Resilience and Fragility in Global Banking: Impacts on Emerging Economies

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ABSTRACT

Banks lend through syndicates to diversify risk but colending relationships are sticky. This paper finds a colender effect and, as suggested by theory, with both resilience and fragility provided by the colender network. We exploit a new database of cross-border syndicated lending to developing countries from 1993 to 2020. Central players propagate shocks, while shocks to fringe banks have little impact. The global financial crisis and the appearance of South-South lenders prompted a decline in network centrality and higher network density with more connections between a declining number of participants. There was a sharp fall in lending with the onset of the Covid-19 crisis and we find evidence of a colender effect in the propagation of the shock. Lending subsequently recovered given the demand for liquidity and then with economic recovery.

JEL classifications: F34, G21, L14
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1. Introduction

After the global financial crisis, and as debt levels rose across the world for both sovereigns and corporates, cross border financial flows including bond financing and syndicated lending have increased – see Cortina et al (2021) and Icard and Turner (2019). The global financial crisis impacted bank lending and highlighted the interconnectedness and network characteristics of the global banking system. Given connections between banks, a negative shock to one institution affected the ability of others to continue to lend – see Hale et al (2019) for a recent analysis and Allen and Gale (2000) for a pre-global financial crisis account. At the start of the Covid-19 crisis there was considerable concern that developing countries might suffer from a systemic Sudden Stop in capital flows but while there were large portfolio outflows early in the crisis, many developing-economies maintained access to international capital and there was considerable international bond issuance and cross-border bank lending through 2020 – see Cavallo and Powell (2021) focusing on Latin America.

In this paper, we focus on the cross-border syndicated loan market and lending to developing countries. In the literature to date, most papers have been concerned with actual exposures between banks (for example credit or derivative positions). In contrast, we explore contagion between banks that co-lend through syndicates. Previous theoretical and empirical work suggests that co-lending relationships are sticky, they are not formed immediately nor without cost – see for example Nirei et al (2016) and the references therein. If the co-lenders of a bank reduce the extent of their participation in the market given a negative shock, then given the frictions involved this may impact the lending of the bank in question.

There has been considerable previous empirical work on bank inter-dependence (Hale et al., 2019; Cingano, Manaresi and Sette, 2016; Iyer and Peydró, 2011).[2] Theoretical work has tended to focus on shock propagation in a network of financial institutions linked to one another via unsecured debt contracts. While some analysis suggests that more interbank connections

[2] For example, Hale et al. (2019), analyze how financial shocks in foreign markets are transmitted through the web of bank connections by considering at cross-border lending to other banks (exposure to banks in countries that are experiencing systemic banking crises). The authors find that crisis exposures are associated with lower bank profitability and smaller corporate loan volumes (to foreign, small and non-core borrowers). Cingano, Manaresi and Sette (2016) document that the crunch in the Italian interbank market during the 2007-9 financial crisis led banks with larger exposures to this market to curtail credit, with negative effects on firm investment. Iyer and Peydró (2011) study contagion effects in the Indian interbank market, showing that after the failure of a large bank, banks exposed to it experience large deposit withdrawals, suffer a loss of profitability and cut back loans, propagating the shock to the real sector.

enhance financial stability (Kiyotaki and Moore, 1997; Allen and Gale, 2000; Freixas, Parigi and Rochet, 2000), others see more dense connections as destabilizing, and potentially leading to systemic collapse (Vivier-Lirimont, 2006; Gai, Haldane and Kapadia, 2011; Blume et al., 2011, 2013). Acemoglu et al. (2015) reconcile these seemingly conflicting views in a model where both forces are at play. If negative shocks impacting financial institutions are sufficiently small, densely connected financial networks may enhance the resilience of the financial system, whereas dense interconnections among central players may become a mechanism for the propagation of larger shocks, rendering the network more fragile.

While these papers tend to focus on exposures, we focus on co-lending relations and the impact that co-lenders may have on banks' lending to developing economies. Nirei, Caballero and Sushko (2015) develop a model of syndicate formation and given a calibration and simulation exercise they find that the withdrawal of a bank from a syndicate provokes ripple effects through the market with syndicate dissolving if co-lenders cannot commit funds.

To the best of our knowledge, our paper is the first detailed empirical study of shock propagation through co-lending relationships in the international syndicated lending network. We consider various ways in which shocks may originate and propagate drawing on ideas from network analysis. We differentiate between shocks that impact central lenders versus those on the periphery and we allow for heterogeneous impacts. More specifically, we analyze the impacts on lending and shock-propagation through the network if there is a crisis in a bank's home country, or a crisis in countries where a bank has exposure.

We find that cross-border bank lending to developing countries is significantly reduced when the home country of a bank is hit by a systemic banking crisis and when the bank's portfolio is exposed to countries experiencing a crisis. In addition, we show that these shocks may propagate through the network. For example, we find that a bank reduces lending when its co-lenders are hit by a systemic banking crisis in their home country. We find that the network is fragile in the sense that shocks that impact central banks propagate through the network. On the other hand, we find that the network is resilient to shocks that impact fringe banks – there is no significant co-lender effect in these cases. This is consistent with the notion of the network being both fragile and resilient depending on the nature of the shocks.

Given the perceived higher risks and higher capital requirements, loan syndication is particularly important for borrowers in developing and emerging economies. Moreover, syndicate lending co-moves with overall gross flows of loans form private banks and financial institutions (Figure 1),[3] and in 2007, international syndicated loans represented 40 percent of total cross-border flows to emerging markets (De Haas and Van Horen, 2012).

Syndicates are useful as they diversify risk as banks can lend smaller amounts to multiple borrowers through many syndicated loans rather than extending a few large loans to a limited number of clients; they also allow knowledge to be shared and are a useful tool for banks to manage levels of required regulatory capital (Chowdhry and Nanda, 1996; Pichler and Wilhelm, 2001; Tykvová, 2007; Hale, 2012). In this paper, we abstract from how loan syndicates form, and we take the structure of the syndicated market as a given. We are agnostic on what drives the choice of a financial institution to partner with another financial institution. Irrespective of how they originate, once syndicate relationships are formed, they tend to be sticky, highlighting the importance of investigating what happens to banks when they form syndicates with a partner affected by a negative shock.[4]

We find that the syndicated lending network is not highly centralized or dense, there are some central players with many co-lenders (typically the large global banks) but then there are many financial institutions on the periphery with relatively few co-lender connections. The network is highly incomplete in the sense that there are few actual connections compared to the many potential connection that could exist. In addition, the global financial crisis (GFC) had a significant impact on the network. Several large global banks became less central with less co-lender connections after the crisis. Furthermore, emerging economy banks became more important players (South-South lenders), including Chinese banks (see Figure 2). For example, there was a decline in the number of central players from the U.S. and Europe and an increase from China.

A further contribution of the paper is that we investigate the behavior of the syndicated lending market during the Covid-19 crisis. There was a sharp reduction in lending at the onset of the crisis. We also find evidence for a colender effect in the propagation of this shock. Specifically, some banks that are central in the network reduced their lending by more than others. The banks that colent more with these heavily impacted central players before the crisis, reduced their own

[3] As can be seen in Figure 1, syndicate lending co-moves with the overall gross flows of non-guaranteed (PNG) long-term commercial bank lending and public and publicly guaranteed (PPG) commercial bank loans from private banks and other financial institutions. The correlation between the two series is 0.9 in the sample period.
[4] Edges (relations between a pair of banks) are positive and significantly associated at least up to the 10th lag (Table A1).

lending more than those banks that had fewer lending relations with these heavily impacted players. While using a different methodology exploiting the exogeneity of the Covid-19 shock, we find further evidence of a colender effect operating though the central players, in line with our more general results.

Subsequently, cross-border syndicated lending recovered given the demand for liquidity and then economic recovery, in contrast to the global financial crisis (GFC) where the impacts were more persistent. We speculate that while the GFC was a shock to the banking system itself the COVID shock was different. Moreover, there was considerable support from governments and central banks to economies and direct support to banks through public guarantee schemes and other mechanisms that may account for these differences.

The remainder of the paper is organized as follows. In Section 2, we describe the data. In Section 3 we present the empirical strategy. In Section 4 we discuss the results and in Section 5 we introduce a set of robustness checks. Section 6 concludes.

2. Data

We gather data on cross-border syndicate lending to developing countries over the period 1993-2017 through Thomson ONE (from Refinitiv). Information on systemic banking crises is obtained from the dataset of Laeven and Valencia (2018).

2.1 Cross-Border Syndicate Lending

Our main source of data is Thomson ONE, which contains detailed data on syndicate loans at the tranche level for private and some public sector borrowers. The vast majority of loans are to private sector entities. The database provides information on the tranche, the borrower and the lender dimensions, such as: signing date, proceeds amount in USD, years to maturity, spreads, use of proceeds, type of loan, description of the yield, borrower nationality, sector and public status, and finally, lender name, nationality and role. Since Thomson ONE does not provide the exact amount lent by each bank, we assign equal shares to each bank participating in each tranche of each deal.

