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The role of credit lines and multiple lending in financial contagion and systemic events

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ABSTRACT

Banks play a crucial role in providing liquidity to borrowers, particularly during crises (Kashyap et al., 2002 [33]). The existence of multiple lending relationships between banks and borrowers has been seen as an element that reduces the risk of liquidity shortage for debtors (Detragiache et al., 2000). In this paper, we aim to show how the interaction of these two aspects with solvency and liquidity requirements might have implications for the stability of the banking system, which might still need to be fully analyzed.

We show that if other sources of liquidity are unavailable or too costly for banks, multiple lending might be a key element in a systemic liquidity shortage and a large drop in lending to the economy. These findings are particularly relevant for understanding how macroeconomic shocks, such as the relatively recent outbreak of COVID-19, could impact the real economy, as well as for assessing the implications of alternative banking resolution mechanisms.

1. Introduction[1]

Banks are pivotal in providing liquidity to the economy by allowing depositors to obtain liquidity on demand and, at the same time, they are also crucial in granting mostly illiquid loans to borrowers. This liquidity transformation function may have been hindered during crises. Ivashina and Scharfstein (2010) show that banks were more vulnerable to credit-line draw-downs reduced their lending to a greater extent. As illustrated by Acharya and Mora (2015), banks have a natural advantage in providing liquidity to businesses through credit lines and other commitments. However, during the great financial crisis, a significant portion of "toxic" financial instruments found their way into commercial and investment bank balance sheets, raising questions about these institutions' solvency and undermining their capacity to provide backup liquidity to the economy (Kashyap et al., 2002). In this paper, we show one possible mechanism (solvency- and liquidity-based) that might hamper the provision of liquidity by banks, and we provide a quantitative assessment of this risk based on granular data and counterfactual simulations.

Borrowing from many lenders may lead to both advantages and disadvantages for lenders and borrowers. On the one hand, it is beneficial to borrowers because they are less exposed to the hold-up phenomenon (Sharpe, 1990; Rajan, 1992) and, according to Detragiache et al. (2000), they are also less exposed to the risk of their project being prematurely liquidated in cases when lenders run out of liquidity.[2] In case one of the banks lending to a borrower falls short of liquidity, other lenders may easily step in and extend new loans as asymmetric information problems are mitigated (Bolton et al., 2016) thanks to the pre-existence of a credit relationship. It is also beneficial for banks to better diversify their loan portfolios.

In this paper, we show that multiple lending relations might be a source of contagion across banks and systemic liquidity risk. In particular, we show that when other sources of bank funding are unavailable or too costly and banks are hit by large liquidity shocks (e.g., the 2008 global financial crisis), the potential impact of contagion related to multiple lending on total loan volume and available credit lines is economically relevant and might be an important source of systemic risk. Under conservative parameters, the potential impact on the overall volume of loans is close to 1 percent (e.g., Table 6).

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[2] Refer to Gobbi and Sette (2013).

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In the absence of a well-developed secondary market for loans, the contagion mechanism we study is not based on loan fire sales, which lead to a fall in their prices. Instead, it is based on a deleveraging channel. Specifically, we show that if idiosyncratic shocks hit a bank, a certain share of loans previously granted is called the back. While this strategy may alleviate the bank hit by the shock, it propagates the initial shock across the banking system. A possible reason might be that borrowers may react to the unexpected request to pay back their loans by drawing down on available credit lines from other banks to avoid premature liquidation of their project. In such a scenario, a contagion may occur.

Credit lines are pivotal for this contagion channel because they have two specific features (Lins et al., 2010) that help the contagion propagate. First, banks have the option to call back credit lines at short notice (Sufi, 2009; Acharya et al., 2014). Second, credit lines allow borrowers to draw cash very rapidly up to a given limit, implying that as soon as illiquid banks call back credit lines, borrowers can draw liquidity from other credit lines that have been previously extended by other banks. Such borrowing cannot occur with other loan contracts, such as term loans, which banks cannot call back. Consequently, financial fragility may not only exist because banks provide illiquid loans and liquidity on demand to depositors (Diamond and Rajan, 2001), but because they commit to providing liquidity on demand to borrowers as well.

