Non-bank lending during crises

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Abstract

Using data on syndicated loans for a large sample of countries, this paper shows that non-banks curtail their credit by significantly more than banks during borrower-country crises. We provide novel evidence that differences in the value of lending relationships explain most of the gap, even when accounting for lender and borrower characteristics. Unlike for banks, relationships with non-banks – whether measured by duration or frequency – do not improve borrowers' access to credit during crises. The rise of non-banks could therefore lead to a shift from relationship towards transaction lending and exacerbate the repercussions of financial shocks.

JEL Codes: F34, G01, G21, G23.
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1 Introduction

Non-bank financial institutions (non-banks) have steadily increased their global footprint since the Great Financial Crisis (GFC).[1] The shift in financial intermediation from banks to non-banks has raised concerns about detrimental implications for credit supply, financial stability, and the real economy (IMF, 2022). While a large literature investigates the effects of financial crises on bank lending (Claessens, 2017; Buch and Goldberg, 2020), evidence on global non-bank lending during crises is scarce.[2] Moreover, to what extent lending relationships with non-banks alleviate borrowers' credit constraints during downturns remains an open question.

Using global syndicated loan data, this paper provides novel evidence on non-bank lending and the role of lending relationships during financial crises. In a large sample of countries, we establish that non-banks contract their syndicated lending by significantly more than banks during shocks in borrower countries. This 'lending gap' remains statistically significant and large in economic magnitude when we control for observable and unobservable time-varying lender characteristics, including funding models. We find that accounting for the differences in the value of lending relationships – whether measured by duration or frequency – reduces the gap by over two-thirds. Further analysis suggests that lending relationships with non-banks do not improve borrowers' access to credit during local crises.

We use Thomson Reuters' Dealscan database on syndicated loans to classify lenders into banks and non-banks. Around one-third of global syndicated lenders are non-banks. Their origination of syndicated loans to non-financial firms grew twentyfold from 1990 and stands at about 20% of all new syndicated credit today. We compute banks' and non-banks' exposure to financial crises at the lender–borrower country–year level as the stock of outstanding loans extended by a lender to firms in a given crisis country over

[1]Non-banks account for about half of the assets of the global financial system (Financial Stability Board, 2020). On the rise of non-bank credit and its drivers, see Buchak et al. (2018), Nelson et al. (2018), Fuster et al. (2019), Irani et al. (2021), Chernenko et al. (2022), Davydiuk et al. (2020), Gopal and Schnabl (2022), Chen et al. (2023), and Sarto and Wang (2023).

[2]Two notable exceptions are Fleckenstein et al. (2021) and Irani et al. (2021). Emphasizing the importance of funding instability, these papers respectively show that non-banks are highly pro-cyclical lenders and that they were less likely to roll over loans during the U.S. systemic crisis of 2007/08. Other work on non-banks mostly investigates their role in mitigating the effectiveness of monetary policy (see Chen et al. (2018), Elliott et al. (2019), Xiao (2020), Cucic and Gorea (2021), Banerjee and Serena (2021), and Elliott et al. (2021), among others).

the lender's total stock of outstanding syndicated loans. The measure reflects that some lenders are more exposed than others to the same financial crisis. Data on financial crises are obtained from Laeven and Valencia (2020). Our sample covers 83 crisis episodes in 148 countries.

We first establish that non-banks reduce their credit to non-financial firms by substantially more than banks when faced with a financial shock in the borrower country. Specifically, non-banks cut lending by about 50% more than banks. We observe this lending gap after controlling for unobservable time-varying lender heterogeneity through lender parent*year fixed effects, which absorb differences in lenders' funding models. In particular, they control for non-banks' stronger reliance on wholesale funding (Jiang et al., 2020; Xiao, 2020), which could contribute to greater cyclicality of global non-bank lending (Fleckenstein et al., 2021).[3] Differences in funding models therefore seem to not fully explain the stronger decline in non-bank lending during crises in our cross-country sample. Consistent with this argument, when we follow Irani et al. (2021) and group non-banks into those with stable and unstable liabilities, we find the contraction in lending to be equally strong among both groups.

Our analysis faces the common identification challenge that banks and non-banks lend to different borrowers. Indeed, we show that borrowers connected to non-banks are significantly riskier than those that borrow only from banks, even when they are located in the same country and operate in the same industry.[4] In the most stringent specification, we account for these differences in borrower characteristics through borrower*time fixed effects that control for observable and unobservable time-varying borrower fundamentals. These fixed effects capture, for example, firm profitability, management, or leverage, and help separate loan supply from loan demand effects (Khwaja and Mian, 2008; Jiménez et al., 2014). When controlling for borrower-time fixed effects, the lending gap narrows but remains statistically significant and economically large.

In a second step we investigate whether the value of lending relationships can explain the divergence between bank and non-bank credit during crises. For banks, lending relationships have been shown to reduce information asymmetries and lead to better loan

[3] Lender parent*year fixed effects bring additional advantages. They allow us to keep the full set of lenders in our sample, even if there are no balance sheet data available; they account for lender reputation; and they control for the role of internal capital markets among lenders belonging to the same parent.

[4] This result is in line with findings in Chernenko et al. (2022) for mid-sized U.S. borrowers.

terms (Bharath et al., 2011; Ivashina and Kovner, 2011). They thus improve borrowers' access to credit especially during shock episodes (Sette and Gobbi, 2015; Bolton et al., 2016; Beck et al., 2018). Motivated by these findings, we construct measures of lender-borrower relationships with banks and non-banks based on the duration of the relationship, as well as the frequency of previous interactions. To account for the differential effects of relationships in downturns and normal times, we interact these measures with lenders' crisis exposure.

Controlling for relationships and their impact during crises significantly reduces the gap between bank and non-bank lending. Regardless of the relationship measure, the lending gap narrows by over two-thirds to about 10%. The fact that relationships explain a large share of the gap suggests that non-banks behave more like transaction lenders, even if they share a history with a borrower. Our analysis thus offers a novel explanation for the strong contraction of global non-bank lending during crises, complementing findings on the role of funding instability in the U.S. context.

To buttress this novel finding, we follow a large banking literature and examine the impact of lending relationships on loan spreads during crises. In our sample of global syndicated loans, we first confirm previous findings that lending relationships with banks benefit borrowers by reducing spreads during crises. We then show that these benefits are not present for non-bank borrowers. Additionally, we find that during crises, non-banks reduce lending to riskier borrowers by significantly more, despite their specialization and potential informational advantage in this market segment. These findings support the argument that relationships with non-banks provide limited value to borrowers.

We find suggestive evidence that the contraction in non-bank lending has real effects: firms connected to non-banks see a significantly stronger decline in overall syndicated lending during financial crises. Consequently, their investment rates decline by relatively more. However, in interpreting these results, an important caveat is that the firm-year level analysis does not allow us to control for all unobservable confounding factors.

Our findings are robust along various dimensions. We show that lenders' industry specialization or the geographic diversification of their loan portfolios do not explain the lending gap. These factors have been linked to higher bank credit supply during crises (De Jonghe et al., 2020; Doerr and Schaz, 2021). In terms of relationships, an alternative measure based on total amounts instead of duration or frequency yields similar results. Within credit lines, which are more likely to remain on balance sheet and are hence potentially more affected by relationships, we also find that the gap substantially narrows after accounting for relationships. Controlling for lead arranger status (i.e., accounting for the fact that lead arrangers engage in screening and monitoring of borrowers) in addition to relationships has only a modest effect on the lending gap. This suggests that discrepancies in the value of relationships do not just reflect lenders' role in a syndicate. Consistent with the argument that lending relationships are especially important when informational frictions are more pronounced, we find that the importance of relationships in explaining the lending gap is less pronounced in the U.S., which has one of the best-developed and most transparent lending markets. Our key findings also remain after we aggregate data to the lender–borrower country–year level, split borrowers into public or private firms, exclude investment banks from the non-bank sample, exclude lenders from major countries, or restrict the sample to large lenders.

Taken together, our results suggest that the growth of non-bank lenders could amplify the effects of financial instabilities on the real economy. The rising footprint of non-banks could lead to a shift away from relationship towards transaction lending, with potentially negative consequences for borrowers' access to credit during crises. Moreover, our results for the global syndicated loan market suggest that non-bank lenders do not act as shock absorbers or asset insulators during financial crises (Chodorow-Reich et al., 2021; Elliott et al., 2021). As corporate indebtedness has reached historical highs (IMF, 2021), the rise of non-bank lenders and the strong contraction in their lending to highly-leveraged borrowers during crises is a particularly worrying finding.

Our findings have two important implications for policy. First, existing policy proposals focus mostly on non-bank financial institutions' contribution to liquidity stress in money markets (Quarles, 2020; Hauser, 2021; Hubbard et al., 2021). Our results suggest that non-bank lending to non-financial firms also warrants close attention and monitoring. And second, while regulation enacted after the GFC has arguably made banks more resilient, non-banks' greater presence and sharper contraction in lending might offset some of these gains during crises. Policy makers should take into account that risks may migrate across the financial system in response to tighter bank regulation, calling for a holistic perspective to financial regulation.[5]

[5] See also the discussion in Irani et al. (2021).

Literature and contribution. Our paper contributes to two strands of literature. First, we speak to the literature investigating non-bank lending. This work has largely focused on monetary policy shocks in single-country settings. Building on the insight that deposits flow out of banks during episodes of monetary tightening (Drechsler et al., 2017), Chen et al. (2018) show that contractionary monetary policy leads to deposit flows from banks into non-banks in China. Accordingly, non-bank lending expands while bank lending contracts. Xiao (2020) supports this finding with a structural model: Shadow banks offset around one-third of the reduction in commercial bank deposits during monetary policy tightening cycles in the U.S. by serving a more price-sensitive clientele. For Denmark and the U.S., respectively, Cucic and Gorea (2021) and Elliott et al. (2019) provide complementary evidence that non-banks moderate the impact of monetary policy on credit supply and the real economy. Elliott et al. (2021) do so in a cross-country setting.

Beyond monetary policy, recent evidence for the U.S. shows that non-banks cut their lending by more during episodes of market-wide uncertainty. Irani et al. (2021) show that loans funded by non-banks were less likely to be rolled over during the GFC. Fleckenstein et al. (2021) find non-bank syndicated lending to be more sensitive than bank lending to the financial cycle and that non-bank lending contracted by more during the GFC and Covid crisis. Both papers link this pro-cyclicality to U.S. non-banks' greater funding volatility. Our result that non-banks cut lending by relatively more during crises in borrower countries provides external validity to these results. In addition, our novel findings on the importance of lending relationships suggest that, in the global syndicated loan market, forces beyond funding stability also play an important role in shaping non-bank lending during crises.[6]

[6] Different factors could explain why funding instability does not fully account for the contraction in non-bank lending in our global sample. First, we exploit cross-sectional variation in dozens of financial crises across borrower countries, rather than variation in aggregate conditions or market-wide uncertainty in the U.S. During the U.S. financial crisis of 2007/08, the most severe financial crisis since the Great Depression, runs on financial institutions amplified the broad tightening of funding conditions (Brunnermeier, 2009). Effects on global funding conditions are likely less pronounced during more local financial crises. Second, our global sample covers the universe of lenders in the global syndicated loan market, which differ from their U.S. counterparts. The funding of non-U.S. banks in particular, which make up a sizable share of our sample, could be more cyclical than that of their U.S. counterparts because of their dependence on the wholesale U.S. dollar funding market (Ivashina et al., 2015). Related, non-bank lenders in our sample are mostly finance companies, investment banks, and insurance companies. They might differ in their funding volatility from CLOs, the dominant non-bank lender in the U.S. And third, the U.S. has one of the best-developed and most transparent lending markets (Beck et al., 2010), so lending relationships might be less important than in other countries. Indeed, when we restrict the sample to U.S. borrowers and lenders only, we find that the importance of relationships in explaining

Second, we contribute to work on the effects of financial crises on credit supply and the importance of lending relationships. For banks, a large literature finds that nationality is an important determinant of loan supply and that global banks transmit shocks across markets (Cetorelli and Goldberg, 2012; Schnabl, 2012; Giannetti and Laeven, 2012; De Haas and Van Horen, 2013; Popov and Van Horen, 2015; Hale et al., 2020; Doerr and Schaz, 2021). Claessens (2017) and Buch and Goldberg (2020) provide excellent overviews. Related work investigates the benefits of lending relationships for borrowers (Bharath et al., 2011; Ivashina and Kovner, 2011) and finds that relationships with banks alleviate borrowers' credit constraints during crises (Sette and Gobbi, 2015; Bolton et al., 2016; Beck et al., 2018). Our paper provides novel evidence that non-banks reduce lending by more than banks during crises and that – unlike for banks – lending relationships with non-banks do not provide material benefits to borrowers.