We have data on cross-border syndicated loans between 1993 and September 2020. The data on systemic banking crises is available until 2017, so we focus our attention on the behavior of syndicated lending in the period 1993-2017. In addition, in section 4.2 we provide a description of how syndicated lending and the network are performing to December 2020 given the ongoing Covid-19 shock.

In total, there are 16,628 loans provided by 2,543 banks in 147 developing countries for 8,398 borrowers in 1993-2017. Summary statistics for the loans and the data collapsed at the bank-year level can be found in Table 1. The average number of lenders per loan is 7.5, and the average amount in real terms is 293 million dollars (Panel A). Almost 90 percent of lenders are from advanced economies, and developing countries benefitting from cross-border syndicate lending cover most regions across the world (see Figure 3).

We restrict our attention to 285 banks that lend 95 percent of the total amount lent to developing countries in 1993-2017. The average number of lenders per loan is 6.8, and the average loan amount is 279 million dollars (Panel B). We configure a panel dataset to observe each bank throughout the sample.

2.2 Systemic Banking Crises

We exploit the updated dataset of systemic banking crises by Laeven and Valencia (2018) to assess how shocks propagate through the network of banks participating in the syndicate loan market. A banking crisis is defined as systemic if there are significant signs of financial distress in the banking system (e.g., bank runs, losses in the banking systems, bank liquidations) or if there are significant banking policy intervention measures in response to significant losses in the banking system. We restrict our focus to systemic banking crises between 1993 and 2017. With this information, we are able to account for banking crises in the home country of the lending bank, for the exposure of the lending bank to borrower countries that are facing a systemic banking crisis, and for the proportion of each bank's co-lenders affected by a systemic banking crisis in their home country. We will also be able to distinguish the proportion of central co-lenders affected by a crisis among all co-lenders and the proportion of periphery (or fringe) co-lenders affects by a crisis, where we define central co-lenders as the banks that appear at the 75th percentile of the distribution of betweenness centrality, a measure of connectedness of each bank in the network. In the literature on networks, the betweenness of a given node (or bank) states how often it appears on the shortest path between nodes in the network, that is, how many pairs of other banks are not directly connected but are related exclusively through the given bank (Caballero, Candelaria and Hale, 2009).

Once we collapse the dataset at the bank-year level, we are left with 7,125 observations (Table 1, panel C). The information on banking crises is not available for all countries, hence, once we merge this dataset with the reduced syndicate lending sample data, we are left with 232 banks that have 88 percent of the market share in our baseline regression.

2.3 Network

Figure 4 provides one illustration of the co-lender network. Each bubble (or node, in network terminology) represents a bank lending in the international network of syndicate lending. The size of each bubble represents the total amount lent by that bank to other countries in the last year of the sample (2017), while the color of each bubble represents the country of origin of the bank. Table 2 provides selected network statistics. Banks have on average 45 co-lenders per year, but the distribution of centrality is skewed such that there are a few players with many co-lenders and then a long tail of banks with few co-lenders.

The network of the banks or nodes that lend to developing economies through syndicate loans has changed throughout our sample period. Characteristics of the banks in the network such as "Degree," which is the number of connections or edges[5] the node has to other nodes, and "Closeness Centrality," defined as the reciprocal of the average distance from a given starting node to all other nodes in the network, have decreased since the global financial crisis (Figure 5). Moreover, the general density of the network has fallen, that is, the network is less complete than before in terms of possible edges: each bank has fewer connections and is more distant from other nodes in the network (less centralized).

From a Kolmogorov-Smirnov test on the equality of the pre- and post- crisis distributions of centrality and degree values of banks, it is apparent that pre-crisis values are significantly larger than the values post GFC. That is, the network became less dense, and banks became less central over time. This is reflected in the cumulative distribution of bank centrality and degree values over time, which shifted towards less centrality and smaller degree (Figures 6-7).

3. Empirical Strategy

To analyze how shocks propagate in the international network of syndicated lending, we adopt a lagged dependent variable model with bank fixed effects:

[5] Edges are defined as the number of links or relations between banks.

$$y_{it} = \alpha_0 + \theta y_{it-1} + \alpha_1 home\ shock_{it-1} + \alpha_2 exposure\ shock_{it-1} + \alpha_3 prop\ of\ colenders\ in\ crisis_{it-1} + \delta_i + \delta_t + \varepsilon_{it} \quad (1)$$

where y_{it} is the total amount lent to developing countries by bank i (natural logarithm of real million USD). *Home shock$_{it}$* is a dummy representing a year of systemic banking crisis in the home country of lending bank *i*. *Exposure shock$_{it}$* represents the percentage of bank i's portfolio exposed to borrower countries k in a systemic banking crisis. *Syndicate shock$_{it}$* is the proportion of co-lenders of bank i affected by systemic banking shocks in their countries. δ_i and δ_t are bank i and year fixed effects, respectively. ε_{it} are standard errors clustered at the country level. Since the presence of a lagged dependent variable and bank fixed effects might cause a bias, we will reconduct the analysis through a system-GMM.

4. Results

4.1 Response to Crises: Direct and through Co-Lenders

We start the analysis by exploring which shocks affect bank lending. The results of estimating equation (1) are reported in Table 3. We add fixed effects progressively across the columns: in column (1) we do not control for any fixed effect, in column (2) we add bank fixed effects, in column (3) we add year fixed effects, and in our preferred specification, column (4), we add both bank and year fixed effects. The estimated coefficient of the lagged dependent variable is positive and significantly different from zero across specifications,[6] but it does not give any cause for concern that there might be a unit root. The estimated coefficient of *degree$_{t-1}$*, i.e., the number of unique co-lenders, is also positive and significant, indicating that any additional co-lender that a bank had at time *t-1* predicts an increase in the bank's lending at time *t*. Once we control for year fixed effects (columns 3-4), we observe that when a bank experiences a shock in its home country, its cross-border lending to developing countries decreases. Specifically, if a country experiences a systemic banking crisis, its banks decrease their cross-border lending through syndicated loans to developing countries by 29 percent. Exposure to countries that experience a crisis is also detrimental for a bank's cross-border lending: an additional 10 percent of a bank's portfolio

[6] Having both a lagged dependent variable and bank fixed effects will produce a bias in the estimates known as Nickell bias, which should be small given the long time series we exploit (25 years). When adopting a system GMM, results are robust (see Section 5).

exposed to countries suffering from a systemic banking crisis decreases the bank's lending by 5 percent.

Co-lenders also impact bank lending, indicating that shocks propagate through the network. As the literature suggests some co-lenders are more important than others, we distinguish between central and peripheral co-lenders to examine whether the centrality of co-lenders can affect the propagation of shocks. In Table 4 we report the baseline results (column 1) and what happens when we separate the proportion of periphery co-lenders in crisis from the proportion of central co-lenders in crisis (column 2). As can be seen, we find evidence that the shock from co-lenders propagates only through central co-lenders. The effect is quantitatively meaningful. If an additional 10 percent of a bank's central co-lenders are hit by a crisis at home, then that is associated with a fall in that bank's lending by 7 percent. To put actual dollar values on this, on average (across banks and years), each bank has 49 co-lenders and on average, 3 central co-lenders with a crisis in their home country. Given that the average amount lent by a bank is 773 million in real (2012) US dollars per year, 1 more central co-lender in a crisis implies a fall in lending of 204 million 2012 US dollars due to the "co-lender effect."

In column (3) we assess whether banks that are central in the international syndicate loan network are more resilient or vulnerable to shocks to co-lenders: the coefficient of the interaction between the dummy indicating whether the bank is central and the co-lenders shock is not significantly different from zero, indicating that fringe banks and central banks are impacted by shocks to co-lenders with the same strength. Last, we evaluate whether shocks to central or fringe co-lenders have different impacts on central or fringe banks. The results in column (4) indicate that it is always shocks to central co-lenders that negatively affect banks, independently of whether the bank being impacted is located in the periphery or it is a central player.

4.2 The Covid-19 Shock

The previous analysis employed the available data on systemic banking crises to 2017. This section describes the more recent developments in the syndicated lending network, using information available up to December 2020. While to our knowledge there has been no systemic banking crisis in a major economy, there have been impacts on bank balance sheets, mitigated in many jurisdictions by actions to make regulations more flexible - see Beck and Keil (2021) for an analysis of the impacts of the Covid crisis on US banks, Bats et al (2020) for an analysis across market versus bank-based financial systems and see Powell and Rojas-Suarez (2020) and Cavallo and Powell (2021) for discussion on the case of Latin American banks during Covid.

In Figure 8, we plot a 4-months moving average of syndicated lending to developing countries, national and cross-border, between January 2018 and December 2020. A sharp decrease in both types of syndicated lending was evident in March 2020, but starting in September 2020, both types of lending recovered. The syndicated lending network in 2020 had a lower number of banks participating and there were less edges in total. At the same time the density of the network increased – indicating more edges between the smaller number of participants and higher bank interconnectedness (Figure 9).