At least two amplification factors can intervene during the propagation of the liquidity shock, leading to a possible systemic liquidity shortage and reduction in available credit, and consequently, in economic growth. From the lenders' side, Heider et al. (2015) show that during a crisis, banks "hoard" liquidity for precautionary reasons and are not willing to lend even to other banks. In a crisis, when the risk of a bank not being able to roll over its debt increases, banks "hoard " liquidity by lending less, more expensively, and at longer-term maturities (Acharya and Skeie, 2011). In our setup, banks hoard liquidity by calling back credit lines by an amount that is far beyond what would be needed to restore their pre-shock liquidity holdings. From the borrowers' perspective, Ivashina and Scharfstein (2010) shows that during the 2008 crisis, firms tended to draw as much money as they could from their credit lines for precautionary reasons. Therefore, borrowers may also "hoard " liquidity once asked to pay back some of their credit lines. In our setup, borrowers draw money from credit lines beyond what is strictly required to compensate for the reduction in their exposure to credit lines. In this paper, we quantify the impact of these two amplification mechanisms and show that the initial idiosyncratic liquidity shock is more widely propagated within the banking system and real sector.

During financial turmoil, banks might have the incentive to obtain liquidity from their borrowers, asking them to reduce the amount of credit drawn from the credit lines they have been granted. In normal times, banks do not rely on this source of liquidity because it is costlier in comparison to others. The interest rates banks charge on credit lines (i.e., signifying that the opportunity cost banks have to pay once they call back credit lines and forgo revenues from lending) are usually much higher than those at which they can borrow in the interbank market. Furthermore, incumbent banks that cut back on credit lines may also run the risk of their borrowers terminating their relationship with them and switching to other banks, thus forgoing the benefits of the soft information gathered through repeated interactions. However, in a crisis, banks may be severely rationed in the interbank market or can only borrow at very high costs. In this situation, cutting back on credit lines might be cheaper than borrowing in the interbank market. For these reasons, it should be emphasized that this channel for the contagion operates once the interbank market is already impaired or when banks lack collateral that would make them eligible for refinancing at central banks.

Simulations show that banks are exposed to contagion because of common exposures in the credit market and that the risk is particularly high when banks hoard liquidity. Our results are particularly relevant for understanding how macroeconomic shocks, such as the recent outbreak of coronavirus 2019 (COVID-19), could propagate within the economic system as a whole. They are also useful in assessing the consequences of alternative resolution mechanisms.[3] Banking supervisors may indeed have the option to restructure or liquidate banks when they experience financial difficulties and, among other factors, the existence of a dense network of multiple credit lines may lead supervisors to opt for the restructuring of banks instead of liquidating them because, in this latter case, a contagion mechanism similar to the one investigated in this paper might be triggered.

Our study is related to the literature on inter-bank contagion.[4] Since the seminal works by Rochet and Tirole (1996), Allen and Gale (2000), and Freixas et al. (2000), many papers have investigated the role of direct financial interlinkages among banks,[5] showing them as a potential source of financial contagion.[6] This notion is also related to the literature that has investigated how systemic events may stem from indirect linkages among banks and, in particular, from common asset holdings and fire sales (Kiyotaki and Moore, 1997; refer to Shleifer and Vishny, 2011, for a recent survey). However, in our study, we explore how commonalities in lending might be a source of contagion that is not based on fire sales but on the ability of banks to call back loans. This mechanism is not present in the list of contagion channels mentioned in Freixas et al. (2015). To our knowledge, this study provides the first counterfactual exercise of a potentially relevant source of systemic risk that has been unnoticed until now. The rest of the paper is structured as follows. Section 2 describes the data and its main characteristics. In Section 3, we outline the contagion channels and in Section 4, we report the results of the simulations. In Section 5, we compare the newly identified contagion channel with those already studied in the literature, and Section 4 concludes the study.

2. Stylized facts and data about multiple lending interbank networks

Before describing the data, we provide stylized facts on the importance of credit exposure commonalities as a potential channel for the contagion. Firms draw down their credit lines during a crisis, as shown by Ivashina and Scharfstein (2010) for the subprime crisis, and similar evidence exists from the COVID-19 crisis as well (Greenwald et al., 2020; Kapan and Minoiu, 2021). Simultaneously, banks may call back loans when they experience financial difficulties in meeting regulatory solvency and liquidity requirements. According to a survey run by the Bank of Italy (INVIND), the percentage of firms asked by banks to reduce their bank debt exposure sharply increased in 2011 and continued to increase in the following years (Table 1). This rise is also confirmed when we examine the data available in the Italian Credit register, from which it is possible to build an indicator of the number of cases wherein banks called back credit lines before and during the crisis.