2 Data and descriptive statistics

This section explains the data sources and construction of the main variables. It then provides summary statistics.

2.1 Data and variable definitions

Thomson Reuters' Dealscan database provides detailed information on syndicated loans. Syndicated loans are originated jointly by a group of financial institutions to a single borrower. The lending syndicate includes at least one lead institution (also called lead arranger) and usually further participants. Lead arrangers negotiate terms and conditions of deals, perform due diligence, and organize participants.[7] Compared to other types of loans, syndicated loans are on average larger in volume and extended to larger borrowers.

Syndicated lending is an important source of financing for firms, in particular larger ones (Chodorow-Reich, 2014; Cerutti et al., 2015). It represents around three-quarters of total cross-border bank lending to non-financial corporations in both high- and middle-

the lending gap is less pronounced, consistent with results in Fleckenstein et al. (2021).

[7]Lending in the syndicated loan market is organized in packages and facilities: a package is a loan agreement between a borrower and a group of lenders, and each package can contain one or more facilities. Our basic unit of observation is the facility.

income economies (Doerr and Schaz, 2021). Non-banks have a significant presence in the syndicated loan market in all regions and sectors, both in terms of total and cross-border lending (Elliott et al., 2021; Aldasoro et al., 2022). Their origination of syndicated loans to non-financial firms grew twentyfold over the last 30 years and represents about 20% of all new syndicated credit today.

Dealscan provides detailed information on syndicated loans at origination, including loan amount, maturity, and interest, as well as the identity and type of lenders and borrowers. We follow prior literature and restrict our sample in the following ways. We focus on syndicated lending to non-financial, non-utility firms, drop incomplete deals (with status "cancelled", "suspended", or "rumour"), and deals with no information on loan amounts. We manually identify and exclude lenders and borrowers linked to governments and government institutions, such as development banks. As Dealscan may report both the origination and amendments of the same deal (Roberts, 2015), we further drop deals containing the phrase "amends" or "amendment of" in their associated comments. We then convert all deal values to 2012 U.S. dollars.

Information on the share that each syndicate participant contributes to a given facility is available only for a subset of the deals. To assign facility amounts to individual lenders in case of missing lending shares, or for loan facilities with aggregate lending shares totaling more than 110%, we follow prior literature and split facility volumes on a pro-rata basis among all lenders in the syndicate.[8] Finally, we drop loans smaller than $10,000 (less than 1% of observations).

We classify lenders into banks and non-banks based on Dealscan's institution classification scheme. Accordingly, our focus is on the actual participation by types of bank and non-bank syndicate members, as in Lim et al. (2014) and Elliott et al. (2021).[9] For example, investment banks, finance companies, and mutual funds are considered as non-bank institutions. We amend the Dealscan classification by matching a majority of unclassified or "other" lenders to banks and non-banks based on keyword search, and manually reclassifying a number of lenders.[10] Non-banks differ from banks along several

[8] See Giannetti and Laeven (2012); De Haas and Van Horen (2013); Chodorow-Reich (2014); Bräuning and Ivashina (2020). A general finding in the literature is that alternative methods of splitting deal volumes do not materially affect results (Cerutti et al., 2015; Doerr and Schaz, 2021). Our main results are robust to alternative methods of splitting volumes (unreported).

[9] A lender is a bank in our sample if it belongs to one of the following types: African bank, Asia-Pacific bank, Eastern European / Russian bank, foreign bank, Middle Eastern bank, mortgage bank, thrift / S&L, U.S. banks and Western European banks. Elliott et al. (2021) adopt a similar classification.

[10] Consistent with our definition of non-banks, some major investment banks grouped into banks by

dimensions, including the absence of deposit insurance and a generally lighter regulatory burden. One important difference is that non-banks, whose funding structure is dominated by wholesale borrowing (Jiang et al., 2020), serve a more price-sensitive clientele (Xiao, 2020). Moreover, non-banks often lack access to the liquidity provided by central banks (Irani et al., 2021).

To identify banking crises we rely on Laeven and Valencia's (2020) (LV henceforth) Systemic Banking Crises Database. These data provide country-year-level information on episodes of financial distress for a large number of countries up until 2018. Over our sample period from 1995 to 2018 it reports 83 distinct banking crises.[11] Panel (a) in Figure A2 plots the number of countries in crises in each year of our sample. There is a concentration of financial turmoil around the late 1990s (Asian financial crisis) and from 2008 onward (Great Financial Crisis).

Based on these data, we define lenders' exposure to crisis countries as follows:

$$crisis\ exposure_{l,c,t} = \frac{loan\ volume_{l,c,t-1} \times banking\ crisis_{c,t}}{loan\ volume_{l,t-1}}, \tag{1}$$

where $loan\ volume_{l,c,t-1}$ denotes the total amount of outstanding loans granted by lender l to borrowers in country c as of $t-1$, $loan\ volume_{l,t-1}$ denotes total outstanding loans by lender l to *all* countries, and $banking\ crisis_{c,t}$ is a dummy variable which equals one if borrower country c had a banking crisis in year t as defined by LV, and zero otherwise. *Crisis exposure* thus reflects that not all lenders are equally exposed to financial crises in a given country. Rather, it captures that lenders with greater loan exposure to borrowers in crisis countries are likely more affected than lenders with lower exposure.[12]

Dealscan are reclassified as non-banks. Examples include Macquarie Bank, RBC Capital Markets, and Nomura Holdings. Lenders with SIC code 6211 classified by Dealscan as banks are reassigned to non-banks, following Lim et al. (2014). In a few cases (notably Morgan Stanley), Dealscan classifies lenders into a generic category named "corporations". We unpack this category using our manual procedure. We identify 3,026 out of 4,118 unclassified immediate lenders as banks or non-banks. For more details, see also Aldasoro et al. (2022).

[11] The two conditions defining a banking crisis by LV are significant signs of financial distress in the banking system (such as bank runs, large losses, and/or bank liquidations), and significant banking policy intervention measures in response to losses in the banking system. Crises episodes can last for more than one year.

[12] Note that exposure is based on the stock of outstanding loans in a country. Syndicated loans are often sold on the secondary market, especially in the U.S., which could lead to measurement error in exposure. However, as long as the likelihood of a loan sale in a country across banks and non-banks is uncorrelated with their exposure to the market, this measurement error would lead to an attenuation bias. In the Online Appendix, we provide evidence in Table A4 that there is no systematic correlation between the likelihood of being a lead arranger (which are known to retain more of their loans on balance sheet)

To measure lending, we focus on the total amount of new syndicated credit extended by lender l to borrower b in a given year. Loan-level observations are aggregated to the lender-borrower-year level. To account for the formation and termination of lending relationships, we construct lending based on a panel with loan amounts of zero in the years immediately before and after lender-borrower observations with positive credit amounts (extensive margin). The literature has highlighted the importance of lending along the extensive margin for syndicated credit (Giannetti and Laeven, 2012; Giannetti and Saidi, 2019; Elliott et al., 2021).[13] As we saturate our empirical model with a rich set of fixed effects, the sample is restricted to lenders and borrowers with at least two observations in a given year. As syndicated loans usually entail a group of lenders, the loss in sample size is negligible.

We measure the strength of lending relationships in terms of their duration and frequency. First, we capture the *duration* of a lending relationship by the number of years passed since the first syndicated loan recorded between a lender and a borrower since the late 1980s. This common measure proxies for lenders' accumulation of private information on borrowers (Petersen and Rajan, 1994; Degryse and Ongena, 2005; Sette and Gobbi, 2015). Second, the *frequency* measure counts the total number of syndicates involving a specific lender-borrower pair over the past five years prior to the origination of a new loan (Bharath et al., 2007; Ivashina et al., 2008; Bharath et al., 2011; Ivashina and Kovner, 2011, among others).[14] Finally, for robustness tests we compute the total amount of new loans between lender l and borrower b over the past five years, normalized by the total amount of new loans taken by the borrower over the same time frame. For all three measures, we set the value to zero if there was no previous relationship.

We combine Dealscan data with data on listed firms from Compustat, following Chava and Roberts (2008). Overall, more than 13,000 firms in 90 countries in our regression sample are matched to Compustat. We collect information on a variety of firm characteristics and compute leverage as long term debt plus current liabilities over equity. Table A1 in the Online Appendix reports summary statistics.

and exposure to countries. Importantly, there is no systematic difference in this correlation between banks and non-banks.

[13] As we show in robustness tests, our findings extend to the intensive margin.

[14] The frequency of a lending relationship between lender l and borrower b in year t is measured by the total number of loans extended by lender l to borrower b from year $t-5$ to $t-1$, with the possibility of lender l participating in multiple facilities over the past five years. Bharath et al. (2007) argue that a five-year window is appropriate, as it corresponds to the typical time until the next refinancing for the firms' borrowing through syndicated loans.

We also construct a number of variables to measure borrower risk. First, we classify borrowers as risky if their average all-in drawn spread across all syndicated loans in a given year exceeds the 75^{th} percentile across the distribution of spreads across all borrowers in a given two-digit industry.[15] As borrowers on the syndicated loan market tend to be large firms, a higher interest rate compared to industry peers could indicate that they are seen as relatively more risky (see also Blickle et al. (2020)). Second, and closely related, we classify borrowers as risky if their spread in a given year exceeds the 75^{th} percentile across the distribution in their country (Elliott et al., 2021). And third, we use information on firm leverage from Compustat. We define firms as risky if they lie in the top tercile of the leverage distribution in a given year, as highly-leveraged firms are especially sensitive to negative shocks (Giroud and Mueller, 2017; Kalemli-Özcan et al., 2022).