Moreover, there is a notable difference in the reaction of the network comparing the GFC and Covid-19 when exploring how nodes and edges changed by country of origin of banks. While the number of US and European banks decreased significantly in the GFC, the number of Chinese bank participants was relatively stable. In 2020, however, the number of Chinese and US banks participating in the syndicate lending network was relatively stable. It was largely European banks that withdrew (Figure 10, panel A). The number of edges exhibits different patterns too. While the number of edges with European, US, and Chinese banks all decreased in the GFC (albeit with some heterogeneity), in 2020 the number edges with European and US financial institutions decreased, whereas the edges with Chinese financial institutions increased (Figure 10, panel B). Considering the gross changes in edges (creation of new connections and destruction of existing ones), these changes in 2020 were not driven by a different pace in the creation of new edges but rather by participants withdrawing from the network (Figure 10, panel C). In other words, while US and European banks withdrew, the creation of new edges by Chinese banks allowed the overall pace of new edges to be maintained.

Finally, we investigate the propagation of the COVID shock through the network. We noted that there was considerably heterogeneity across the banks that are central in the network, some reduced their lending considerably, while others were less impacted. We therefore decided to examine whether this heterogenous impact propagated through the network via a colender effect in line with our previous results.

There was a significant decrease in lending by the median bank among those considered central in the network during the Covid-19 shock. We chose to define the hardest hit banks among those that are central as those that reduced their lending by more than the reduction of this median bank. To do this we consider the decrease in lending between the 6 months before Covid-19 truly impacted most countries (September 2019 - February 2020) and the six months thereafter (March 2020 – August 2020). In total, there are 57 banks that are central in the network and that we consider as the hardest hit.

We then analyze the lending of the non-central banks in the network, dividing them into two categories: those non-central banks that were more exposed to these hardest hit entities, through prior lending relationships, and non-central banks that were less exposed. Again, we consider the reduction in the lending of these non-central banks between the two 6-month periods (September 2019 to February 2020 and March 2020 to August 2020).

There are 177 non central banks that lent in the pre-pandemic 6-month period and that lent through syndicates with the central players during 2019. For each of these banks we calculate the share of their colenders that were central in the network and that were the hardest hit (i.e.: whose lending fell the most due to the pandemic). Figure 11, panel A plots the distribution of this variable. The figure shows that for most fringe banks, around half of their colenders that are central in the network were hit hardest but there are some that were more exposed (a higher share of banks central in the network that were hit the hardest) and some were less exposed. Indeed a few of these non-central banks lent exclusively with banks that were hit hardest among the category of the central players (100% share) and some did not lend at all with these banks that were hit the hardest (a zero share).

We chose to compare the most exposed quartile of non-central banks (there are 49 non central banks with a share of colenders that are central in the network and were hit the hardest during the pandemic that exceeds 58%, that defines the top quartile) with the quartile of banks least exposed (there are 41 non central banks with a share of colenders among the central banks hit the hardest by the pandemic that is less than 43% and this defines the bottom quartile).

The most exposed quartile of fringe banks reduced their lending during the pandemic considerably more than the least exposed group. For example, the median non-central bank in the most exposed quartile reduced its lending by 71% (comparing the six months before the pandemic to the first 6 months of the pandemic), while the median bank in the least exposed category reduced its lending by 45%. This result is a first confirmation that the colender effect was also present during the pandemic.

A number of non-central banks reduced their lending to zero, comparing the six months prior to and the first six months of the pandemic – so a 100% reduction in lending. To further confirm the colender effect during this period we then calculate the proportion of non central banks that reduced their lending to zero in the most exposed versus least exposed groups – the top and bottom quartile of the share of colenders central in the network and most hard hit during the pandemic. 44% of the most exposed group reduced their lending by 100%, while only 24% percent reduced their lending to zero in the least exposed group. This 20% difference is statistically significant at the 5% level despite the small number of banks in this analysis (Table 5, column 1). Alternatively, we estimate how the probability of reducing lending by 100% changes through a logistic regression model, and find that being in the most exposed group increases the log odds of reducing lending by 100% by 0.93 (Table 5, column 3). Moreover, considering the probability to reduce lending to zero in the first six months of the pandemic, across all the 177 non central banks, we find that this probability is increasing in the share of 2019 lenders that were central in the network and were hit the hardest due to the pandemic (Figure 12, panel B), as the coefficients on the share variable in a linear probability model (Table 5, column 2) and in a logistic regression model (Table 5, column 4) are positive and statistically significant.

5. Robustness Checks

We found in our empirical results that shocks propagate through central co-lenders, where central co-lenders are defined as the top quartile in the distribution of betweenness centrality. But this result might depend on the particular cut-off or the definition of centrality adopted. Hence, we redo the analysis changing the definition of central lenders in two ways. First, we redefine central co-lenders as banks in the top 10^{th} percentile of the distribution of betweenness centrality. As can be seen in column (1) of Table 6, the main results do not change: banks are hit when there is a shock to their central co-lenders with this tighter definition.

Second, we adopt a different measure of connectedness in the network literature, namely closeness centrality. Closeness of bank *i* is the inverse of the number of banks that bank *i* has to go through on average to reach other banks in the network. The lower the closeness centrality of bank *i,* the more distant bank *i* is from all the other banks in the network. The results are in column (2) of Table 7, and again the main result (that it is the central lenders that propagate shocks) are unchanged.

As a further robustness check we take out outliers from the database. Specifically, we winsorize the variable of yearly cross-border amounts lent by banks at the 1 percent level, then take its logarithm, and then re-estimate our baseline model. As can be seen in columns (3)-(4), again the results do not vary.

Our database was created considering banks that are active in the international syndicated loan market. Still, we have some years in which some banks do not lend. As a further robustness check, we restrict the sample to only those banks that lend every year. In this restricted sample, 83 percent of banks are central (vs. 36 percent in the original sample[7]) and on average banks have a much higher number of co-lenders per year (115 on average vs. 49 in the original sample). The fringe players in this restricted sample are on average less on the outside of the periphery compared to the previous sample. As can be seen in column (5), a shock to co-lenders negatively affects the amount lent by banks, even in this reduced sample. Moreover, while shocks to central co-lenders affect bank lending, in addition we find that shocks to fringe co-lenders are also relevant in this setting. We suggest this result is due to the fact that the fringe banks in this reduced sample are more like intermediate players, as we have eliminated the banks that are on the outside of the periphery of the network.

Estimating a fixed effects model in the framework of a dynamic panel data model may generate biased estimates, if the time dimension is short, and the number of banks (in this case) is large. In fact, our panel is relatively long and so we do not think this is a significant problem for

[7] We define banks as being central if their betweenness centrality is above the 75^{th} percentile in the wider dataset. As discussed, we narrow the sample to 232 banks and we end up with 36 percent of banks in that smaller sample being defined as central.

the baseline model presented above. To see if we are correct, we re-estimate equation (1) through a system-GMM approach as suggested by Blundell and Bond (1998). This also has the potential advantage of addressing endogeneity by using lagged variables as instruments. Specifically, we use a set of moment conditions where lagged levels are used as instruments for the lagged dependent variable in the difference equations and lag differences in the level equation. We employ Windmeijer's (2005) finite sample correction to report standard errors. To avoid instrument proliferation, we first instrument with 3 to 6 lags of the lagged dependent variable (Table 7, column 1) and we instrument with 3-15 lags (column 2). The results are very reassuring, as all the main results are unchanged in both cases. The proportion of co-lenders in crisis has a negative and significant effect on the amount lent by the bank. When we disentangle the effect of central and fringe co-lenders, we continue to find that the shock is transmitted through central co-lenders (columns 3-4) and not through fringe players.

Both the validity of the instruments and the presence of serial correlation in the residuals can be tested. The Hansen test, reported at the bottom of the table, suggests that overidentifying restrictions are valid for all specifications. The Arellano-Bond test for autocorrelation of residuals in differences confirms that differenced residuals do not exhibit significant AR(3) behavior, that is, third lags of endogenous variables are appropriate instruments for their current values.[8]

6. Conclusions

Syndicated lending allows banks to diversify risk and manage capital effectively, this may be particularly useful and enhance lending to developing countries, where risk perceptions tend to be elevated. But syndication appears to be sticky. A shock that reduces one bank's lending in this market may have impacts on the ability of its co-lenders to continue to lend. Theoretical models suggest both resilience and fragility in banking networks depending critically on the nature of the shock and how it impacts the network.

A main contribution of our paper is to show evidence for this theoretical notion, as we find that the co-lender effect is driven by shocks to co-lenders that are central in the network, while shocks that hit banks on the periphery have little impact. In addition, we find evidence that banks

[8] We start instrumenting with the third lag because differenced residuals appear to follow an AR(2) process, making second lags of endogenous variables inappropriate instruments.

that have a banking crisis in their home country or have exposures to countries that suffer a banking crisis reduce lending in this market.

Furthermore, we find that the network became less dense, and centrality declined after the global financial crisis. The preexisting, large global banks became less central and new players entered, such as South-South lenders including the Chinese official banks.

The Covid-19 crisis prompted a sharp reduction in lending but not all banks were affected equally. We again find evidence of a colender effect as the colenders of those more heavily impacted central players also reduced their lending more strongly.