[3] Our paper contributes to the literature on bank resolution regimes (refer to Beck et al., 2020, for a very recent cross-country comparison of resolution schemes.) This study reinforces the view that banking crisis management requires careful attention to the implications of alternative resolution schemes in terms of systemic risk. We show that a clear assessment of indirect links among banks, such as those investigated in this study, arising from common exposures in the credit market, is necessary to avoid the unintended consequences of a banking crisis.

[4] Due to the liquidity transformation activity, banks are exposed to depositors' runs, as shown by Diamond and Dybvig (1983). Bank runs may lead to systemic crises because banks are financially interconnected.

[5] The literature has gone beyond the interbank lending market (e.g., van Lelyveld and Liedorp (2006) and has also taken into account cross holdings of share and bonds and fire-sales on assets (Gai et al., 2011). Karas et al. (2008).

[6] Upper (2011) reviews some of the potential channels related to both the asset and the liability sides of banks.

Table 1
Evidence on banks calling back available credit lines during the sovereign debt crisis.
Source: Survey on Industrial and Service Firms (Bank of Italy).

	Firm with less than 50 employees	Firm with less than 100 employees	Firm with more than at least 101 employees
2010	3.9	4.5	4.7
2011	8.9	8.3	9.0
2012	10.7	7.8	8.5
2013	8.3	6.9	8.0
2014	4.8	8.1	5.2
2015	5.4	4.7	4.1

Note: Share of firms reporting that credit lines have been called back (percentage points).

According to the Italian Credit register, between the end of 2011 and 2012, firms borrowing from more than one bank recorded a decrease of approximately 90 billion in credit lines outstanding at the end of 2011. This reduction was only partially compensated for by an increased drawing on existing credit lines (approximately 40 billion) and new credit lines (30 billion), pointing to a much higher propensity for banks to reduce their outstanding credit lines.

We rely on Italian Credit register (CR) data to identify interbank networks related to multiple lending.[7] The CR maintained by the Bank of Italy contains detailed information on loans granted to each borrower whose total debt from a bank is above 30,000 euros (75,000 euros before January 2009; no threshold is required for bad loans.). The CR collects end-of-month outstanding loans broken down by maturity, currency, and type of contract (mortgages, advances against receivables, and credit lines) and the type of collateral posted. Furthermore, for each exposure, it is possible to distinguish between the amount of lending used by the borrower and that granted by the lender. All the data are from the end of 2011. It is worth highlighting that in all the analyses, we focus on callable credit lines, that is, credit lines that banks can call back unilaterally and with short notice.

To identify the network arising from lending commonalities, let $c_{i,h}$ be the amount of money borrower h withdrew from the credit line extended by bank i, and $g_{i,h}$ is the corresponding amount granted. Then, the amount of money borrower h can still obtain from that credit line is the margin $m_{i,h}$ defined as the difference between the amount granted and the amount withdrew ($m_{i,h} = g_{i,h} - c_{i,h}$). In the case of callable credit lines, the maximal amount bank i is entitled to call back from borrower h is equal to $c_{i,h}$, that is, the outstanding loan amount. We also assume that a bank, once hit by a shock, also zeros the margins available to borrowers by terminating the loan (i.e., by zeroing the amount granted). This mechanism has no direct impact on the liquidity a bank may obtain from its borrowers but it is useful to avoid draw-downs on the credit lines the bank itself has granted.

To explore how multiple lending might trigger financial contagion, we start by assuming that a borrower, borrower h, has obtained a credit line from two banks, bank i and bank j, and that bank i is hit by a shock to its liquidity or regulatory capital. We also assume that borrower h pays back the loan to bank i by relying only on the margin available in the credit line granted by bank j. While this hypothesis is extreme, it is reasonable in a crisis when also borrowers are hit by a shock. However, even in normal times, as liquidity holdings prove to be costly for borrowers, they rely on credit lines to address unexpected liquidity needs. Notably, the flexibility in using credit lines is the main rationale for their existence. If we assume that borrowers' source of liquidity is given by the margins available on credit lines that have been granted,[8] the amount that bank i can effectively obtain back from borrower h is $c_{i,h}$ if $c_{i,h} < m_{j,h}$, where $m_{j,h}$ is the margin available to borrower h on the credit line granted by bank j; otherwise, bank i collects a smaller amount of cash equal to $m_{j,h}$.

Naturally, borrower h may not be the only borrower bank i has in common with bank j. Let $H_{i,j}$ be the set of M borrowers that banks i and j have in common. Then, the maximal amount of liquidity bank i can "obtain" by bank j by calling back the credit lines granted to all borrowers belonging to $H_{i,j}$ set is equal to:

$$L_{i,j} = \sum_{h \in H_{i,j}}^{M} \min\left(c_{i,h}, m_{j,h}\right) \tag{1}$$

where $h = 1, \ldots, M$.