2.2 Summary statistics

Our sample covers the years from 1995 to 2018 and includes information on 9,600 lenders (of which 32% are non-banks) and 41,188 borrowers. It comprises a total of 1,222,273 lender-borrower-year observations. Non-banks extend on average 11% of all new credit in the global syndicated loan market during our sample period, and almost one-fifth of all new credit towards the end of our sample. They originate a significant share of all syndicated loans to borrowers located in all regions and sectors, with a share of foreign lending similar to banks (for further details on non-bank lenders in the syndicated loan market, see Aldasoro et al. (2022)).[16]

In our sample, non-banks have higher average exposure to banking crises (5.5% vs. 7.3%, see Figure A2, panel b). In general, loans by non-banks are larger in volume and carry considerably higher interest rates (170 basis points (bp) vs. 270 bp), but are of similar maturity as bank loans; credit lines comprise about 40% of all non-bank loans, compared to 50% for banks. Table 1 provides descriptive statistics for our main variables. The unit of observation is the lender–borrower–year level. The average crisis exposure equals 6.7%, with a standard deviation of 20%, implying that in a given year about 7% of all loans are originated to borrowers in a crisis country.

[15]The all-in drawn spread is the interest rate spread over LIBOR paid by the borrower for each dollar drawn from the loan, together with annual or facility fees.

[16]The bulk of non-bank syndicated lending is accounted for by investment banks and finance companies.

Among mid-sized U.S. borrowers, Chernenko et al. (2022) show that non-banks lend to firms with higher leverage and lower profitability. To the extent that non-banks also serve riskier borrowers globally, this could affect their lending behavior compared to banks. To investigate non-banks' borrower pool, in the Online Appendix we estimate regressions at the lender–borrower–year level and show that riskier borrowers are significantly more likely to obtain a loan from a non-bank (see Table A2). The significant differences across borrowers suggest that non-banks specialize in lending to riskier firms, in line with the observation that non-banks grant loans with higher spreads. These findings highlight the importance of accounting for observable and unobservable borrower characteristics, as we will discuss in what follows.

3 Empirical strategy and results

This section analyzes bank and non-bank lending during crises, as well as its drivers. It first explains the empirical strategy and then presents the results.

3.1 Empirical strategy

The baseline specification tests whether bank and non-bank lending evolve differently during financial turmoil in the country of the borrowing firm. We estimate the following specification:

$$\begin{aligned} log(credit)_{l,b,t} &= \beta_1 \; crisis\ exposure_{l,c,t} + \beta_2 \; non\ bank_l \\ &\quad + \beta_3 \; crisis\ exposure_{l,c,t} \times non\ bank_l + \phi_{l,b} + \psi_{l,t} + \tau_{b,t} + \varepsilon_{l,b,t}. \end{aligned} \tag{2}$$

The dependent variable $log(credit)_{l,b,t}$ denotes the log of new credit extended by lender l to borrower b in year t. The main analysis focuses on lending along the extensive margin, so it uses the log of one plus new credit.[17] The variable $crisis\ exposure_{l,c,t}$ measures the exposure of lenders to a given borrower country c that experiences a crisis in year t, as defined in Equation (1). Note that Equation (2) focuses on crises in borrower countries, which mitigates the concern that a shock to the lender is the cause of the financial crises

[17] Our results are insensitive to other transformation methods, such as the inverse hyperbolic sine (IHS) transformation (see Table A3). We also show that our results are similar along the intensive margin.

– a concern that would be more relevant if we were to analyze shocks to lenders' home markets. The dummy *non bank*$_l$ takes on a value of one for non-banks and a value of zero for banks.

All regressions include lender*borrower fixed effects ($\phi_{l,b}$), which control for unobservable and time-invariant lender and borrower heterogeneity (such as industry, location, or distance). We thereby exploit only the variation within the same lender-borrower combination over time.[18] These fixed effects, combined with a dependent variable in levels, imply an interpretation in changes. We cluster standard errors at the lender's parent level and borrower country level to account for serial correlation within the same borrower country across firms and time, as well as among borrowers of the same lender, and control for lender nationality (foreign vs domestic) throughout.[19]

The main coefficient of interest in Equation (2) is β_3, which indicates whether non-bank lending declines by more or less than bank lending during crises in borrowing countries. However, any observed differential lending behavior between banks and non-banks could in principle be driven by confounding factors at both the lender and borrower level, affecting the estimate of β_3. We address this concern through the inclusion of granular time-varying fixed effects.

One potentially confounding factor is the difference in funding structure between banks and non-banks. Recent literature, mostly in the U.S. context, shows that non-banks rely more on wholesale funding. U.S. banks, on the other hand, are predominately funded with retail deposits (Jiang et al., 2020).[20] Suppliers of wholesale funding are generally more price sensitive. Together with limited access to central bank liquidity, this could make non-bank funding more fragile (Fleckenstein et al., 2021; Irani et al., 2021). One important aspect to keep in mind, however, is that in the global syndicated loan market a significant share of lending by non-U.S. banks is dollar denominated (Ivashina et al., 2015). With limited access to U.S. dollar retail deposits, these banks must rely on more-volatile wholesale dollar funding markets (Aldasoro et al., 2022).

To control for differences in funding models, we include lender parent*year fixed effects

[18] In our data, the probability of obtaining a loan in year t conditional on obtaining a loan in year $t-1$ from the same lender equals one-third for loans from both banks and non-banks.

[19] Clustering at the lender (as opposed to lender parent) level generally increases the precision of our estimates, but has the drawback of not accounting for potential correlation among observations across lenders belonging to the same parent.

[20] See also Chen et al. (2018); Xiao (2020), and Elliott et al. (2019).

($\psi_{l,t}$). Not only do these fixed effects control for aggregate factors affecting all lenders (e.g. the global financial cycle), they also absorb any observable and unobservable time-varying lender heterogeneity, for example size, profitability, or the reliance on wholesale funding. There are a number of additional advantages to this approach. First, since there exists only scant balance sheet data for non-banks (especially in a cross-country setting), lender parent*year fixed effects allow us to keep the full set of lenders in our sample, while controlling for differences in funding conditions and other lender characteristics. Second, the fixed effects account for lender reputation, which has been shown to matter for syndicated loan origination (Sufi, 2007). And third, they control for the role of internal capital markets among lenders belonging to the same parent (Cetorelli and Goldberg, 2012).

Beyond lender characteristics, a common challenge to identification is that banks and non-banks could serve different clients. As discussed in Section 2.2, firms borrowing from non-banks are on average riskier, which could affect any observed differences in lending. We address this challenge through the inclusion of granular time-varying fixed effects ($\tau_{b,t}$ in Equation (2)) either at the country-industry-size level (De Jonghe et al., 2020), or at the borrower level. With borrower*time fixed effects, we compare lending by banks and non-banks to the same borrower in the same year (Khwaja and Mian, 2008; Jiménez et al., 2014).

3.2 Results

Figure 1 examines bank and non-bank lending during crises non-parametrically. It plots the evolution of the log of new credit by banks (black dashed line) and non-banks (blue solid line) in a four-year window around banking crises. Each series is standardized to a value of one in the year before the crisis. Loan volumes follow a similar trend for both types of lenders in the years preceding a crisis, increasing by about 5%–10%. However, they diverge sharply once the crisis hits, indicated by a value of one on the horizontal axis. While both lender types see a contraction in credit, the decline is almost twice as large for non-banks.

Section 3.2.1 analyzes this pattern in greater detail, while Section 3.2.2 investigates the role of lending relationships in explaining the lending gap between banks and non-banks.

3.2.1 Non-bank lending during crises

Table 2 shows that non-banks reduce their lending by relatively more than banks during financial crises. Column (1) uses crisis exposure as explanatory variable. It exploits variation within each lender-borrower connection by using fixed effects at the lender*borrower level and controls for unobservable time-varying shocks common to all lenders and borrowers through year fixed effects. The negative and significant coefficient on crisis exposure suggests that for the average lender, lending declines significantly during crises. In terms of magnitude, a one standard deviation increase in local crisis exposure leads to an additional decline in lending by 9.7% (0.21×-0.460).

Column (2) adds the interaction term with the dummy *non-bank*.[21] The coefficient of interest (β_3) on the interaction term is highly significant and negative. Lending by non-banks declines by more relative to banks during banking crises in borrower countries. A one standard deviation higher exposure is associated with a 8.3% decline in loan volume by banks, but a 22.5% decline by non-banks.

To control for unobservable time-varying differences across lenders, including their funding models, column (3) includes lender parent*time fixed effects. Non-banks still cut their global lending by significantly more than banks during crises. The modest change in the estimated coefficient suggests that, in the global context, differences in funding models do not explain the gap in lending between banks and non-banks around crises.

This result, which differs from findings in the U.S. context (Fleckenstein et al., 2021), could arise for a number of reasons. First, our identification exploits cross-country variation in borrower-country financial crises, rather than a systemic shock such as the U.S. financial crisis of 2007/08. The U.S. crisis, the most severe global financial crises since the 1930s, led to a broad and pervasive tightening of funding conditions (Brunnermeier, 2009). The majority of financial crises have more circumscribed effects – especially when assessed from a global cross-country perspective. Second, our sample covers the universe of lenders in the global syndicated loan market, including many non-U.S. banks. Funding for these banks could be more cyclical than that of their U.S. counterparts, in part reflecting their reliance on wholesale dollar funding markets (Ivashina et al., 2015), which might make them more sensitive to changes in the financial cycle. And third, our set of global non-bank lenders is dominated by finance companies, investment banks, and insurance

[21] The coefficient on the non-bank dummy is absorbed by lender*borrower fixed effects.

companies, while CLOs are the dominant non-bank lender in the United States. These lenders potentially differ in their funding volatility. In support of these arguments, below we show that the relative contraction in lending is similar when we group non-banks according to whether they have stable or unstable liabilities, following the classification in Irani et al. (2021).

In addition to potential differences in lender characteristics, our analysis faces the common identification challenge of separating loan demand from loan supply. The estimated coefficients in column (3) could reflect differences in (observable and unobservable) borrower characteristics, for example credit demand. We address this challenge by including time-varying granular fixed effects.

In column (4), we first enrich our specification with time-varying fixed effects at the borrower country–sector–size level.[22] As shown in Degryse et al. (2019), these 'ILST' fixed effects are a good proxy for unobservable time-varying factors that could affect the loan demand of borrowers of distinct lenders differentially. When we compare lending by banks and non-banks to firms of similar size in the same country and industry, borrowing from a non-bank remains statistically different from borrowing from a bank during crises. However, compared to column (3), the coefficient halves in magnitude, consistent with the argument that non-banks serve riskier clients with weaker credit demand during a crisis.

To further tighten identification, column (5) includes borrower*time fixed effects. These fixed effects allow shocks to affect each borrower heterogeneously at each point in time. We thereby control for unobservable time-varying borrower fundamentals, such as profitability, size, leverage, or funding demand. Essentially, we compare the same firm borrowing from banks and non-banks in a given year, while using only the within variation of each lender-borrower combination for estimation (Khwaja and Mian, 2008; Jiménez et al., 2014). After absorbing any unobservable borrower characteristics (including but not limited to loan demand), our estimates therefore likely reflect loan supply effects. Lending by non-banks declines by significantly more than lending by banks also in this saturated specification. In terms of magnitude, the estimated coefficient on the interaction term is similar to that in column (4). Increasing crisis exposure by one standard deviation decreases loan supply by an additional 6.6% for non-banks relative to banks.

[22] Size refers to the quartiles of the distribution of total syndicated borrowing across firms in each year.

In sum, Table 2 shows that lending by non-banks declines by significantly more during crises relative to banks. Differences in funding models, which explain non-banks' greater lending pro-cyclicality in the U.S. context, appear to play a lesser role in explaining bank vs. non-bank lending during borrower-country crises in the global context. While borrower characteristics explain about half of the estimated difference in lending behavior, the gap between bank and non-bank lending during crises remains statistically significant and economically sizeable.