Still, in contrast to the experience after the GFC syndicated lending recovered relatively quickly. The shock was of course quite different and not to the banking sector per se. In addition, governments and central banks gave strong support to economies and to financial sectors. We also found that while the number of banks and lending relationships (edges in the network) declined the density of the network rose.

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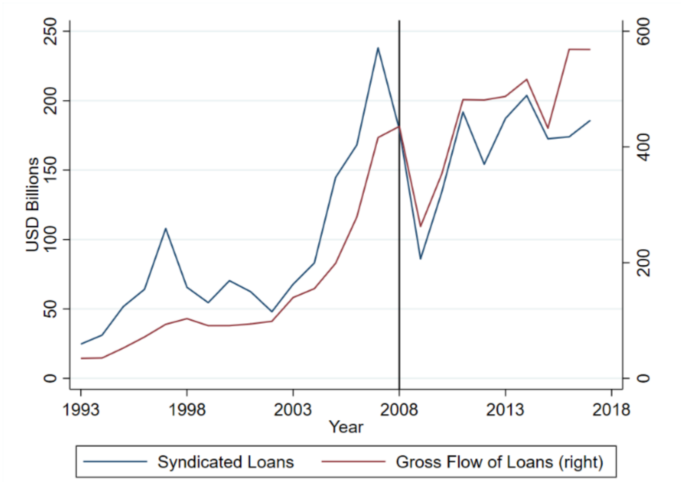
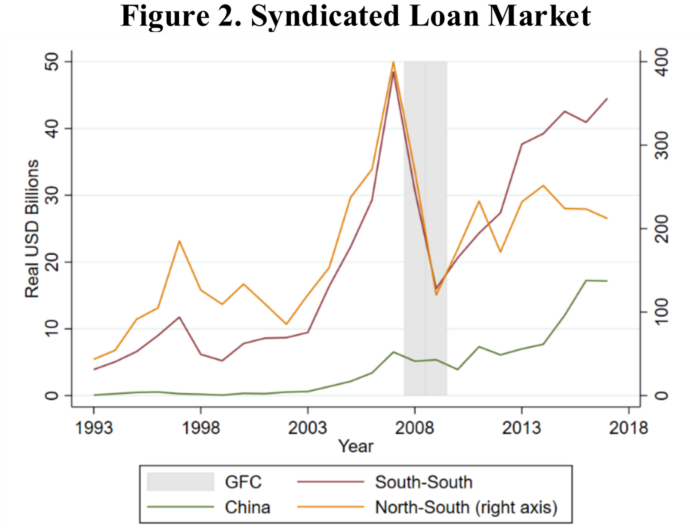
Tables and Figures

Figure 1. Cross-Border Syndicated Lending Is an Important Element of Total Gross Credit Flows to Developing Countries



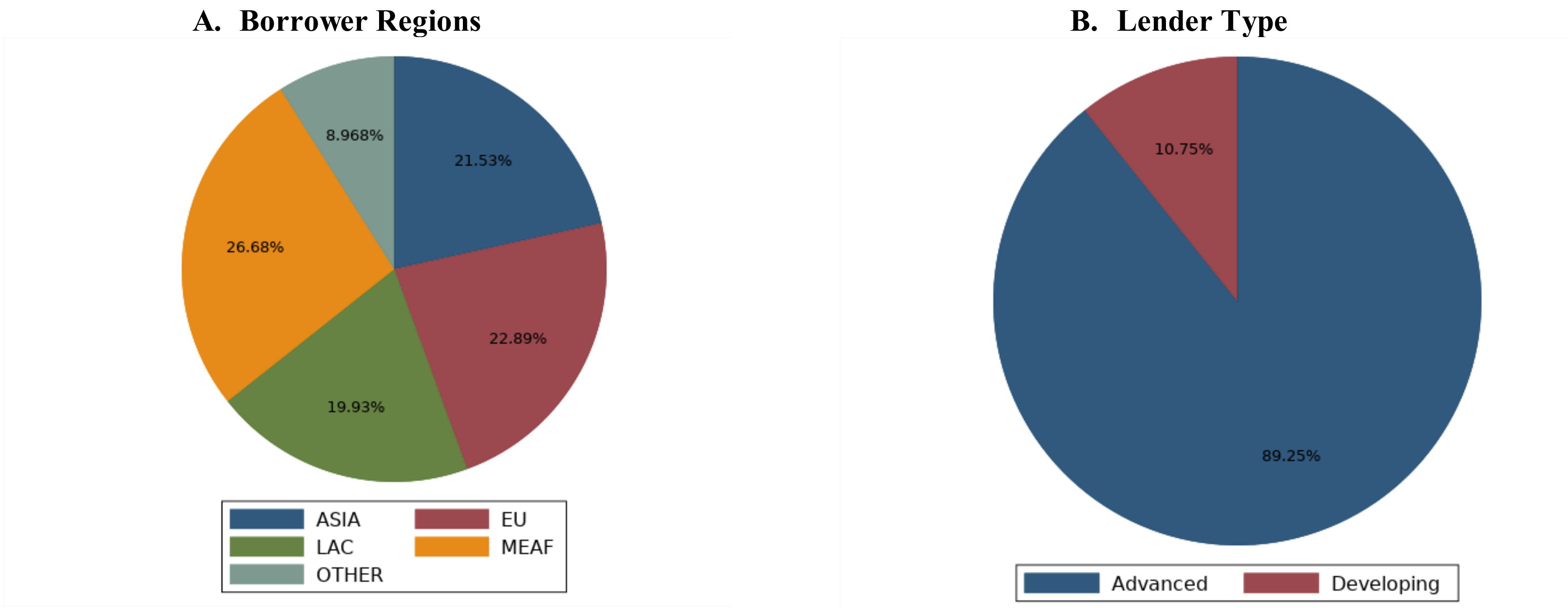
Note: The figure shows the co-movement between the nominal amount of Syndicated Loans and the Gross Flow of Loans for low and middle-income countries during 1993-2017. The agreement of new syndicated lending is closely associated with the actual flow (disbursements) of commercial lending to developing countries. Gross flow of loans is the gross flows (disbursements) of non-guaranteed (PNG) long-term commercial bank loans and public and publicly guaranteed (PPG) commercial bank loans from private banks and other financial institutions from World Bank data.
Source: Authors' calculations based on Refinitiv and World Bank International Debt Statistics.

Figure 2. Syndicated Loan Market



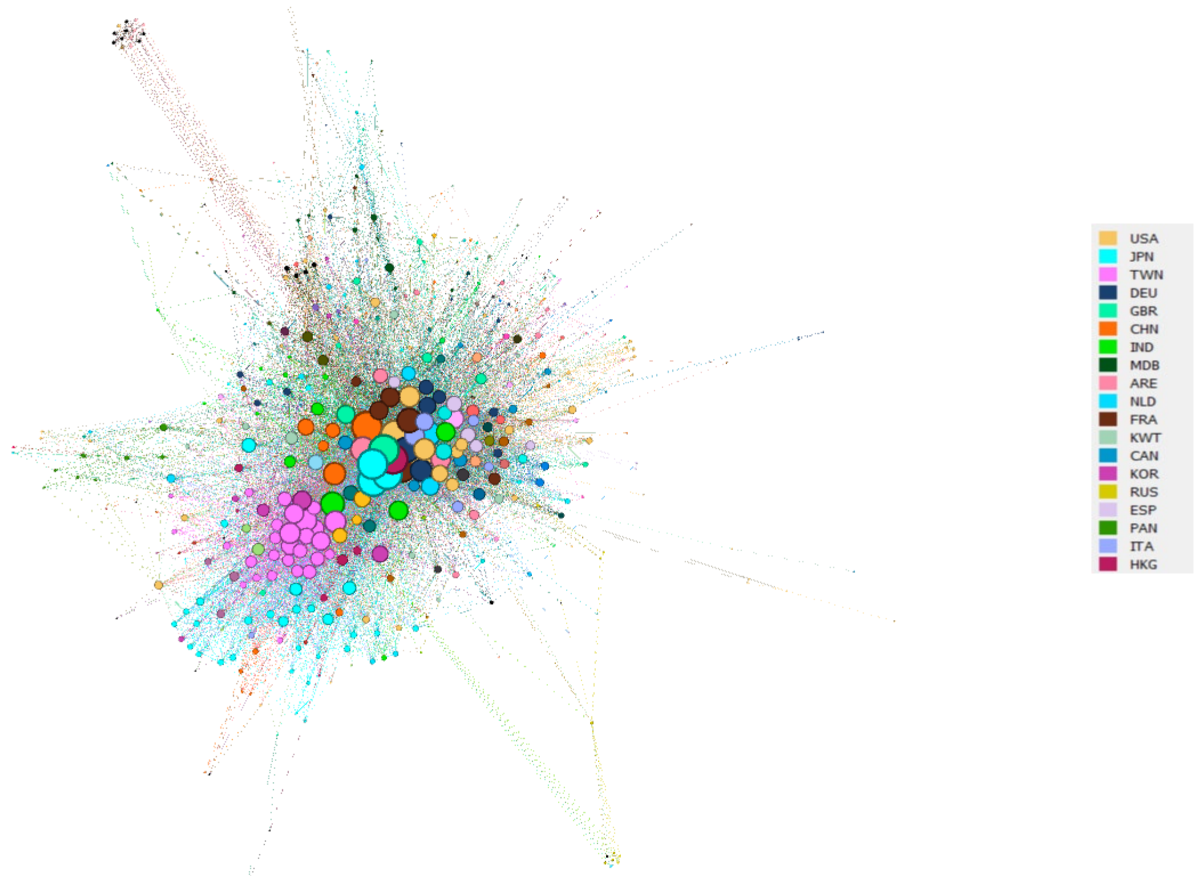
Note: The figure shows the evolution of syndicate lending to Emerging and Developing Economies (South) by lenders during 1993-2017.
Source: Authors' calculations based on Refinitiv.