In the case borrower h was granted credit lines by more than two banks, for each bank i, we can identify a set B_i of banks that are connected to bank i (i.e., all intermediaries that have granted a credit line to bank i's borrowers):

$$B_i = \left\{ j : L_{i,j} > 0 \right\} \tag{2}$$

The maximal amount that bank i may obtain by calling back the credit lines it had granted to all common borrowers is:

$$L_i = \sum_{h \in H_{i,j}} \min\left(c_{i,h}, \sum_{j \in B_i} m_{j,h} \right) \tag{3}$$

Here, we assume that whenever $c_{i,h} < \sum_{j \in B_i} m_{j,h}$ borrower h draws liquidity from each bank as a proportion of the overall available margins, otherwise they draw as much as they can from all banks (for more details see Appendix A).

In this setup, each $L_{i,j}$ may be considered as the (i,j) entry of a matrix L of all "credits" each bank i holds for all j banks, where the overall matrix represents the whole network of banks arising from the existence of multiple credit lines.

Following this argument, we computed the matrix of bilateral exposures between banks based on data obtained from the Italian CR. Since the end of 2011, the total amount of margins available on credit lines granted to non-banks was 352 billion, of which 230 billion were borrowers with multiple lending relations. The network originating from multiple lending relations does not seem to be very concentrated. The first five banks accounted for approximately one-third of the total potential usage of the credit lines of other banks. To reach at least 90 percent of all usable credit lines, we must consider more than 100 banks. The number of links was more than 60,000. With respect to the interbank deposit and bond and equity exposure networks,[9] a multiple lending network is much more dispersed. For unsecured interbank deposits, the first five banks accounted for almost 50 percent of the total by the end of June 2011. As a result, the network based on multi-lender loans appeared more dispersed but greater in volume with respect to the unsecured interbank market.[10]

At the end of 2011, the multiple lending relationship networks amounted to 230 billion euros, whereas the total value of interbank unsecured exposures, wherein either the borrower or the lender was an Italian bank, was approximately 750 billion euros, of which more than

[7] The use of granular information for financial stability purposes has become more and more popular in the literature (e.g., van Roy et al. (2017).

[8] In other terms, we assume that borrowers are not able to liquidate assets to obtain cash and the only source of extra liquidity for them is the available margin on other credit lines.

[9] We obtain information on all types of bilateral interbank exposure via supervisory reports. Italian banks have to report to the Bank of Italy the outstanding end-of-month gross bilateral exposure relative to different interbank claims (loans, bonds, shares). Supervisory reports cover all Italian banks, locally incorporated banks, and branches of foreign banks. The data allowed us to distinguish between different maturities (overnight, up to 18 months, and over 18 months), seniority, currencies of denomination, and counterpart nationalities. It is also possible to distinguish between secured and unsecured claims.

[10] Until the recent long-term refinancing operation, the unsecured segment represented the most relevant part of the interbank positions (refer to Cappelletti et al. and 2011.

Table 2
Statistics on multiple lending network.
Source: Supervisory data.

	Interbank deposit network	Interbank cross-holding of assets network	Multiple lending network
Number of nodes	782	299	646
Number of relations	3988	3231	16,956
Degree distribution			
Mean	5	4	25
Median	2	0	17
p10	0	0	0
p90	8	4	55
Betweenness			
Max	264,863	63,492	44,820
Mean	892	458	303
Median	13	0	0
Eigenvector centrality			
Max	0.00	0.16	0.17
Mean	−0.02	0.02	0.02
Median	−0.02	0.01	0.00
PageRank			
Max	82	91	727
Mean	10	2	151
Median	7	0	133

Note: Units of banks and bilateral inter-banks relations over the relevant network. To have comparable figures, we consider only Italian banks.

Table 3
Descriptive statistics on loans by borrower.
Source: Italian credit register.

	Min	p10	Median	p90	Max
Loan by borrower (1)	2	2	2	5	125
Loan by borrower (2)	0.001	16	62	299	327,400
Total value of loans by borrower (2)	0.002	35	160	1166	1,617,000
Value of the largest loan (2)	0.001	24	96	578	1,118,000
Share of the largest loan over total loan (3)	9%	37%	60%	89%	100%

Note: (1) Units. (2) Value of loans in mln Euro. (3) Percentage points.