3.2.2 The value of lending relationships

Lending relationships with banks reduce inefficiencies from information asymmetries (Ivashina and Kovner, 2011) and can benefit borrowers through better loan terms. Relationships are especially valuable when borrower transparency is low (Bharath et al., 2011), for example during periods of heightened uncertainty or crises: Sette and Gobbi (2015) and Beck et al. (2018) show that lending relationships alleviate borrowers' credit constraints during episodes of economic shocks. Bolton et al. (2016) argue that relationship banks offer credit at more favorable terms to firms than transaction banks in a crisis.

We now investigate whether differences in the value of lending relationships can explain the gap in lending between banks and non-banks during crises. Motivated by prior literature that emphasizes the importance of relationships during crises, we include an interaction term of different relationship measures with the *crisis exposure* in Equation (2) .

Table 3 shows that accounting for lending relationships significantly narrows the difference in credit provision between banks and non-banks. All regressions are saturated with borrower*time fixed effects to control for unobservable time-varying differences across borrowers. Column (1) measures relationships via the lender-borrower relationship duration. In line with previous literature, the coefficient on the interaction term with crisis exposure is positive and highly significant: having a previous relationship with a lender is on average associated with better access to credit during crises. Importantly, relative to the baseline specification ($\beta = -0.314$ in Table 2, column (5)), the coefficient on the interaction term of *non-bank* and *crisis exposure* declines by almost 50% in magnitude, to -0.167. It remains significant at the 1% level.

We obtain a similar picture when we measure relationships via interaction frequency, i.e., the number of loans previously extended by a lender to a borrower. In column (2) the coefficient on the interaction term between relationship and crisis is positive and highly significant. The coefficient on the interaction term of *non-bank* and *crisis exposure* now equals -0.124, a fall of over 60% compared to the baseline specification. When we include both relationship measures and their interactions with crisis exposure in column (3), these conclusions remain unaltered. In the Online Appendix, we confirm these results in specifications with a triple interaction term between crisis exposure, the non-bank dummy, and relationship measures (see Figure A3).

In sum, columns (1)–(3) in Table 3 suggest that lending relationships benefit firms by less during a crisis when borrowing from a non-bank, compared to borrowing from a bank. We will investigate this aspect in more detail below, where we analyze the effects of relationships on loan rates during financial shocks.

In columns (4) and (5), we examine two other potential determinants of the lending gap: lenders' industry specialization and their portfolio diversification. Paravisini et al. (2022) and Blickle et al. (2021) show that banks often specialize in narrow markets, and De Jonghe et al. (2020) find that banks' industry specialization can protect borrowers from shocks. Doerr and Schaz (2021) further establish that lenders with a geographically diversified loan portfolio supply more credit during borrower-country crises. To measure lenders' industry specialization, we compute the share of loans originated to borrowers in industry i out of lender l's total loan originations in year t. To measure geographic diversification, we construct a lender-year level Herfindahl-Hirschman index (HHI) of lenders' loan portfolio shares across countries and define diversification as one minus the HHI.[23]

Column (4) includes lenders' industry specialization as well as diversification, interacted with crisis exposure. The magnitude of the coefficient on the interaction term of *non-bank* and *crisis exposure* declines only modestly to -0.282 (relative to column (5) in Table 2). The small drop in the coefficient size suggests that these factors do not explain the differences in lending behavior between banks and non-bank during crises.[24] This

[23]The industry share and diversification are defined as follows: $share_{l,i,t} = loans_{l,i,t}/loans_{l,t}$ and $diversification_{l,t} = 1 - \sum_{j=1}^{J^l} s^2_{l,c,t}$, where l is lender, i is industry, c is country and t time, and $s_{l,c,t}$ measures the share of a lender l's loans to borrowers in country c relative to its total loans in year t.

[24]Note that including industry specialization or diversification without additional control variables in the regression yields positive coefficients on the interaction term with banking crisis, in line with previous findings (unreported).

picture is reinforced when we include the interaction terms in the specification saturated with our relationship measures in column (5).

Relationships and loan spreads. To further investigate the value of lending relationships we analyze how they affect the spread on syndicated loans during crises. We expect that lending relationships mitigate the detrimental effects of crises on the spreads of bank loans (see Bharath et al. (2011), Sette and Gobbi (2015), or Bolton et al. (2016)). We add to this literature by exploring whether these effects differ for non-banks.

Motivated by previous studies, we estimate variants of the following regression:

$$\begin{aligned} spread_{l,b,t} &= \rho_1 crisis_{c,t} + \rho_2\ relationship_{l,b,t} \\ &\quad + \rho_3\ crisis_{c,t} \times relationship_{l,b,t} + \phi_{l,b} + \psi_{l,t} + \tau_{b,t} + \varepsilon_{l,b,t}. \end{aligned} \tag{3}$$

The dependent variable is the average spread on loans originated by lender l to borrower b in year t. The variable $crisis_{c,t}$ takes on a value of one during a financial crisis in borrower country c. The variable $relationship_{l,b,t}$ is a measure of the lending relationship, based on either duration or frequency. We cluster standard errors at the lender parent level, as well as firm-country level, to account for serial correlation within the same borrower country across firms and time, as well as among borrowers of the same lender. We include the full set of fixed effects at the lender-borrower, lender-time, and borrower-time level. We expect $\rho_1 > 0$, i.e., a higher spread during crises. We further expect relationships to mitigate the effect of a crisis on spreads, so $\rho_3 < 0$.

Table 4 confirms that relationships with banks lead to relatively lower loan spreads during crises but that this is not the case for non-banks. Column (1), with lender*borrower and lender parent*year fixed effects, shows that the spread increases by about 25 basis points during crises (0.2 standard deviations) on average. Column (2) reports results for Equation (3) with relationships measured through the duration. The coefficient ρ_3 is negative and significant at the 1% level, suggesting that a longer lending relationship is associated with a lower spread – consistent with the literature.

In column (3) we further add interaction terms with the non-bank dummy. While longer relationships benefit bank borrowers during crises, the positive coefficient on the triple interaction term indicates that the spread rises for non-bank borrowers. Note also that the interaction of *non-bank* and *relationship* yields a negative coefficient. Non-banks appear to not charge higher spreads in non-crisis times to borrowers with which they have a longer relationship. This pattern contrasts with relationship banks (Bolton et al., 2016). Columns (4) and (5), where we replicate columns (2)–(3) but measure relationships with the number of loans (frequency), provide a similar picture.

In sum, results in Table 3 and Table 4 indicate that a significant part of the gap in lending is explained by the fact that a lending relationship offers greater benefits to borrowers when the lender is a bank. It appears as if non-bank lenders behave more like transaction or arm's length lenders, both during crisis and non-crisis times, even if they have a pre-existing relationship with a borrower.

What could explain the difference in the value of lending relationships between banks and non-banks? Theory suggests that banks can benefit from forming stronger relationships with borrowers in various ways, ranging from the ability to share information or monitor collateral, to securing future lending and non-lending business with the borrower (see Ongena and Smith (2000) and Bharath et al. (2007) for an overview). At the core of such arguments lies the notion that relationships can lower the cost of information production, and that banks have a superior ability to collect borrower information (Rajan, 1992).[25] Beyond informational advantages, banks' access to core deposits allows them to provide liquidity services and insure clients against credit shocks, benefiting relationship borrowers (Berlin and Mester, 1999; Strahan, 2008). Against this background, non-banks' relative disadvantage in providing non-lending services, as well as their reliance on wholesale funding, might lower the value they obtain from investing in lending relationships. A detailed investigation of why banks and non-banks value syndicated relationships differently is an interesting area for future research.

4 Risky borrowers, real effects, and robustness

In this section, we first investigate whether borrower risk influences non-bank lending. We then analyze the real effects of the contraction in non-bank lending during crises. Finally, we perform a series of robustness tests.

[25] In line with the argument that relationships are especially valuable when borrower transparency is low (Bharath et al., 2011), below we show that relationships explain less of the lending gap in a sample restricted to U.S. borrowers and lenders only. This finding reflects that the U.S. has one of the best-developed and most transparent lending markets (Beck et al., 2010) and is consistent with results in Fleckenstein et al. (2021).

Lending to high-risk borrowers. Table A2 in the Online Appendix shows that non-banks specialize in lending to riskier, more leveraged borrowers. Previous literature has established that banks' specialization can benefit borrowers during crises, as banks have superior knowledge about borrowers' quality or internalize spillovers (Giannetti and Saidi, 2019; De Jonghe et al., 2020; Blickle et al., 2021). Guided by this work, we investigate whether non-banks shield risky borrowers during crises, compared to banks.

Table 5 shows that during crises non-banks cut lending to riskier borrowers by more. All specifications estimate variants of Equation (2) along the extensive margin, once without and once with borrower*time fixed effects. Columns (1)–(2) classify firms as risky if their average spread exceeds the yearly 75^{th} percentile in the borrowers' country. Columns (3)–(4) look at firms with spreads above the yearly 75^{th} percentile in the borrowers' two-digit industry. Columns (5)–(6) focus on those firms with balance sheet leverage in the upper tercile of the distribution. Across specifications, non-banks reduce loan supply by more than banks during crises (negative coefficient on *crisis exposure* $\times$ *non-bank*), but the effect is even more pronounced among riskier borrowers – as indicated by the negative and significant coefficient on the triple interaction term. Note that the coefficient on *non-bank* $\times$ *high-risk borrower* is positive throughout, in line with the finding that non-banks serve riskier clients.

These findings point to an important contrast between banks and non-banks. Banks' specialization can benefit borrowers, and especially so during crises. In contrast, non-banks' specialization in lending to riskier borrowers does not mean that risky borrowers connected to non-banks profit from better access to credit during crises than those connected to banks. These results reinforce the argument that relationships with non-banks provide limited benefits. While relationships with banks improve loan terms especially when borrower transparency is low (Bharath et al., 2011), as might be the case for risky borrowers during crises, the same does not hold for non-banks.

Real effects. To analyze whether exposure to non-banks has real effects in terms of firm investment, we aggregate the data to the firm-year level. If firms can easily substitute syndicated loans from non-banks with other forms of credit (e.g. bonds or trade credit), the substitution could offset the credit contraction of individual non-banks. Changes in non-banks' loan supply will only have real effects if firms can at most partially substitute the fall in non-bank credit. We run variants of the following regression:

$$\begin{aligned}\Delta y_{b,t} = &\gamma_1\ BC_{c,t} + \gamma_2\ \textit{connected to non-bank}_{b,t-1} \\ &+ \gamma_3\ BC_{c,t} \times\ \textit{connected to non-bank}_{b,t-1} + \phi_b + \tau_t + \mathbf{X}_{b,t-1}\boldsymbol{\beta} + u_{b,t}.\end{aligned} \tag{4}$$

The dependent variable $\Delta y_{b,t}$ is either the log difference of total syndicated loan volume of borrowing firm b across all its lenders in year t, or the change in its investment rate. The banking crisis dummy ($BC_{c,t}$) varies at the country level and equals one during banking crisis years in firm country c. The variable *connected to non-bank*$_{b,t-1}$ is a dummy with a value of one if a firm received a loan from at least one non-bank in the year prior to the crisis and zero if it received loans from banks only. ϕ_b denotes firm fixed effects and τ_t denotes year or country*industry*year fixed effects. We additionally control for firms' log of total assets, return on assets, and long-term debt over total assets (captured in vector $\mathbf{X}$, lagged by one year). We cluster standard errors at the firm-country level, i.e., the level of the shock. A coefficient of $\gamma_3 < 0$ would indicate that non-bank connected firms see a stronger fall in overall syndicated loan volume and investment. However, in interpreting the results, an important caveat to keep in mind is that firm-level regressions do not allow us to fully control for unobservable confounding factors.