Figure 3. Syndicated Loan Market Participants



Note: Panel A depicts the distribution of syndicate loans by borrower region and panel B shows the share of Advanced and Developing lender countries share during 1993-2017.
Source: Authors' calculations based on Refinitiv.

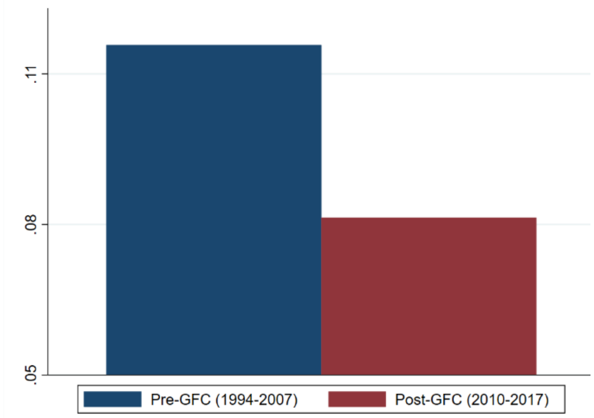
Figure 4. 2017 Network



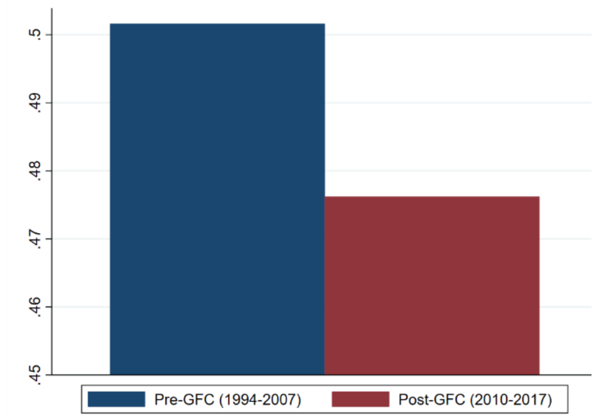
Note: Figure 4 illustrates the lending network for 2017. Each bubble represents a bank, and the size of each bubble is in proportion to amount lent. The colors show the nationalities of the banks in question. Banks (bubbles) are placed close to each other when they syndicate loans together. As it is common for banks from the same country to form syndicates, bubbles of the same color tend to be close to each other. At the center of the network are the large global banks from the United States, Europe and Japan. Taiwan is also important in the cross-border syndicated loan market, and some Chinese banks have now become central players. There are some clusters quite far away from the central mass. Typically, these consist of banks from some emerging countries that also participate in cross-border lending but that do not co-lend much with the central players.
Source: Authors' calculations based on Refinitiv.

Figure 5. Network Measures: Centrality and Density

A. Density

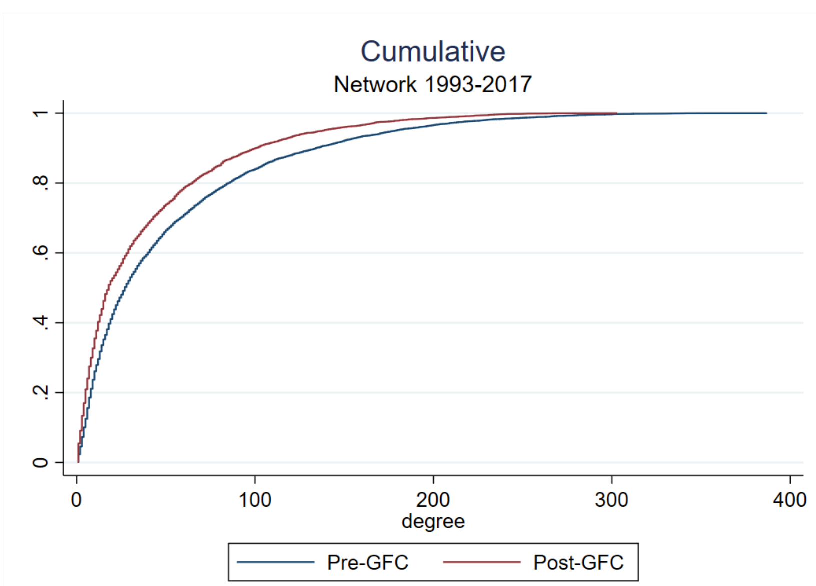


B. Centrality



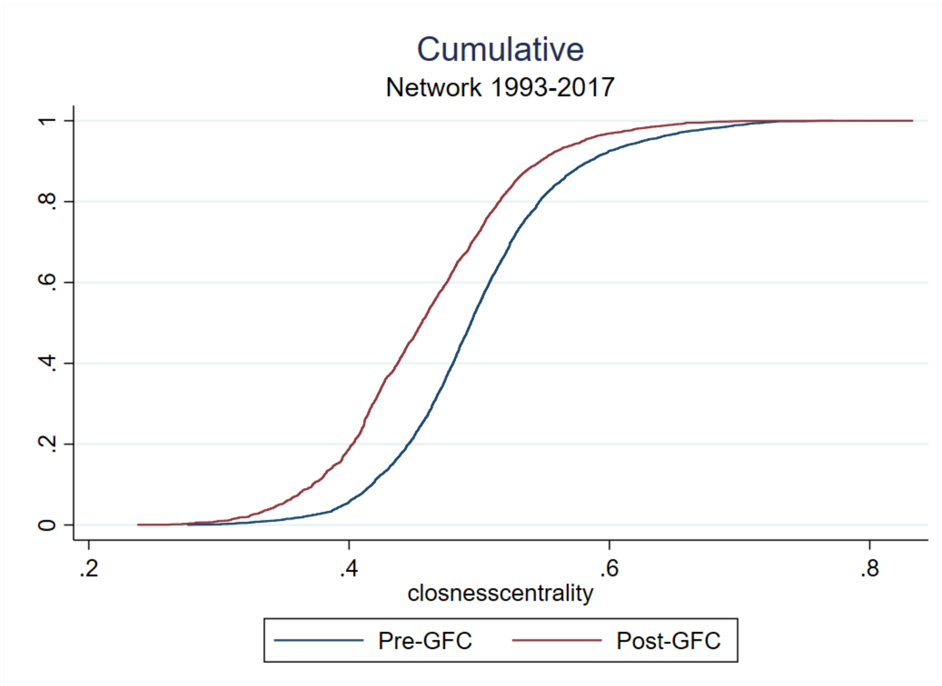
Note: This figure shows that average network characteristics are different if we compare the pre and the post GFC periods. In Panel A, Density, which is a measure of how close the network is to complete, has fallen after the GFC. In Panel B, Centrality also decreased in the Post-GFC period, indicating that the banks are less connected to other banks in the network.
Source: Authors' calculations based on Refinitiv.

Figure 6. The Cumulative Distribution Bank Degree before and after the Global Financial Crisis



