha^B\right)}{d\sigma} = \frac{w^{NB}\frac{\bar{\sigma}}{\sigma^2}}{\bar{q} - w^{NB}\frac{\bar{\sigma}}{\sigma}} - \frac{\delta\gamma 2\sigma}{w^B + \delta\gamma\sigma^2}$$

This is > 0 iff:

$$\frac{w^{NB}\frac{\bar{\sigma}}{\bar{\sigma}}}{q - w^{NB}\frac{\bar{\sigma}}{\sigma}} > \frac{2\delta\gamma\sigma^2}{w^B + \delta\gamma\sigma^2}$$

$$\Rightarrow \frac{w^B}{\gamma\sigma^2} + \delta > 2\delta\frac{\bar{q} - w^{NB}\frac{\bar{\sigma}}{\sigma}}{w^{NB}\frac{\bar{\sigma}}{\sigma}}$$

$$\Rightarrow \delta < \frac{1}{2}\frac{w^{NB}\frac{\bar{\sigma}}{\sigma}\frac{w^B}{\gamma\sigma^2}}{\bar{q} - \frac{3}{2}w^{NB}\frac{\bar{\sigma}}{\sigma}} \equiv \bar{\delta}^L < \bar{\delta}^C, \text{ because } w^{NB}\frac{\bar{\sigma}}{\sigma} < \bar{q}$$

This implies, based on the model, that if bank leverage is counter-cyclical then $\delta < \bar{\delta}^L < \bar{\delta}^C$, and therefore nonbank lending is more cyclical.

A2.2 Wealth Effects

Next, we show that the nonbank lending share falls when all intermediaries make losses which reduces their wealth. In addition, bank leverage rises. To simplify the analysis we assume that banks and nonbanks have the same wealth, and then we look at a synchronous change in wealth of both banks and nonbanks.

This yields the following expression for the nonbank lending share:

$$\frac{X}{q} = \frac{w\frac{\bar{\sigma}}{\sigma}}{\bar{q} - \delta\frac{\bar{q} - w\frac{\bar{\sigma}}{\sigma}}{\frac{w}{\gamma\sigma^2} + \delta}} = \frac{w\frac{\bar{\sigma}}{\sigma}\left(\frac{w}{\gamma\sigma^2} + \delta\right)}{\bar{q}\frac{w}{\gamma\sigma^2} + w\frac{\bar{\sigma}}{\sigma}} = \frac{\frac{\bar{\sigma}}{\sigma}\left(\frac{w}{\gamma\sigma^2} + \delta\right)}{\bar{q}\frac{1}{\gamma\sigma^2} + \frac{\bar{\sigma}}{\sigma}}$$

Thus the nonbank lending share declines when intermediary wealth w falls. Intuitively, nonbanks' leverage is independent of their wealth, and thus nonbank lending falls when their wealth declines. This leads to a higher return on the risky asset because of firms' downward sloping loan demand. Thus, banks are now willing to take on a higher leverage, and thus for the same decline in wealth as for nonbanks, bank lending does not fall as much as nonbank lending. The rise in bank leverage when the wealth of both banks and nonbanks falls can be directly inferred when plugging equilibrium excess loan returns in the FOC for banks:

$$\alpha^B = \frac{\bar{q} - w\frac{\bar{\sigma}}{\sigma}}{w + \delta\gamma\sigma^2}$$