Table 6 shows that non-bank connected firms see a significantly stronger decline in loan volumes and investment rates. Column (1) shows that total syndicate loan volume for the average firm falls during financial crises. Column (2) adds interaction effects and shows that the fall in loan volume is stronger among non-bank connected firms. We account for potentially confounding trends at the country–industry level with borrower-country*industry*year fixed effects. In essence, we compare firms located in the same country and industry in a given year. For the investment rate, column (3) also shows a significant negative effect of non-bank exposure during crises. Coefficients increase in magnitude and significance when we focus on firms with a low number of lender connections in columns (4)–(5), for which replacing lost funding may be more difficult.

Taken together, these results provide suggestive evidence that firms are unable to perfectly substitute the fall in syndicated lending from non-banks with other sources. Moreover, firms with a limited ability to substitute across lenders are apparently more affected by the contraction in non-bank credit.

Relationships. Results in Table 3 and Table 4 suggest that differences in the value of relationships explain a sizeable share of the lending gap between non-banks and banks. In Table 7 we shed further light on this finding. First, we consider an alternative measure of relationship strength based on total lending by a given lender to a given borrower in the past five years, normalized by the borrower's total new borrowing over the same period (Bharath et al., 2011; Ivashina and Kovner, 2011). Column (1) shows that the coefficient of the interaction between crisis exposure and the non-bank indicator decreases by close to 50% (relative to column (5) in Table 2), similar to our findings for measures based on duration and frequency. Combining the three measures of relationships confirms this finding, as shown in column (2). Our result that relationships provide less value to non-bank borrowers does hence not depend on the specific relationship measure used.

The value of relationships may also play out differently depending on the type of loans. Insofar as a loan type is more likely to remain on balance sheet, as is the case for credit lines (Drucker and Puri, 2009), it should be more sensitive to relationships. Should accounting for lending relationships not narrow the lending gap between banks and non-banks among credit lines, it would thus speak against our argument. Columns (3) and (4) report results for Equation (2) with the log amount of credit lines as dependent variable.[26] Among credit lines, controlling for relationships reduces the residual lending gap by almost 60%.[27]

We also control for whether a lender is a lead arranger of at least one loan to a borrower in a given year. Lead arrangers are in charge of screening and monitoring, and often build up a reputation in the syndicated loan market.[28] Our relationship measures might partly reflect these aspects rather than the value of relationships alone. In columns (5) and (6) we focus on the sample with information on lead arranger status (i.e. the intensive margin). We find that controlling for the lead arranger status in addition to relationships has only a modest effect on the lending gap, suggesting that the value of relationships is a salient difference between banks and non-banks.

Finally, we restrict the sample to U.S. borrowers and lenders only. Fleckenstein et al. (2021) show that lending relationships do not explain U.S. non-banks' greater sensitivity

[26] As noted above, credit lines comprise about 40% of all non-bank loans, compared to 50% for banks.

[27] Consistent with these arguments, we find that relationships narrow the lending gap by significantly less (close to 30%) among loans of type "term loan B", which are typically sold on the secondary market.

[28] Lead arrangers in our sample are defined as those classified as lead arranger in Dealscan and lenders whose role include the word "arranger", as well as those with the following role: lead bank, bookrunner, admin agent, syndications agent, documentation agent, agent, facility agent and security agent.

to the excess bond premium. Relationships may play a smaller role in the U.S. as it has one of the best-developed and most transparent lending markets (Beck et al., 2010). Columns (7) and (8) provide support for this argument: the effect of lending relationships in narrowing the lending gap between banks and non-banks during financial crises is less pronounced in the U.S. sample. Accounting for relationships narrows the gap by less than 20%. These results highlight the additional insights obtained from examining non-bank lending in a multi-country setting.

Robustness. Table 8 reports a number of additional robustness tests. Column (1) further investigates the role of lenders' funding models in our global sample of crises. To this end, we follow Irani et al. (2021) to group non-banks into those with a stable and unstable funding structure. Insurance companies and pension funds are grouped as non-banks with stable liabilities, while those with unstable liabilities include investment banks, hedge funds, and other investment funds. Results for Equation (2) show that the contraction in non-bank lending is equally strong among non-banks with stable and unstable liabilities (0.311 vs. 0.314). These results reinforce the argument that differences in funding models do not fully explain the stronger decline in non-bank lending during crises in our global sample. Columns (2) and (3) focus only on the the GFC. Column (2) first documents a stronger decline in non-bank lending also during the GFC, consistent with previous findings (Fleckenstein et al., 2021). Column (3) further controls for the baseline relationship measures and shows that while the coefficient on the interaction term declines in magnitude, it does so by considerably less than in Table 3. These results complement those in columns (7) and (8) in Table 7 and underscore the argument that the value of lending relationships during local crises in a global sample may differ from that during a systemic crisis in a single-country setting.

In column (4), we aggregate lending to the lender-borrower country-year level and then estimate regressions similar to Equation (2). Consistent with our lender-borrower-level results, it shows that the interaction coefficients between lenders' crisis exposure and the non-bank dummy are negative and statistically significant. Controlling for time-varying borrower-country characteristics, a one standard deviation increase in crisis exposure results in a 7.6% relative contraction of aggregate lending by non-banks relative to banks. That is, not only do non-banks contract lending to individual borrowers, but also do so at the country level. Columns (5) and (6) show that, relative to banks, non-bank lending to public and private borrowers is reduced by a similar amount.

In panel (b), column (1) establishes that results are robust to the exclusion of investment banks from our non-bank group, even if, in principle, investment banks could have close ties with banks. Column (2) keeps only lenders from the major markets (the U.S., Japan, and the U.K.) and finds that non-banks still contract their lending by more than banks during crises. Similar findings are obtained when we restrict the sample to major lenders, defined as those who contribute more than $10 billion in 2012 prices over our sample period (column 3). We confirm in columns (4) and (5) that our main results remain robust when we use the growth rate of new credit as the dependent variable.[29] Column (6) shows that non-banks contract their lending by more than banks also along the intensive margin, i.e. when we do not account for the formation and termination of lending relationships.

Finally, in Table A3 in the Online Appendix, we show that our main results are insensitive to the inverse hyperbolic sine transformation of the dependent variable.

5 Conclusion

The importance of non-bank financial institutions has steadily increased in recent decades. It has become a key objective of policy makers and academics to better understand their effects on credit supply, financial stability, and the real economy (Schnabel, 2021; Aramonte et al., 2022).

The rising footprint of non-banks could lead to a shift away from relationship towards transaction lending. With corporate indebtedness at historic highs (IMF, 2021), the strong contraction in non-bank lending to highly-leveraged borrowers during crises is particularly worrying. Non-banks' rise could exacerbate the consequences for the real economy during episodes of negative shocks.

Existing policy proposals have mostly focused on the need to monitor non-bank financial institutions due to their contribution to liquidity stress in money markets (Quarles, 2020; Hauser, 2021; Hubbard et al., 2021). Our findings suggest that non-bank lending also warrants close attention. Moreover, while post Great Financial Crisis regulation has arguably made banks more resilient, non-banks' greater presence might offset some of

[29] To account for variations in the extensive margin, the growth rate is defined as $\frac{Credit_{l,m,t}-Credit_{l,m,t-1}}{0.5(Credit_{l,m,t}+Credit_{l,m,t-1})}$ with $m = b$ (borrower) in column (4) and $m = c$ (country) in column (5).

these gains during crises. Policy makers should take into account that risks may migrate across the financial system in response to tighter bank regulation, calling for a holistic perspective to financial regulation.

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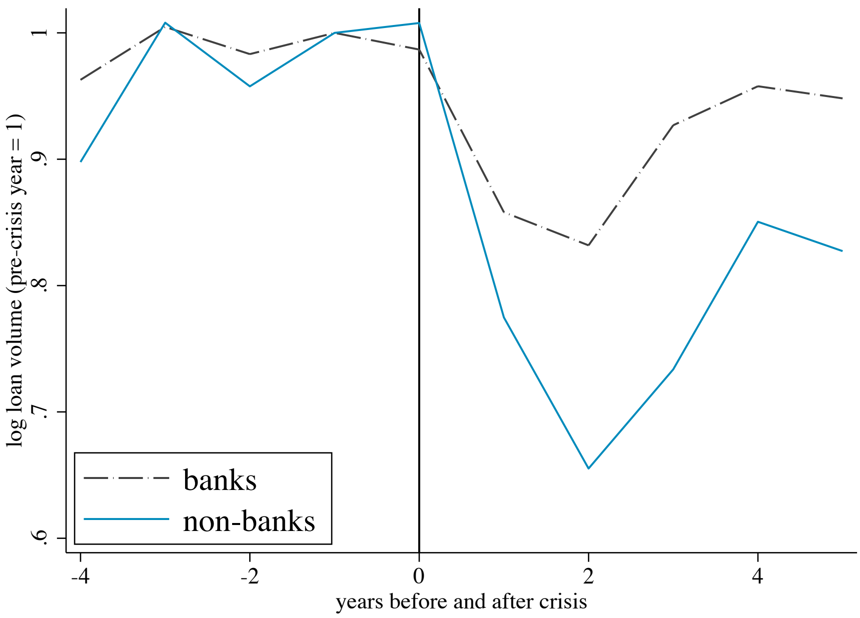
A Figures and tables

Figure 1: **Bank and non-bank lending during a crisis**



This figure plots the evolution of average new credit in logs in the years prior to, during, and after a financial crisis. Series are normalized to a value of one in the year of the crisis. A value of zero on the x-axis denotes the year of the crisis in the borrower country. We split the sample into lending by non-banks (blue solid line) and banks (black dashed line). Both lender types see a decline in loan origination during the crisis and the following years, but non-banks see a stronger fall. There are no differential pre-trends.

Table 1: **Summary statistics**

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
log(loan amount)	1,222,273	2.001	1.998	0	9.788	1.942
crisis exposure	1,222,273	.057	.2	0	.992	0
lending relation: duration (years)	1,222,273	2.081	3.193	0	29	1
lending relation: frequency (# loans)	1,222,273	1.591	1.993	0	46	1
industry lending share	1,192,719	.062	.154	0	1	.01
lender diversification	1,222,273	.526	.409	0	1	.561
spread	231,473	169.574	126.047	15	625	145

This table reports summary statistics for the main variables in our analysis at the lender-borrower-year level.