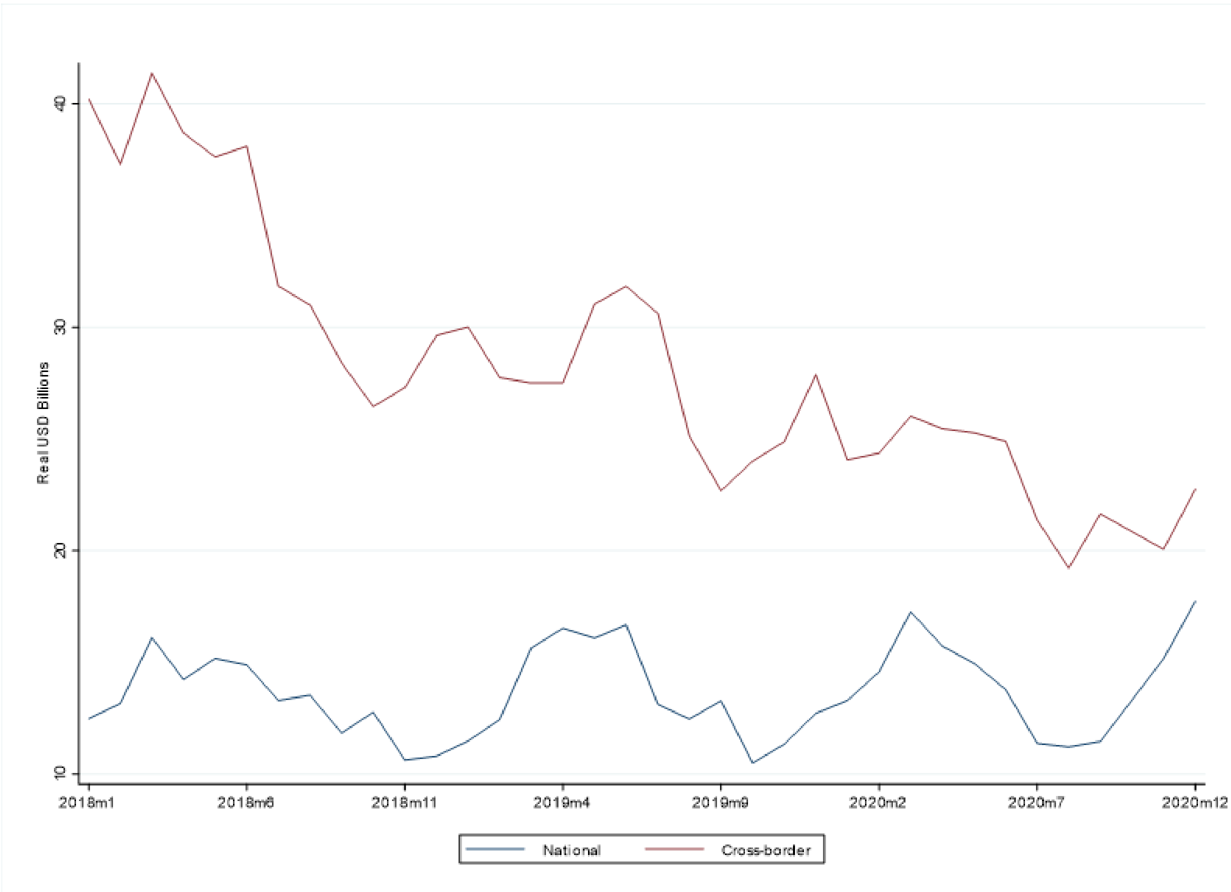
Note: The figure illustrates how the cumulative frequency distribution of the Degree shifts to the left after the GFC, implying that the banks in the network have fewer connections with other banks.
Source: Authors' calculations based on Refinitiv.

Figure 7. The Cumulative Distribution of Bank Closeness Centrality before and after the Global Financial Crisis



Note: The figure illustrates how the cumulative frequency distribution of the Centrality shifts to the left after the GFC, implying that the banks in the network are less central.
Source: Authors' calculations based on Refinitiv.

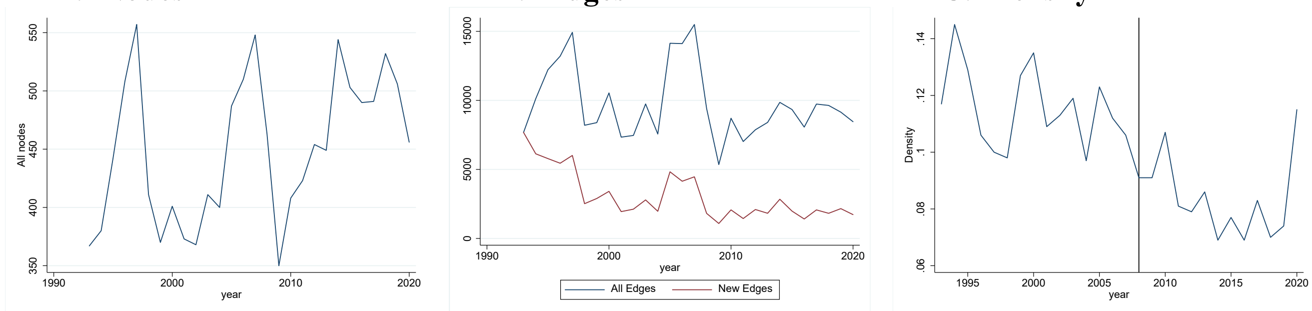
Figure 8. Syndicated Lending to developing economies after the Covid-19 shock by type of finance



Note: The figure illustrates 4-months moving averages of syndicated lending (real USD billions) to developing economies in January 2018-December 2020, both cross-border and national, by announcement date.
Source: Authors' calculations based on Refinitiv.

Figure 9. Network Measures Trends: Nodes, Edges and Density

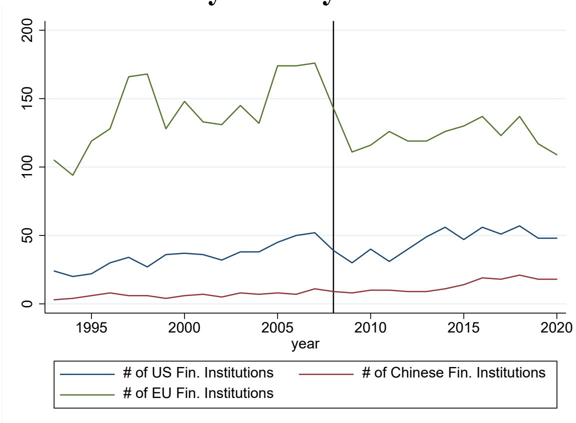
A. Nodes **B. Edges** **C. Density**



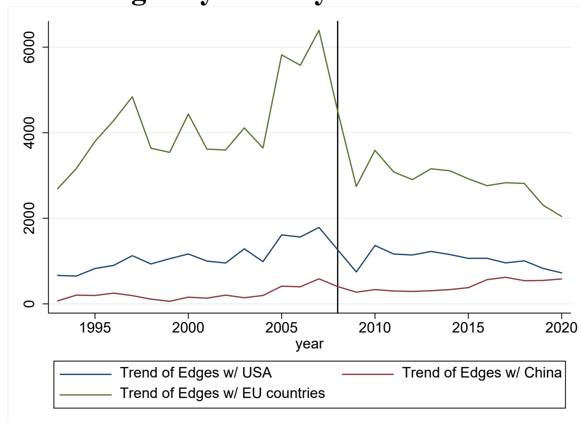
Note: This figure shows that dynamics of network characteristics, specifically of nodes, i.e. the number of banks in the network (Panel A), of edges, i.e. co-lending relationships between financial institutions (Panel B), and density (Panel C).
Source: Authors' calculations based on Refinitiv.

Figure 10. Trends in Nodes & Edges with US, Chinese and European Financial Institutions

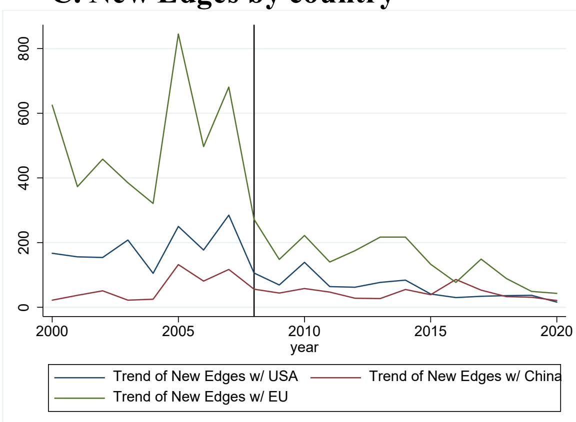
A. Nodes by country



B. Edges by country



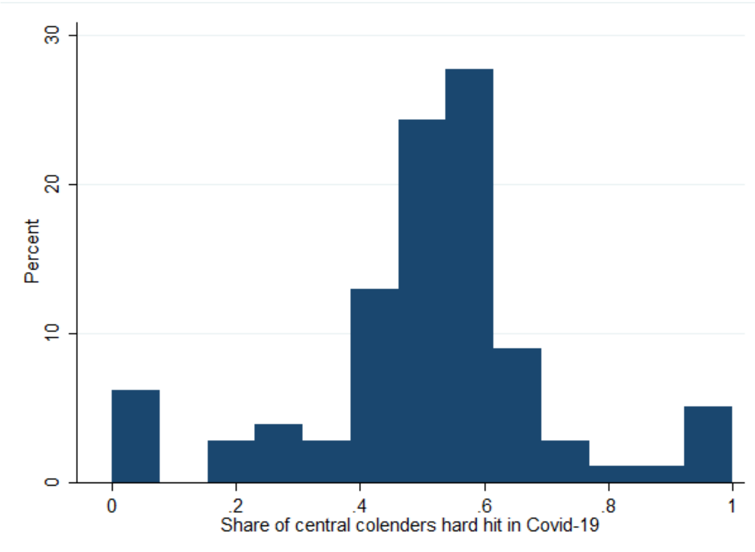
C. New Edges by country



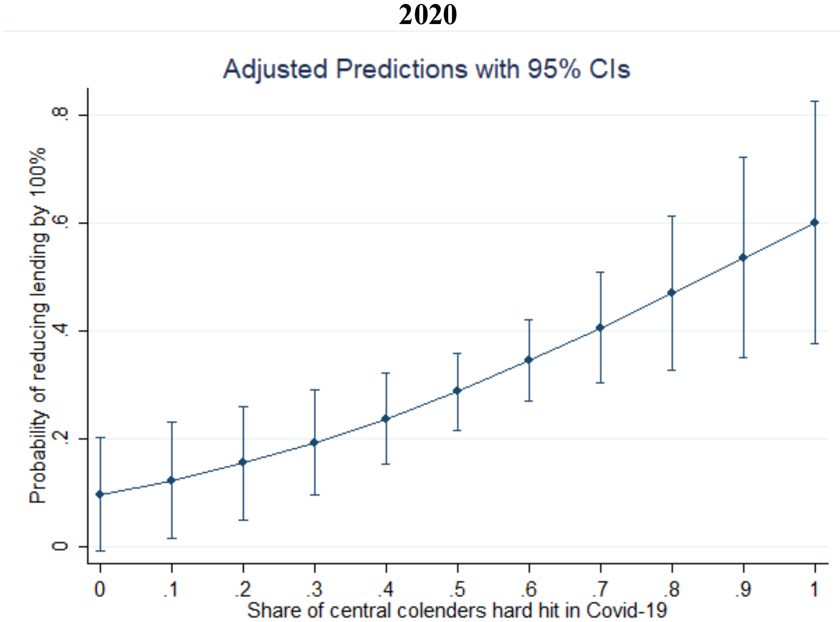
Note: This figure shows that dynamics of network characteristics by country of origin of financial institutions, specifically of nodes, i.e. the number of banks in the network (Panel A), of edges, i.e. co-lending relationships between financial institutions (Panel B), and new edges, i.e. co-lending relationship that had not existed before -or at least since 1993, when they can be observed- (Panel C).