70 percent was distributed among banks affiliated with the same group. Focusing only on intermediaries headquartered in Italy, that value reduces to approximately 250 billion euros, of which approximately 190 million existed within the same banking group. The network of Italian banks related to the cross-holding of assets amounted to approximately 120 billion. Table 2 reports commonly used indices to describe the topology of a network originating from banks' common exposures in the credit market.[11] Kok and Montagna (2016) show that standard network centrality measures can seriously underestimate the real contagion risk faced by a network. The number of connected banks is similar when we consider both the networks related to multiple lending and those originating from bilateral exposure in the interbank market. In contrast, the interconnections are much less diffused if we consider only the cross-holding of bonds and shares. Instead, if we consider that the number of banks connected to the network related to multiple lending is much denser, with higher average relationships for each bank and indicators of centrality (e.g., PageRank and Eigenvector centrality).

On average, borrowers with more than one credit line have less than five outstanding credit lines, even though some borrowers exhibit a much higher number of credit lines. Median borrowers have two credit lines with a total value of 160,000 euros and with one bank having a majority (Table 3).

3. Multiple lending and financial contagion in a crisis

In this section, we describe how contagion propagates within the banking system due to banks' common loan exposures. As generally assumed in the literature on systemic risk (refer to Upper, 2011), we run many simulations assuming that liquidity or capital shock hits one bank at a time (until we consider all banks) and assess the extent to which the contagion occurs. As far as measures of contagion are concerned, we consider (a) the number of cases where at least one additional bank becomes illiquid and (b) the extent to which the overall credit extended by banks is impacted.

We start with an illustrative example wherein there are three banks, four borrowers, and a set of outstanding credit relations (refer to Fig. 1; credit lines are denoted as solid black lines). We assume that bank A is hit by a liquidity shock. Next, to regain its pre-shock liquidity holdings, bank A asks borrowers 1, 2, and 3 to repay part of the callable loans. In our set-up borrower may rely only on the margins available on credit lines granted by other banks. This notion is again an extreme hypothesis but is reasonable in a crisis when firms and households may fall short of liquidity. Therefore, bank A can obtain cash only from borrowers 2 and 3 (liquidity inflows from borrowers 2 and 3 are indicated by the solid red lines) as they withdraw liquidity from banks B and C (see dashed red lines).[12]

This stage represents the first round of the simulation. However, due to the outflows of liquidity related to the draw-downs of borrowers 2 and 3, Bank B can become illiquid. Consequently, in the second round, bank B may be forced (similar to bank A) to call back the credit lines granted to borrowers 2 and 3 (solid blue lines). At this stage, however, only borrower 3 can pay back part of the loan granted by bank B because borrower 2's margin available at bank A has been zeroed by

[11] See Acemoglu et al. (2015), Cont et al. (2013), Degryse and Nguyen (2007), Iori et al. (2006), Karas et al. (2008), Furfine (2003) and Sheldon and Maurer (1998).

[12] Borrower 1 is unable to pay back even part of the amount used on the credit line granted by Bank A because Borrower 1 only borrows from Bank A.

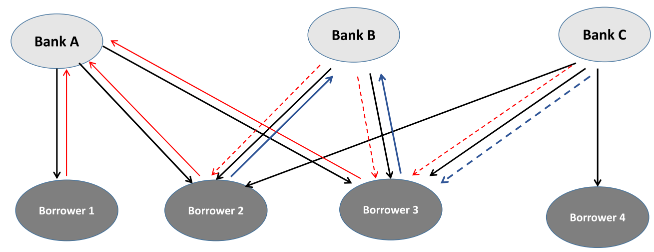

Fig. 1. Multiple lending network and contagion. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

bank A when it falls short of liquidity. While borrower 3 might still have margin available from bank C. Only the liquidity inflow obtained by bank B (solid blue line) comes from bank C (dashed blue line). The contagion stops only when no other bank becomes illiquid or all margins have been zeroed.

This simple example shows that the propagation of the contagion depends on the two drivers. First, banks falling short of liquidity call back loans, and in particular, the amount used on the credit lines granted directly impacts the propagation of the contagion. Second, in response to the shock, banks zero available margins on credit lines. This also impacts the propagation of the contagion as banks are sequentially affected by the contagion. The multiple lending network shrinks, leading to two opposing effects. On the one hand, contagion has less room to propagate because the network tends to be gradually less interconnected. On the other hand, the network tends to be gradually less complete, which means that, in line with Allen and Gale (2000), the network becomes less resilient.