Table 2: **Non-banks supply less credit during financial crises**

VARIABLES	(1) log(credit)	(2) log(credit)	(3) log(credit)	(4) log(credit)	(5) log(credit)
crisis exposure	-0.460***	-0.395**	-0.187	-0.010	-0.023
	(0.168)	(0.162)	(0.185)	(0.082)	(0.074)
crisis exposure × non-bank		-0.679***	-0.790***	-0.380***	-0.314***
		(0.032)	(0.233)	(0.052)	(0.036)
Observations	1,222,273	1,222,273	1,220,620	1,220,523	1,220,491
R-squared	0.220	0.220	0.300	0.835	0.866
Lender*Borrower FE	✓	✓	✓	✓	✓
Year FE	✓	✓	-	-	-
Lender Parent*Year FE	-	-	✓	✓	✓
ILST FE	-	-	-	✓	-
Borrower*Year FE	-	-	-	-	✓

This table reports results at the lender-borrower-year level (see Equation (2)). The dependent variable is the log of one plus new credit extended each year to each borrower. Crisis exposure denotes lenders' exposure to borrower-country financial crises and is computed following Equation (1). The dummy non-bank takes on a value of one if the lender is a non-bank. Standard errors are clustered at the lender parent and borrower country level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: **Accounting for lending relationships and other potential determinants**

VARIABLES	(1) log(credit)	(2) log(credit)	(3) log(credit)	(4) log(credit)	(5) log(credit)
crisis exposure	-0.212***	-0.163***	-0.207***	0.003	-0.158***
	(0.061)	(0.058)	(0.053)	(0.080)	(0.057)
crisis exposure × non-bank	-0.167***	-0.124***	-0.118***	-0.282***	-0.106***
	(0.017)	(0.029)	(0.028)	(0.035)	(0.024)
relation: duration	-0.957***		0.274***		0.294***
	(0.050)		(0.031)		(0.032)
crisis exposure × duration	0.259***		0.052***		0.039***
	(0.021)		(0.017)		(0.014)
relation: frequency		-1.182***	-1.314***		-1.257***
		(0.067)	(0.080)		(0.084)
crisis exposure × frequency		0.222***	0.175***		0.174***
		(0.045)	(0.053)		(0.045)
industry lending share				1.849***	1.606***
				(0.171)	(0.145)
crisis exposure × industry lending share				0.036	0.132
				(0.148)	(0.133)
lender diversification				0.033	0.041
				(0.042)	(0.033)
crisis exposure × lender diversification				-0.024	-0.087**
				(0.046)	(0.038)
Observations	1,220,491	1,220,491	1,220,491	1,162,306	1,162,306
R-squared	0.871	0.879	0.879	0.869	0.880
Lender*Borrower FE	✓	✓	✓	✓	✓
Lender Parent*Year FE	✓	✓	✓	✓	✓
Borrower*Year FE	✓	✓	✓	✓	✓

This table reports results at the lender-borrower-year level (see Equation (2)). The dependent variable is the log of one plus new credit extended each year to each borrower. Crisis exposure denotes lenders' exposure to borrower-country financial crises and is computed following Equation (1). The dummy non-bank takes on a value of one if the lender is a non-bank. Columns (1)-(3) augment the baseline regression Equation (2) with measures of the strength of lending relationships (based on duration and frequency) in logs. Column (4) studies the role of industry specialization, with the share calculated as the amount of new lending extended by a lender to a 2-digit SIC industry as a share of total new lending originated by the same lender. Column (5) explores the importance of portfolio diversification, by including 1 minus the Herfindahl-Hirschman index of a lender's portfolio concentration in lending across borrower countries. The margin of analysis is the extensive margin. Standard errors are clustered at the lender parent and borrower country level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: **Spread and lending relationships**

VARIABLES	(1) spread	(2) duration spread	(3) duration spread	(4) frequency spread	(5) frequency spread
crisis	25.513***				
	(4.163)				
relation		-0.157	-0.060	-1.192***	-1.087***
		(0.115)	(0.125)	(0.199)	(0.219)
crisis × relation		-0.626***	-0.730***	-0.610***	-0.847***
		(0.078)	(0.112)	(0.132)	(0.132)
crisis × non-bank			-1.065		-1.695
			(2.060)		(2.390)
non-bank × relation			-1.451**		-1.740***
			(0.602)		(0.635)
crisis × non-bank × relation			1.872***		3.774***
			(0.209)		(0.382)
Observations	231,473	222,562	222,562	222,562	222,562
R-squared	0.869	0.990	0.990	0.990	0.990
Lender*Borrower FE	✓	✓	✓	✓	✓
Lender Parent*Year FE	✓	✓	✓	✓	✓
Borrower*Year FE	-	✓	✓	✓	✓

This table reports results at the lender-borrower-year level (see Equation (3)). The dependent variable is the average all-in-spread drawn between a lender-borrower pair, weighted by loan size. Column (1) includes the Laeven and Valencia (2020) financial crisis dummy as explanatory variable. Column (2) includes the duration of the lending relationship as the measure for relationship strength (in logs). Column (3) further includes interaction terms with the non-bank dummy. Columns (4) and (5) use relationship frequency (in logs). Standard errors are clustered at the lender parent and borrower country level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: **Non-banks lend less to risky borrowers during crises**

VARIABLES	(1) DS country spread log(credit)	(2) DS country spread log(credit)	(3) DS industry spread log(credit)	(4) DS industry spread log(credit)	(5) CS lev log(credit)	(6) CS lev log(credit)
crisis exposure	-0.196**	-0.023	-0.187*	-0.023	0.021	0.020
	(0.093)	(0.042)	(0.094)	(0.041)	(0.127)	(0.137)
crisis exposure × non-bank	-0.087***	-0.027	-0.080***	-0.035	-0.779***	-0.495***
	(0.002)	(0.024)	(0.007)	(0.023)	(0.218)	(0.118)
exposure × high-risk borrower	0.185***	0.185***	0.061***	0.086***	-0.144***	0.046
	(0.008)	(0.039)	(0.007)	(0.018)	(0.034)	(0.028)
non-bank × high-risk borrower	0.176***	0.114***	0.094***	0.061***	0.087*	0.142***
	(0.012)	(0.013)	(0.015)	(0.011)	(0.052)	(0.050)
exposure × non-bank × high-risk borrower	-0.143***	-0.129***	-0.112***	-0.044**	-0.159**	-0.190***
	(0.026)	(0.013)	(0.016)	(0.019)	(0.071)	(0.043)
Observations	231,473	222,562	231,473	222,562	295,097	292,507
R-squared	0.778	0.938	0.778	0.938	0.455	0.698
Lender*Borrower FE	✓	✓	✓	✓	✓	✓
Lender Parent*Year FE	✓	✓	✓	✓	✓	✓
Borrower*Year FE	-	✓	-	✓	-	✓

This table reports results at the lender-borrower-year level (see Equation (2)). The dependent variable is the log of one plus new credit extended each year to each borrower. Crisis exposure denotes lenders' exposure to borrower-country financial crises and is computed following Equation (1). The dummy non-bank takes on a value of one if the lender is a non-bank. Risky borrowers are defined by a relatively high all-in-spread (above the 75^{th} percentile of all firms in the same country (column (1)-(2)) or in the same industry (column (3)-(4))). Column (5) and (6) define risk via a high-leverage indicator (upper tercile). Standard errors are clustered at the lender parent and borrower country level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: **Real effects of non-bank dependence**

VARIABLES	(1) Δ loan volume	(2) Δ loan volume	(3) Δ investment	(4) low connection Δ loan volume	(5) low connection Δ investment
crisis	-0.113**				
	(0.046)				
connected to non-bank		-0.551***	-0.000	-0.299***	-0.001
		(0.034)	(0.001)	(0.030)	(0.003)
crisis × connected to non-bank		-0.082**	-0.013***	-0.417***	-0.019***
		(0.040)	(0.003)	(0.059)	(0.003)
Observations	14,602	13,510	13,115	2,668	2,591
R-squared	0.139	0.247	0.333	0.488	0.444
Firm-level controls	✓	✓	✓	✓	✓
Borrower FE	✓	✓	✓	✓	✓
Year FE	✓	-	-	-	-
Borrower Ctry*Year FE	-	-	-	-	-
Borrower Ctry*Industry*Year FE	-	✓	✓	✓	✓

This table reports results at the borrower-year level (see Equation (4)). It shows the effects of having a connection to a non-bank during a crisis episode on firm-level outcome variables. The dependent variable in columns (1), (2), and (4) is the annual change in the total volume of syndicated lending. Columns (3) and (5) use the annual change in the investment rate, defined as the ratio between capital expenditure and fixed assets. The crisis dummy varies at the country level and equals one during banking crisis years in the firm country. The variable *connected to non-bank* is a dummy with a value of one if a firm received a loan from at least one non-bank in the year prior to the crisis and zero if it received loans from banks only. Columns (4) and (5) focus on firms borrowing from a small number of lenders (first tercile of the distribution). Standard errors are clustered at the borrower country level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: **Robustness tests – relationships**

VARIABLES	(1) log(credit)	(2) log(credit)	(3) credit line log(credit line)	(4) credit line + relation log(credit line)	(5) with LA info log(credit)	(6) LA*crisis log(credit)	(7) US log(credit)	(8) US log(credit)
crisis exposure	-0.001	-0.036	0.010	0.003	0.024	0.017		
	(0.065)	(0.057)	(0.027)	(0.032)	(0.034)	(0.031)		
crisis exposure × non-bank	-0.186***	-0.127***	-0.227***	-0.098***	-0.052**	-0.045*	-0.342**	-0.266**
	(0.015)	(0.023)	(0.023)	(0.037)	(0.024)	(0.025)	(0.143)	(0.110)
relation: amount	-0.532***	-0.295***						
	(0.029)	(0.034)						
crisis × amount	0.043	-0.016						
	(0.032)	(0.031)						
relation: duration		0.451***		0.279***	0.117***	0.109***		1.197***
		(0.024)		(0.046)	(0.012)	(0.011)		(0.175)
crisis × duration		0.021		0.039**	-0.027***	-0.025***		-0.261***
		(0.020)		(0.017)	(0.007)	(0.007)		(0.059)
relation: frequency		-0.930***		-0.940***	-0.080***	-0.083***		-2.090***
		(0.102)		(0.147)	(0.011)	(0.012)		(0.226)
crisis × frequency		0.144***		0.022	0.018	0.016		-0.274***
		(0.049)		(0.077)	(0.017)	(0.016)		(0.074)
lead arranger (LA)						0.255***		
						(0.022)		
crisis × lead arranger (LA)						-0.007		
						(0.018)		
crisis dummy						0.000		
						(0.000)		
Observations	1,220,491	1,220,491	1,220,491	1,220,491	360,225	360,225	65,300	65,300
R-squared	0.878	0.880	0.877	0.884	0.956	0.957	0.889	0.901
Lender*Borrower FE	✓	✓	✓	✓	✓	✓	✓	✓
Lender Parent*Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Borrower*Year FE	✓	✓	✓	✓	✓	✓	✓	✓

This table reports robustness tests on the value of non-bank lending relationship during crises. The dependent variable is the log of one plus new credit extended each year to each borrower. Crisis exposure denotes lenders' exposure to borrower-country financial crises and is computed following Equation (1). The dummy non-bank takes on a value of one if the lender is a non-bank. Columns (1) and (2) add an alternative measure of bilateral lending relationship intensity: the amount of borrowed by a given firm from a given bank normalized by the total amount borrowed by the firm over the past five years. Columns (3) and (4) focus on the response of credit lines. Columns (5) and (6) restrict the sample to those with lead arranger (LA) information available and add a lead arranger dummy (and the interaction with the banking crisis dummy). Columns (7) and (8) restrict the sample to U.S. borrowers and lenders around the Great Financial Crisis. The margin of analysis is the extensive margin for columns (1)-(4) and (7)–(8) and the intensive margin for columns (5)-(6). Standard errors are clustered at the lender parent and borrower country level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8: **Additional robustness tests**