Source: Authors' calculations based on Refinitiv.

Figure 11. The Covid-19 Shock
A. Share of Central Colenders Hard Hit in 2020



B. Probability of Reducing Lending as a Function of the Share of Central Colenders Hard Hit in 2020



Note: Panel A shows the distribution for fringe colenders in 2019 of their share of central colenders that will be subsequently hard hit in the 6 months following the Covid-19 shock (March 2020 – August 2020). Panel B depicts the adjusted probabilities of reducing lending by 100% for the same fringe colenders between the 6-month prior the Covid-19 shock (September 2019-February 2020) and after (March 2020-August 2021) as a function of the share of their central colenders hard hit by the pandemic. Probabilities are calculated from the logistic regression model presented in Table 5, column 4. Confidence intervals at 95% significance level.
Source: Authors' calculations based on Refinitiv.

Table 1. Summary Statistics

	Obs.	Mean	Std. Dev.	Min	Max
Panel A. Loans					
Amount of loans (Real USD, millions)	16,628	292.5	490.2	2.701	8,580
Number of lenders per loan	16,628	7.525	6.776	1	69
Panel B. Loans (Reduced Sample)					
Amount of loans (Real USD, millions)	16,510	279.3	480.9	1.350	8,580
Number of lenders per loan	16,510	6.809	6.126	1	58
Panel C. Bank-Year level Data					
Amounts of loans (Real USD, millions)	7,125	648.1	1,752	0	28,771
Number of co-lenders	7,125	53.93	63.82	0	387
Bank in country with systemic crisis	5,800	0.103	0.304	0	1
Portfolio exposed to crisis (%)	7,125	5.442	17.72	0	100
Proportion of co-lenders in crisis (%)	7,125	7.711	17.21	0	100
Central Lenders	7,125	0.345	0.475	0	1

Note: The table reports descriptive statistics for selected variables in our analysis. Loan characteristics correspond to the loan-bank-year panels, and can be found in Panels A, B and C. Panel A contains the full sample of syndicated loans to developing countries in 1993-2017. In Panel B we restrict the sample and keep the 285 banks that lend 95 percent of the total amounts lent through syndicated loans to developing countries in 1993-2017. Finally, Panel C reports the variables used in our regressions in the bank-year dataset.
Source: Authors' calculations based on Refinitiv and Laeven and Valencia (2018).

Table 2. Network Summary Statistics

	Obs.	Mean	Std. Dev.	Min	Max
Density	25	0.103	0.0207	0.0690	0.145
Degree	11,111	45.36	53.88	1	387
Closeness Centrality	11,111	0.491	0.0944	0.238	1
Betweenness Centrality	11,111	245.1	838.4	0	17,808

Note: The table reports descriptive statistics for network characteristics relevant for our analysis. Density is calculated for the network at the year level. Degree, closeness centrality and betweenness centrality are calculated at the bank-year level.
Source: Authors' calculations based on Refinitiv.

Table 3. Effect of Shocks on Bank Lending

	(1)	(2)	(3)	(4)
	Amount Lent Real USD (ln)	Amount Lent Real USD (ln)	Amount Lent Real USD (ln)	Amount Lent Real USD (ln)
Amount Lent Real USD (ln) $_{t-1}$	0.6436***	0.5013***	0.6109***	0.4370***
	(0.033)	(0.041)	(0.040)	(0.053)
Degree $_{t-1}$	0.0094***	0.0075***	0.0110***	0.0109***
	(0.001)	(0.001)	(0.001)	(0.002)
Home Shock $_{t-1}$	-0.1609	-0.1461	-0.2855**	-0.2874**
	(0.148)	(0.178)	(0.111)	(0.117)
Exposure Shock $_{t-1}$	-0.0101***	-0.0116***	-0.0049***	-0.0051***
	(0.002)	(0.002)	(0.002)	(0.002)
Proportion of co-lenders in crisis $_{t-1}$	-0.0051***	-0.0038**	-0.0087***	-0.0073**
	(0.002)	(0.002)	(0.003)	(0.003)
Bank FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes
No. Banks	232	232	232	232
No. Lender Countries	45	45	45	45
Average Dep. Var.	4.130	4.130	4.130	4.130
Average Home Shock	0.106	0.106	0.106	0.106
Average Exposure Shock	5.822	5.822	5.822	5.822
Proportion co-lenders in crisis	8.137	8.137	8.137	8.137
Observations	5,568	5,568	5,568	5,568
R-squared	0.664	0.697	0.680	0.714

Note: The table reports estimations of equation (1). In column (1) no fixed effects are added; in column (2) we control for bank fixed effects (FE); in column (3) we control for year FE; in column (4) we control for both bank and year FE. The dependent variable in all specifications is Amount; the natural logarithm of amount (in real USD) lent by a bank in cross-border syndicated lending to developing countries. All regressions include a constant term (coefficients not shown). These regressions are based on the reduced sample where we keep banks with 88 percent of the market share of syndicate loans. Our sample period is 1993-2017 and the dimension of the panel is Bank-Year. Standard errors are clustered at the country level; *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' calculations based on Reifinitiv and Laeven and Valencia (2018).

Table 4. The Role of Fringe and Central Co-lenders

	(1) Amount Lent Real USD (ln)	(2) Amount Lent Real USD (ln)	(3) Amount Lent Real USD (ln)	(4) Amount Lent Real USD (ln)
Amount (ln) $_{t-1}$	0.4370***	0.4374***	0.4273***	0.4276***
	(0.053)	(0.053)	(0.054)	(0.054)
Degree $_{t-1}$	0.0109***	0.0109***	0.0094***	0.0094***
	(0.001)	(0.001)	(0.001)	(0.001)
Home Shock $_{t-1}$	-0.2874**	-0.2911**	-0.2838**	-0.2889**
	(0.117)	(0.112)	(0.115)	(0.113)
Exposure Shock $_{t-1}$	-0.0051***	-0.0051***	-0.0051***	-0.0052***
	(0.002)	(0.002)	(0.002)	(0.002)
Proportion of Co-lenders in Crisis $_{t-1}$	-0.0073**		-0.0065**	
	(0.003)		(0.003)	
Proportion of Fringe Co-lenders in Crisis $_{t-1}$		-0.0057		-0.0050
		(0.006)		(0.008)
Proportion of Central Co-lenders in Crisis $_{t-1}$		-0.0077**		-0.0069**
		(0.003)		(0.003)
Central Lender $_{t-1}$			0.3111***	0.3152***
			(0.102)	(0.108)
Proportion of Co-lenders in Crisis $_{t-1}$ # Central Lender $_{t-1}$			-0.0015	
			(0.003)	
Proportion of Fringe Co-lenders in Crisis $_{t-1}$ # Central Lender $_{t-1}$				-0.0004
				(0.010)
Proportion of Central Co-lenders in Crisis $_{t-1}$ # Central Lender $_{t-1}$				-0.0025
				(0.004)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. Lenders	232	232	232	232
No. Lender Countries	45	45	45	45
Average Dep. Var.	4.130	4.130	4.130	4.130
Average Home Shock	0.106	0.106	0.106	0.106
Average Exposure Shock	5.822	5.822	5.822	5.822
Proportion Co-lenders in Crisis	8.137	8.137	8.137	8.137
Proportion Fringe Co-lenders in Crisis over Total Co-lenders	2.152	2.152	2.152	2.152
Proportion Central Co-lenders in Crisis over Total Co-lenders	5.985	5.985	5.985	5.985
Observations	5,568	5,568	5,568	5,568
R-squared	0.714	0.714	0.715	0.715

Note: The table reports estimations of equation (1). All columns present both bank and year FE. The dependent variable in all specifications is Amount; the natural logarithm of amount (in real USD) lent by a bank in cross-border syndicated lending to developing countries. All regressions include a constant term (coefficients not shown). These regressions are based on the reduced sample where we keep banks with 88 percent of the market share of syndicate loans. Our sample period is 1993-2017 and the dimension of the panel is Bank-Year. Standard errors are clustered at the country level; *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' calculations based on Reifinitiv and Laeven and Valencia (2018).