The contagion mechanism described above is triggered by liquidity shocks. However, the contagion may propagate in the same way when a bank falls short of regulatory capital. In this case, banks do not call back credit lines to regain their liquidity holdings, but to reduce the amount of lending (i.e., risk-weighted assets), which, in turn, reduces the amount of regulatory capital needed. In what follows, we consider two possible types of shocks and triggers for a bank to become illiquid: (a) liquidity shocks implying the risk of bank i breaching a liquidity requirement such as the liquidity-covered ratio (LCR) or (b) a capital shock implying the risk of falling short of regulatory capital and breach solvency requirements.

More formally, we assume that when bank i is hit by an idiosyncratic shock to liquidity or capital, it calls back a share α of the amount used on the credit lines and zeros the available margins on all outstanding credit lines. The initial shock may propagate to other banks because we assume that all borrowers of bank i, named H_i, will draw money from the available unused credit lines granted by other banks to pay back the loans granted by bank i.[13] Consequently, all other banks lending to borrowers included in H_i are hit by an unexpected increase in their lending volumes due to the outflow of liquidity from them to bank i. Growth in their lending may lead to a shortage of regulatory capital or high-quality liquid assets (HQLA), sufficient for other banks to become illiquid or under-capitalized. In turn, those banks may call back at least part of the granted credit lines and, similar to bank i, propagate the contagion further to banks that were not hit in the first round. This process may go even further if these other banks face regulatory capital or a liquidity shortage, and they would need to call back at least part of the granted credit lines. The contagion mechanism stops only once no bank faces any liquidity or regulatory shortage or when all banks have been infected and, consequently, they have zeroed all the available credit line margins. Indeed, in the latter case, it is impossible to further draw liquidity from other banks.

As mentioned before, the propagation of the initial shock depends on two triggers that may cause other banks to become illiquid or under-capitalized and consequently call back available "callable" credit lines. The first relates to liquidity requirements (liquidity channels). Particularly, we assume that a bank becomes illiquid if the total liquidity outflow is such that its HQLA fall below a certain threshold that is equal to $\delta \times HQLA$, with δ between 0 and 1, and where HQLA are computed according to the Basel 3 Liquidity Coverage Ratio (LCR) rules. Let $L = \delta' \times HQLA$ be the amount of liquidity outflows that bank j suffers because of bank i illiquidity, and bank j becomes illiquid if $\delta' > \delta$. The liquidity coverage requirement maintains a minimum liquidity buffer over a 30-day horizon to cover any net cash outflows occurring in market-wide idiosyncratic stress scenarios.[14] If liquidity requirements δ are already in place, δ represents the distance of banks from the minimum requirement.[15]

The second trigger relates to capital requirements. Withdrawals from available credit lines also imply an increase in banks' capital requirements that may induce deleveraging and a reduction in their loan exposure (solvency channel). According to the Capital Requirements Regulation (CRR; Article 166(8)) "for credit lines that are unconditionally cancellable[16] at any time by the institution without prior notice, or that effectively provides for automatic cancellation due to deterioration in a borrower's creditworthiness, a conversion factor (θ) shall apply" to the exposure amount that is relevant to compute risk-weighted assets (RWA). Therefore, a rise in the withdrawn amount increases bank capital requirements (i.e., the actual solvency ratio decreases). As a consequence of an unexpected increase in withdrawn credit lines (which corresponds to a fall in the unused amount of credit lines), banks would also suffer an increase in capital absorption. If this latter effect is large enough, then banks would reduce lending, and, as in the case of a liquidity shortage, a possible way to do this is to call back outstanding credit lines. To explore the drivers of contagion, we simulated different scenarios with different thresholds. Specifically, we assume that bank capital falls short of regulatory capital if the increase in the amount of credit lines used is such that the ratio between total capital and risk-weighted assets[17] decreases by more than a certain percentage γ.[18]

In Section 4, we run different simulations corresponding to the alternative behaviors of banks and borrowers and different parameter values (e.g., the initial liquidity shock, α). This approach reflects the difficulty in identifying "true" values for the parameters. Our aim is to assess the potential impact of the aforementioned contagion mechanism and to identify a reasonable range of possible measures, or at least to assess whether the channel for contagion we are investigating exists.

Section 5 compares the multiple lending contagion mechanism (indirect contagion mechanism) with that based on losses in interbank

[13] We do not consider the possibility of borrowers requesting banks for new credit lines or, in general, an increase in the amount of lending granted. This assumption would amplify the contagion given that the newly lent amount would be used to pay back credit lines granted by illiquid banks.