Panel (a)

VARIABLES	(1) log(credit)	(2) GFC log(credit)	(3) GFC + rel log(credit)	(4) ctry level log(credit)	(5) public borrower log(credit)	(6) private borrower log(credit)
crisis exposure	-0.023	-0.144*	-0.115*	-0.169	0.035	-0.067
	(0.074)	(0.53)	(0.50)	(0.156)	(0.073)	(0.062)
crisis exposure × non-bank (stable)	-0.311*					
	(0.168)					
crisis exposure × non-bank (unstable)	-0.314***					
	(0.036)					
crisis exposure × non-bank		-0.314***	-0.230***	-0.378***	-0.348***	-0.324***
		(0.009)	(0.009)	(0.097)	(0.076)	(0.060)
Observations	1,220,491	134,576	134,576	163,881	435,872	580,340
R-squared	0.866	0.905	0.913	0.578	0.827	0.881
Lender*Borrower Ctry FE	-	-	-	✓	-	-
Lender*Borrower FE	✓	✓	✓	-	✓	✓
Lender Parent*Year FE	✓	✓	✓	✓	✓	✓
Borrower Ctry*Year FE	-	-	-	✓	-	-
Borrower*Year FE	✓	✓	✓	-	✓	✓

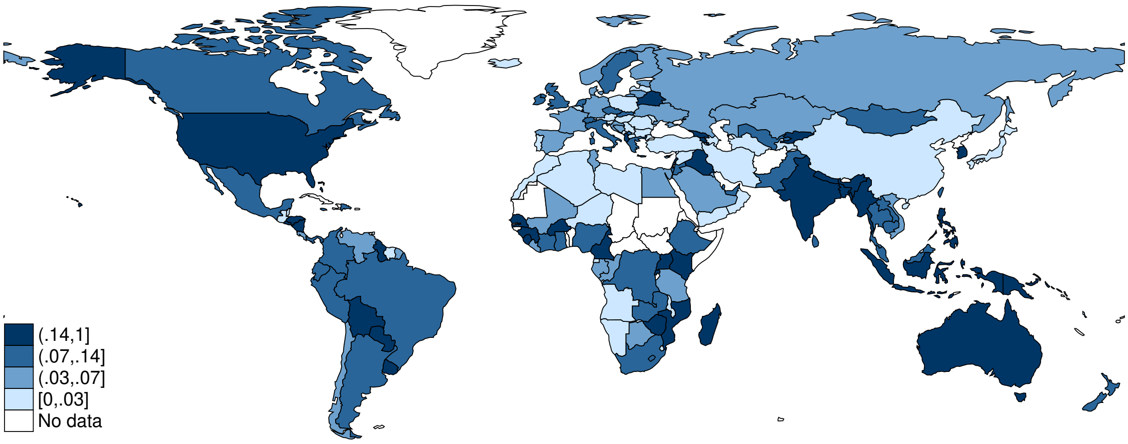
Panel (b)

VARIABLES	(1) no inv. bank log(credit)	(2) US/JP/UK lenders log(credit)	(3) major lenders log(credit)	(4) loan Δ credit	(5) ctry Δ credit	(6) intensive log(credit)
crisis exposure	-0.011	-0.096	-0.027	0.002	-0.083	0.038
	(0.056)	(0.063)	(0.067)	(0.060)	(0.177)	(0.037)
crisis exposure × non-bank	-0.368***	-0.217***	-0.267***	-0.329***	-0.216**	-0.052**
	(0.033)	(0.020)	(0.051)	(0.034)	(0.090)	(0.024)
Observations	1,184,108	658,166	900,549	1,220,491	163,881	360,220
R-squared	0.868	0.861	0.860	0.895	0.374	0.956
Lender*Borrower Ctry FE	-	-	-	-	✓	✓
Lender*Borrower FE	✓	✓	✓	✓	-	-
Lender Parent*Year FE	✓	✓	✓	✓	✓	✓
Borrower Ctry*Year FE	-	-	-	-	✓	✓
Borrower*Year FE	✓	✓	✓	✓	-	-

This table reports various robustness tests and extensions. In panel (a), the dependent variable is the log of one plus new credit extended each year to each borrower. Crisis exposure denotes lenders' exposure to borrower-country financial crises and is computed following Equation (1). The dummy non-bank takes on a value of one if the lender is a non-bank. Column (1) splits non-banks into those with stable and unstable funding. Columns (2) and (3) focus on the years of the GFC, without and with relationships as controls, respectively. Column (4) collapses the data to lender-borrower country-year level and re-estimates Equation (2). Columns (5)–(6) focus on the public and private borrower subset, respectively. In panel (b), the dependent variable is the log of one plus new credit extended each year to each borrower in columns (1)–(3). Column (1) drops investment banks (classified as non-banks) from the analysis. Column (2) focuses on lenders headquartered in U.S., U.K. and Japan, and column (3) restricts the sample to lenders with at least 10 billion 2012 USD total lending over the sample period. Columns (4) and (5) use the growth rate of new lending (extensive margin, $\Delta Credit_{l,m,t}/[0.5(Credit_{l,m,t}+Credit_{l,m,t-1})]$) as the dependent variable, with m = borrower for column (4) and borrower country for column (5). Column (6) focuses on the intensive margin (log($credit$)). Standard errors are clustered at the lender parent and borrower country level. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix

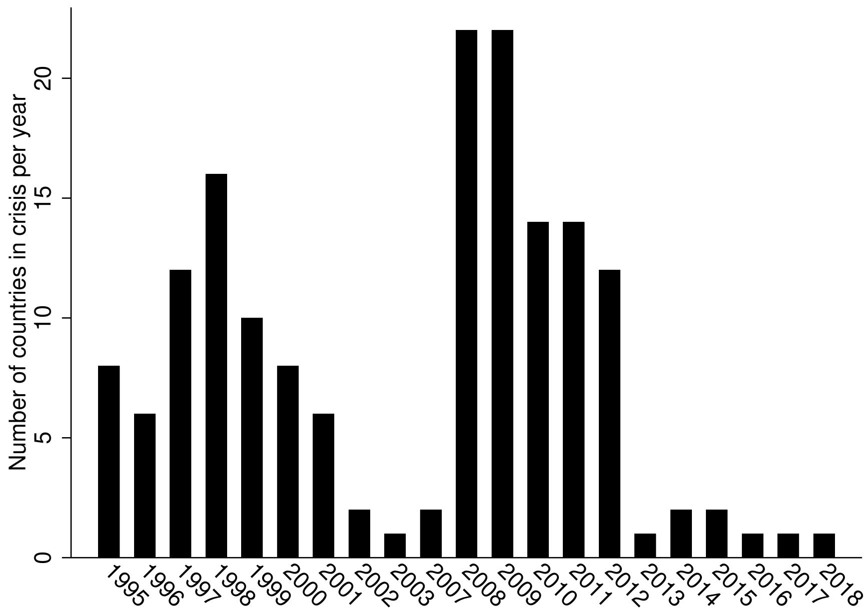
Figure A1: **Country-level loan share of non-banks**



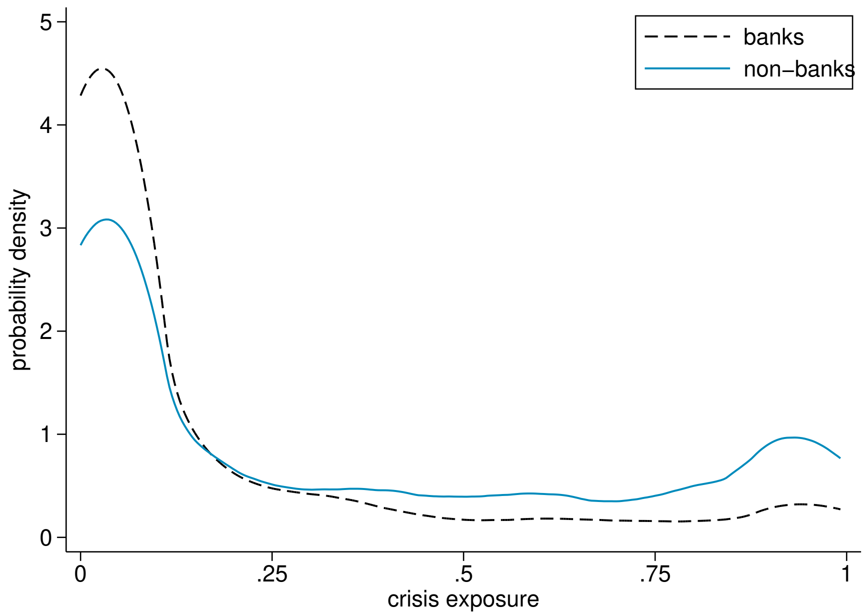
This figure plots the share of syndicated lending (new credit) extended by non-banks to total syndicated credit by country, averaged over the sample period 1995-2018.

Figure A2: **Number of banking crises and crisis exposure**

(a) Number of crises by year



(b) Distribution of crisis exposure for banks and non-banks



Panel (a) plots the number of countries in crises in each year during the sample period 1995-2018. Panel (b) plots the distribution of crisis exposure (defined in Equation (1)) for banks and non-banks across lender–borrower-country cells with non-zero exposure.

Table A1: **Summary statistics – Compustat sample**

Panel (a): Main variables

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
connected to non-bank	43327	.343	.475	0	1	0	0	1
total syndicated loan volume	43327	1614.306	8117.456	.065	509062.9	72.668	255.891	903.99
total syndicated loan volume by non-banks	43327	178.397	1693.39	0	239620.3	0	0	43.377
total number of syndicated lenders	43327	15.488	31.002	1	1134	3	7	16
total number of syndicated non-bank lenders	43327	1.871	10.069	0	660	0	0	1
share of syndicated lenders that are non-banks	43327	.113	.238	0	1	0	0	.111
share of syndicated loan volume by non-banks	43327	.112	.241	0	1	0	0	.1
log(employees)	37191	1.282	1.923	-6.908	7.741	.02	1.361	2.6
log(total assets)	42819	6.955	1.908	-1.995	13.685	5.694	6.927	8.206
return on assets	42601	.063	.091	-.361	.286	.03	.066	.107
long-term debt to assets ratio	42861	.213	.164	0	.716	.085	.191	.31
short-term debt to assets ratio	42088	.283	.153	.037	.729	.167	.257	.374
leverage	42032	2.064	3.142	.114	24.283	.696	1.21	2.13
investment rate	41791	.126	.116	.006	.666	.053	.091	.155
sales growth	40385	.11	.278	-.754	1.302	-.013	.074	.199
log(sales per employee)	37074	5.595	1.005	3.113	8.423	4.978	5.524	6.153
interest coverage ratio	41412	22.009	53.54	-28.8	380.466	3.543	7.712	17.295

Panel (b): Differences between bank and non-bank borrowers

	no NB lender		**has NB lender**		**mean diff.**
	mean	sd	mean	sd	t
total syndicated loan volume	850.76	(4634.32)	3077.76	(12156.14)	-27.34
total syndicated loan volume by non-banks	0.00	(0.00)	520.32	(2861.15)	-30.69
total number of syndicated lenders	9.55	(15.41)	26.87	(46.38)	-57.26
total number of syndicated non-bank lenders	0.00	(0.00)	5.46	(16.62)	-55.42
share of syndicated lenders that are non-banks	0.00	(0.00)	0.33	(0.31)	-181.18
share of syndicated loan volume by non-banks	0.00	(0.00)	0.33	(0.32)	-175.43
log(employees)	1.08	(1.86)	1.66	(1.98)	-27.93
log(total assets)	6.70	(1.85)	7.45	(1.92)	-39.13
return on assets	0.06	(0.09)	0.06	(0.09)	1.33
long-term debt to assets ratio	0.19	(0.15)	0.26	(0.17)	-46.92
short-term debt to assets ratio	0.30	(0.15)	0.26	(0.15)	24.50
leverage	1.83	(2.74)	2.51	(3.77)	-21.02
investment rate	0.13	(0.12)	0.13	(0.11)	-1.54
sales growth	0.10	(0.27)	0.12	(0.29)	-5.28
log(sales per employee)	5.57	(0.98)	5.64	(1.04)	-6.24
interest coverage ratio	26.03	(59.24)	14.35	(39.43)	21.21
Observations	28472		14855		43327

This table reports summary statistics at the borrower-year (firm) level. The sample of firms include borrowers identifiable by both the Compustat and the Dealscan datasets. Panel (b) splits the borrowers into two groups, those that borrow from non-banks and those that do not, and) compares the differences in means by reporting t-statistics. We calculate the return on assets as operating income net of depreciation over total assets. Leverage is defined as long term debt plus current liabilities over equity. The interest rate coverage ratio is computed as earnings (EBITDA) over interest expenses.