Table 5. The Co-lender Shock to Fringe Banks in Covid-19

	(1)	(2)	(3)	(4)
	Linear Probability Model		**Logistic Regression Model**	
	Probability of 100% lending reduction	Probability of 100% lending reduction	Probability of 100% lending reduction	Probability of 100% lending reduction
Colender shock	0.2051**		0.9266**	
	(0.099)		(0.466)	
Share of central colenders negatively shocked in 2020		0.5017***		2.6309**
		(0.167)		(1.028)
Observations	90	177	90	177
R-squared	0.046	0.050		
Average Dep. Var.	0.356	0.305	0.356	0.305
Average Indep. Variable	0.544	0.511	0.544	0.511

Note: The table reports estimations of a linear probability model (columns 1-2) or a logistic regression (columns 3-4) where the dependent variable is a dummy with unit value indicating if a fringe bank colending with central players in 2019 decreased its lending by 100% between the 6-month period before the Covid-19 shock (September 2019-February 2020) and after (March 2020-August 2020). The covariate of interest in columns 1-3 is a dummy equal to 1 if the fringe banks were heavily exposed to central players hit harder by the Covid-19 shock; the covariate of interest in columns 2-4 is the share of central colenders hardly hit by the Covid-19 shock. All regressions include a constant term (coefficients not shown). These regressions are based on a reduced sample including the top and bottom quartile fringe banks by exposure to central players hit in Covid-19 (columns 1-3) or all fringe banks colending with central players in 2019 and lending in syndicates in the 6-month period prior to the pandemic (September 2019- February 2020) (column 2-4). Heteroskedasticty-robust standard errors; *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' calculations based on Reifinitiv.

Table 6. Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Betweenn. Centrality p90	Closeness Centrality p75	Winsorized		Banks that lend every year	
	Amount Lent Real USD (ln)	Amount Lent Real USD (ln)	Amount Lent Real USD (ln)	Amount Lent Real USD (ln)	Amount Lent Real USD (ln)	Amount Lent Real USD (ln)
Amount (ln) $_{t-1}$	0.4368***	0.4374***	0.4385***	0.4390***	0.5392***	0.5417***
	(0.053)	(0.053)	(0.053)	(0.053)	(0.058)	(0.059)
Home Shock $_{t-1}$	-0.2849**	-0.2936**	-0.2829**	-0.2878**	-0.0691	-0.0378
	(0.110)	(0.115)	(0.118)	(0.113)	(0.073)	(0.082)
Exposure Shock $_{t-1}$	-0.0051***	-0.0052***	-0.0051***	-0.0051***	-0.0028*	-0.0025
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Degree $_{t-1}$	0.0109***	0.0109***	0.0108***	0.0108***	0.0034***	0.0034***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Proportion of Co-lenders in Crisis $_{t-1}$			-0.0073**		-0.0193***	
			(0.003)		(0.004)	
Proportion of Fringe Co-lenders in Crisis $_{t-1}$	-0.0078	-0.0041		-0.0053		-0.0261***
	(0.005)	(0.006)		(0.006)		(0.006)
Proportion of Central Co-lenders in Crisis $_{t-1}$	-0.0068*	-0.0081**		-0.0079**		-0.0167***
	(0.004)	(0.003)		(0.003)		(0.005)
Central Lender $_{t-1}$						
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Lenders	232	232	232	232	57	57
No. Lender Countries	45	45	45	45	22	22
Average Dep. Var.	4.130	4.130	4.126	4.126	7.078	7.078
Average Home Shock	0.106	0.106	0.106	0.106	0.100	0.100
Average Exposure Shock	5.822	5.822	5.822	5.822	8.127	8.127
Proportion Central lenders	0.170	0.342	0.356	0.356	0.833	0.833
Proportion Co-lenders in Crisis	8.137	8.137	8.137	8.137	10.66	10.66
Proportion Fringe Co-lenders in Crisis over Total Co-lenders	3.923	1.994	2.152	2.152	3.883	3.883
Proportion Central Co-lenders in Crisis over Total Co-lenders	4.214	6.143	5.985	5.985	6.781	6.781
Observations	5,568	5,568	5,568	5,568	1,368	1,368
R-squared	0.714	0.714	0.713	0.713	0.879	0.879

Note: The table reports estimations of the robustness checks for our baseline regression in equation (1). All columns present both bank and year fixed effects. The dependent variable in all specifications is Amount; the natural logarithm of amount (in real USD) lent by a bank in cross-border syndicated lending to developing countries. In columns (1) and (2) we use a different measure of centrality, in columns (3) and (4) we winsorize the dependent variable at the 1 percent level, and in columns (5) and (6) we restrict the sample to the banks that lent every year. All regressions include a constant term (coefficients not shown). Our sample period is 2000-2017 and the dimension of the panel is Bank-Year. Standard errors are clustered at the country level; *** p<0.01, ** p<0.05, * p<0.1.

Table 7. System-GMM

	(1)	(2)	(3)	(4)
	Amount Lent Real USD (ln)	Amount Lent Real USD (ln)	Amount Lent Real USD (ln)	Amount Lent Real USD (ln)
Amount (ln) $_{t-1}$	0.8421***	0.8095***	0.8543***	0.8225***
	(0.041)	(0.042)	(0.041)	(0.041)
Home Shock $_{t-1}$	-0.2153**	-0.1772**	-0.2513***	-0.2187***
	(0.090)	(0.082)	(0.090)	(0.082)
Exposure Shock $_{t-1}$	-0.0038**	-0.0059***	-0.0047***	-0.0062***
	(0.002)	(0.002)	(0.002)	(0.002)
Degree $_{t-1}$	0.0012	0.0038**	0.0007	0.0031*
	(0.002)	(0.002)	(0.002)	(0.002)
Proportion of Co-lenders in Crisis $_{t-1}$	-0.0157***	-0.0177***		
	(0.003)	(0.003)		
Proportion of Fringe Co-lenders in Crisis $_{t-1}$			0.0034	-0.0033
			(0.007)	(0.007)
Proportion of Central Co-lenders in Crisis $_{t-1}$			-0.0223***	-0.0221***
			(0.004)	(0.004)
Central Lender $_{t-1}$				
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Lag limit	3-6	3-15	3-6	3-15
Instruments	188	243	189	244
Number of banks	232	232	232	232
AR (3)	0.216	0.220	0.204	0.211
Hansen	0.129	0.310	0.147	0.353
Observations	5,568	5,568	5,568	5,568

Note: The table reports the results from estimating a system-GMM. All columns present both bank and year FE. The dependent variable in all specifications is Amount; the natural logarithm of amount (in real USD) lent by a bank in cross-border syndicated lending to developing countries. All regressions include a constant term (coefficients not shown). These regressions are based on the reduced sample where we keep banks with 88 percent of the market share of syndicate loans. Our sample period is 1993-2017 and the dimension of the panel is Bank-Year. Bottom rows report p-values for the Arellano-Bond test for AR(3) in differences and the Hansen test of joint validity of instruments. Windmeijer's finite-sample correction for the two-step covariance matrix, corrected standard errors clustered at the country level in parentheses; *** p<0.01, ** p <0.05, * p<0.1.

Appendix

Table A1. Stickiness of edges in the network

	(1) existing edge $_t$	(2) existing edge $_t$	(3) existing edge $_t$	(4) existing edge $_t$	(5) existing edge $_t$	(6) existing edge $_t$
existing edge $_{t-1}$	0.4951***	0.3307***	0.2968***	0.5896***	0.3765***	0.3369***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
existing edge $_{t-2}$		0.1938***	0.1567***		0.2091***	0.1653***
		(0.001)	(0.001)		(0.002)	(0.002)
existing edge $_{t-3}$		0.1521***	0.0991***		0.1644***	0.1033***
		(0.001)	(0.001)		(0.002)	(0.002)
existing edge $_{t-4}$			0.0548***			0.0503***
			(0.001)			(0.002)
existing edge $_{t-5}$			0.0513***			0.0524***
			(0.001)			(0.002)
existing edge $_{t-6}$			0.0327***			0.0256***
			(0.001)			(0.002)
existing edge $_{t-7}$			0.0291***			0.0248***
			(0.001)			(0.002)
existing edge $_{t-8}$			0.0278***			0.0252***
			(0.001)			(0.002)
existing edge $_{t-9}$			0.0227***			0.0147***
			(0.001)			(0.002)
existing edge $_{t-10}$			0.0360***			0.0412***
			(0.001)			(0.002)
Observations	99,790,569	92,389,016	66,497,975	1,089,645	1,007,878	723,883
R-squared	0.244	0.311	0.342	0.347	0.413	0.426
No. Banks 1	2739	2739	2739	284	284	284
No. Banks 2	2745	2745	2745	283	283	283

Note: The table shows the correlation between a dummy indicating the existence of an edge at time *t* and dummies indicating their existence in previous periods, up to 10 years before.