[14] The new minimum requirements, the LCR were phased-in, beginning with a minimum required level of liquidity of 60% in 2015, which will be increased to 70% in 2016, 80% in 2017, and 100% in 2018.

[15] Based on EBA results of the CRDIV-CRR/Basel III monitoring exercise as of the end of June 2016, the average LCR is 133.7% at end June 2016, while 95.4% of the banks in the sample show an LCR above the full implementation minimum requirement applicable from January 2018 (100%).

[16] Credit lines may be considered as unconditionally cancellable if the terms permit the institution to cancel them to the full extent allowable under consumer protection and related legislation.

[17] Capital and risk-weighted assets are reported in the supervisory data.

[18] Let D_j be the amount of liquidity outflows that bank j suffers because other banks become illiquid. RWAs increase by $(1-\theta)D_j$, where θ is the conversion factor of the additional withdrawn liquidity. The ratio of total capital to risk-weighted assets decreases by $\frac{Capital}{RWA} - \frac{Capital}{(1-\theta)D_j + RWA} = \gamma'$. We assume that the bank j will become undercapitalized if $\gamma' > \gamma$.

assets (direct contagion mechanism). Finally, we allow the multiple lending contagion mechanism to interact with the other contagion channels (Section 6). In particular, because the multiple lending mechanism may also be triggered by a capital shock, we simulate the former together with the channel based on losses on interbank assets (see Upper and 2011 for a survey).

4. Results

In this section, we report the simulation results based on the contagion mechanism described in the previous section. The main aim is to assess whether the multiple lending network can be a source of contagion in the Italian banking system and whether it may represent a source of systemic risk. We simulate different scenarios starting from the baseline one, which is the most conservative, and subsequently augment the contagion mechanism by allowing for banks' and borrowers' liquidity hoarding. It is worthwhile to stress that in our scenarios, we assume that banks have no collateral available to access central bank refinancing operations and that the markets for liquidity and capital are not working or, at least, do not allow banks to restore their liquidity or capital endowments fast enough, as happened during the 2008 financial crisis. This implies that our contagion mechanism works when a crisis is already ongoing.

In Section 4.1, we will show the results of the simulations under the assumption that no significant amplification factors allow the parameters (the initial shocks α) and the two thresholds (δ and γ) to vary (see Section 4.1).

In Section 4.2, in line with Heider, Hoerova and Holthausen (2015), we assume that banks hoard liquidity and call back the amount of credit lines necessary to restore their pre-shock liquidity plus the share α' of all credit lines (Section 4.2). Similarly, borrowers that are asked to pay back credit lines granted by illiquid banks withdraw more money than is needed from their credit lines. There is evidence of such behavior during the subprime crisis (Ivashina and Scharfstein, 2010; Ippolito et al., 2016). Formally, borrowers may withdraw $(1+\beta)$ of the amount that the illiquid bank has called back: they do not simply pay back the loan but they also increase their debt with respect to the pre-shock level. Borrowers may then "hoard" liquidity for precautionary reasons, as banks do. We will assume different values for β in the following simulations, till assuming that borrowers withdraw as much as they can from the credit lines granted to them, i.e. till the point where the margins available on their credit lines have been completely exhausted.

4.1. Baseline scenarios

As anticipated, in each simulation, we assume that an idiosyncratic liquidity shock hits one bank at a time (bank i), which then calls back a percentage α of the outstanding callable credit lines. Assuming that borrowers have no other source of liquidity, they withdraw cash from credit lines granted by other banks. These banks will suffer a liquidity outflow that will imply a deterioration of their liquidity and, due to the increase in lending, a deterioration in solvency ratios. As a result, the initial shock may propagate through the banking system and connected banks may become illiquid (if the implied liquidity outflows reach a certain percentage δ of the available HQLA) or undercapitalized (if regulatory capital falls to a certain share γ of the overall capital).

In the baseline scenario, we analyze the liquidity channel alone. We do not consider that banks may become infected and then call back credit lines because they fall short of capital. We will add this further channel, that is, the solvency channel, later in this paper. In the baseline scenario, we assume that banks become infected after the initial shock call back the amount of loans needed to restore the pre-shock level of liquidity. Hence, contagion across banks does not necessarily imply amplification of the initial shock. The overall decrease in credit in the economy is limited by the initial idiosyncratic shocks. However, in each round of the contagion mechanism, the amount of liquidity available on credit lines in the banking system shrinks because infected banks zero the available credit line margins to avoid further borrowers' runs and further liquidity outflows. This implies that, even without assuming liquidity hoarding by banks and borrowers, the initial shock is amplified by that prudent behavior of banks.