Table A2: **Non-bank lenders and risky borrowers**

Panel (a): No fixed effects

VARIABLES	(1) country spread Pr(non-bank lender)	(2) industry spread Pr(non-bank lender)	(3) leverage Pr(non-bank lender)
high-risk indicator	0.117***	0.119***	0.023***
	(0.004)	(0.004)	(0.004)
Observations	465,002	465,002	404,845
R-squared	0.016	0.016	0.001

Panel (b): Within country-industry-year variation

VARIABLES	(1) country spread Pr(non-bank lender)	(2) industry spread Pr(non-bank lender)	(3) leverage Pr(non-bank lender)
high-risk indicator	0.180***	0.161***	0.040***
	(0.004)	(0.004)	(0.004)
Observations	464,757	464,757	404,845
R-squared	0.144	0.142	0.126
Borrower Country*Industry*Year FE	✓	✓	✓

This table reports results from a series of linear probability models relating the propensity to obtain syndicated loans from non-bank lenders to the riskiness of the borrowers. We estimate regressions at the lender–borrower–year level of the following form: $\textit{non-bank lender}_{l,b,t} = \beta \ \textit{high-risk indicator}_{b,t} + \tau_{c,i,t} + \varepsilon_{l,b,t}$, where the dependent variable is a dummy that takes on a value of one if a loan by lender l to borrowing firm b in year t is made by a non-bank. The explanatory variable *high-risk indicator* is a dummy that takes on a value of one if the borrowing firm is classified as risky. Borrowers are classified as high-risk if the average all-in drawn spread is above the 75^{th} percentile within the headquarters country (column (1)) or within the 2-digit SIC industry (column (2)); or if the leverage is in top third tercile across all borrowers. Panel (a) reports bi-variate regressions with no fixed effects. Panel (b) adds country-industry-year fixed effects. Standard errors are clustered at the borrower level. Results show that riskier borrowers are significantly more likely to obtain a loan from a non-bank. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: **Non-bank lending during crises – IHS transformation**

VARIABLES	(1) IHS(credit)	(2) IHS(credit)	(3) IHS(credit)	(4) IHS(credit)	(5) IHS(credit)
crisis exposure (intensive margin)	-0.458**	-0.028	-0.251***	-0.196***	-0.247***
	(0.202)	(0.086)	(0.071)	(0.068)	(0.062)
crisis exposure × non-bank	-0.793***	-0.361***	-0.189***	-0.142***	-0.132***
	(0.040)	(0.041)	(0.019)	(0.033)	(0.032)
relation: duration			-1.127***		0.279***
			(0.056)		(0.034)
crisis exposure × duration			0.305***		0.065***
			(0.023)		(0.018)
relation: frequency				-1.367***	-1.502***
				(0.074)	(0.088)
crisis exposure × frequency				0.264***	0.206***
				(0.050)	(0.057)
Observations	1,222,273	1,220,491	1,220,491	1,220,491	1,220,491
R-squared	0.206	0.868	0.873	0.880	0.881
Lender*Borrower FE	✓	✓	✓	✓	✓
Year FE	✓	-	-	-	-
Lender Parent*Year FE	-	✓	✓	✓	✓
Borrower*Year FE	-	✓	✓	✓	✓

This table reports results at the lender-borrower-year level (see Equation (2)). We use the inverse hyperbolic sine (IHS) transformation of new credit extended each year to each borrower as the dependent variable. Crisis exposure denotes lenders' exposure to borrower-country financial crises and is computed following Equation (1). The dummy non-bank takes on a value of one if the lender is a non-bank. Columns (1)-(2) estimate the baseline regression Equation (2); columns (3)-(5) augment the baseline regression with measures of the strength of lending relationships (based on duration and frequency) in logs. The margin of analysis is the extensive margin. Standard errors are clustered at the lender parent and borrower country level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: **Lead arranger and country / crisis exposure: Deal-level correlations**

Panel (a): Country exposure

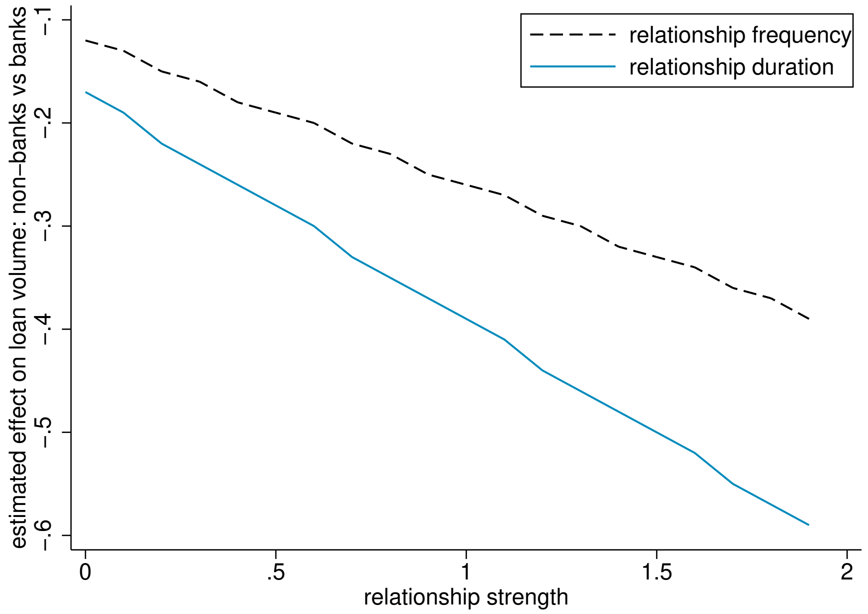
VARIABLES	(1) all lenders P(lead arranger)	(2) bank only P(lead arranger)	(3) non-bank only P(lead arranger)	(4) all lenders: interaction P(lead arranger)
country exposure	-0.031	-0.033	-0.013	-0.033
	(0.065)	(0.069)	(0.081)	(0.069)
country exposure × non-bank				0.020
				(0.085)
Observations	1,030,231	915,750	114,481	1,030,231
R-squared	0.261	0.252	0.340	0.261
Lender Parent × Year FE	✓	✓	✓	✓

Panel (b): Crisis exposure

VARIABLES	(1) all lenders P(lead arranger)	(2) bank only P(lead arranger)	(3) non-bank only P(lead arranger)	(4) all lenders: interaction P(lead arranger)
crisis exposure	-0.316*	-0.338*	-0.179	-0.338*
	(0.182)	(0.194)	(0.159)	(0.194)
crisis exposure × non-bank				0.159
				(0.172)
Observations	1,030,231	915,750	114,481	1,030,231
R-squared	0.263	0.254	0.341	0.263
Lender Parent × Year FE	✓	✓	✓	✓

This table reports results at the syndicated deal level. Panel (a) compares the correlations between a lender's propensity of serving as the lead arranger and its exposure to the country of the borrower. Panel (b) focuses on the correlation between being the lead arranger and the lender's exposure to the borrower's financial crisis. The dependent variable is a dummy indicating whether a lender serves as the lead arranger (identified by the DealScan dataset) for a specific deal. Column (1) in both panels reports results from the entire sample of deals. Columns (2) restricts the sample to bank lenders and columns (3) to non-bank lenders. Columns (4) uses the entire sample of deals but adding the interaction between country or crisis exposure and the non-bank identifier to the regressions. Standard errors are clustered at the lender parent and borrower country level. *** p<0.01, ** p<0.05, * p<0.1.

Figure A3: **Loan volume during crises and relationship strength**



This figure plots the effect of crisis exposure on lending by banks vs. non-banks and how it varies with relationship strength. We estimate the following regression, in which we interact crisis exposure, the non-bank dummy, and different relationship measures: $log(1 + credit)_{l,b,t} = \delta_1 crisis\ exposure_{b,c,t} + \delta_2\ non\ bank_l + \delta_3\ relationship_{l,b,t} + \delta_4\ crisis\ exposure_{b,c,t} \times non\ bank_l + \delta_5\ crisis\ exposure_{b,c,t} \times relationship_{l,b,t} + \delta_6\ non\ bank_l \times relationship_{l,b,t} + \delta_7\ crisis\ exposure_{b,c,t} \times non\ bank_l \times relationship_{l,b,t} + \phi_{l,b} + \psi_{l,t} + \tau_{b,t} + \varepsilon_{l,b,t}$. We then compute the estimated effect of relationship strength on lending during crises, once for banks $(\delta_1 + \delta_3 + \delta_5)$ and once for non-banks $(\delta_1 + \delta_2 + \delta_3 + \delta_4 + \delta_5 + \delta_6 + \delta_7)$. Each line shows the difference between bank and non-bank lending (ie the value of $\delta_2 + \delta_4 + (\delta_6 + \delta_7) \times relationship_{l,b,t}$) on the y-axis for different values of the relationship strength on the x-axis. For simplicity, we set the value of crisis exposure to 1. Note that δ_2 is absorbed by fixed effects. The black dashed line plots values obtained from the log of relationship frequency as relationship measure, the blue solid line values from the log of the relationship duration. Among banks and non-banks with no existing relationship (either frequency or duration) with a firm, non-banks with a crisis exposure of one reduce lending by 12% and 17% more than banks, respectively. This difference increases with relationship length: relative to banks, non-banks with a similarly strong relationship with a borrower cut lending by more the longer the relationship or the more frequent past interactions. These findings are consistent with the results in Table 3 and Table 4, which show that having a relationship with a non-bank provides less benefits (in terms of loan amount and spread) to borrowers than having a similarly strong relationship with a bank. Note that the coefficients obtained from the regressions are $\delta_1 = -0.181^{***}, \delta_3 = -0.115^{**}, \delta_4 = -1.161^{***}, \delta_5 = +0.217^{***}, \delta_6 = -0.242^{***}, \delta_7 = +0.101^{***}$ for frequency and $\delta_1 = -0.224^{***}, \delta_3 = -0.172^{***}, \delta_4 = -0.924^{***}, \delta_5 = +0.248^{***}, \delta_6 = -0.379^{***}, \delta_7 = +0.158^{***}$ for duration.