In the analysis, we first set all the parameters at conservative levels to evaluate the relevance of this type of contagion for financial stability. The value of the initial idiosyncratic shock (α) is set equal to 10%, which is in line with the evidence collected from the survey run by the Bank of Italy on Italian firms (INVIND; see Table 1) during the financial crisis and the variation in the total amount of outstanding credit that occurred between the end of 2011 and 2012, as reported in the supervisory banking data. The threshold for triggering contagion across banks is related to a significant decrease in the liquidity ratio (δ), which is set at 50%; that is, banks react only to quite large liquidity shocks. As a point of reference, the average Liquidity Coverage Ratio among European banks was 133.7% of HQLA at end of June 2016 (EBA 2016). Therefore, the value of the threshold used as a reference in the simulation was conservative.

Table 4 shows the results for different values of the initial idiosyncratic shock; that is, for different values of α. The number of simulations in which contagion occurs (i.e., the number of infected banks that become illiquid is strictly greater than one) and the change in outstanding credit lines, net of the initial idiosyncratic shock, is limited. This reflects the hypothesis that banks react and call back the credit lines granted to their borrowers only if the liquidity shock is relevant compared to the available HQLA (i.e., 50 percent of the total HQLA) and if they just want to restore the initial amount of liquidity. Intuitively, all the metrics are monotonic in the severity of the initial shock (α).

In the second sensitivity analysis, we vary the threshold related to liquidity requirements (δ) that triggers other banks to become illiquid. Table 5 reports the new results, indicating a potentially greater impact for this contagion channel. As the threshold value decreases, the percentage of cases wherein the contagion occurs rises as well, reaching 20%, and lending drops to almost 2 percent when δ is equal to 10 percent and α equals 30 percent.

In previous simulations, we assume that banks react only when they observe a sizable liquidity outflow. However, banks can become aware of the potential risk of liquidity outflows before borrowers start withdrawing money from credit lines (e.g., they can observe what is occurring in other banks and, consequently, react to that information and shut down credit lines quickly). To simulate this scenario, we set the triggering threshold to zero, implying that banks react even to a negligible liquidity outflow. The last rows of Table 5 show a sizable impact when banks react immediately to any liquidity outflow, independent of their amount. This corresponds to a situation wherein panic spreads within the banking system and all banks simultaneously close all the available credit lines as soon as they become aware of a potential withdrawal of cash. In this case, the number of contagious scenarios increases dramatically to approximately 80 percent, whereas the impact on lending does not increase proportionally. This occurrence is due to the fact that banks close down all the available margins at the same time and thus prevent the propagation of the contagion to those who borrow from infected banks.

As previously argued, the contagion may propagate not only because banks fall short of liquidity but also because they may run out of regulatory capital. Indeed, especially when the equity market is impaired, banks can improve their regulatory capital ratios by reducing the volume of risky assets instead of issuing new equities. This strategy is important not only for the shock that triggers the contagion but also for its propagation among banks. When borrowers withdraw money from their credit lines, the lending increases, thus lowering infected banks' capital ratios.

Based on the current rules on capital requirements for the banking sector, for EU banks consisting of capital requirements regulations

Table 4
Simulation results: baseline.

α	α'	δ	Contagion (%) (1)	Average number of illiquid banks (2)	Delta loans (%) (3)	Delta loan (mln) (4)	Delta margin (%) (5)	Delta margin (mln) (6)
10%	0%	50%	1.1%	2.6	−0.002%	−4	−0.1%	−310
20%	0%	50%	2.1%	3.9	−0.004%	−10	−0.1%	−366
30%	0%	50%	2.8%	4.6	−0.007%	−18	−0.2%	−416
40%	0%	50%	3.9%	4.9	−0.011%	−27	−0.2%	−471
50%	0%	50%	4.4%	5.4	−0.015%	−37	−0.2%	−515

Note: (1) Share of cases where the number of illiquid banks is strictly higher than 1, that is, the percentage of cases where more than one (including the initial one) bank became illiquid. (2) The average number of banks that became illiquid due to multiple lending channels after a bank experiences an initial liquidity shock. Notably, (3) and (4) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and millions of euros), whereas (5) and (6) show the change in outstanding available margin on credit line gross of the initial idiosyncratic shock (percentage points and millions of euros).

Table 5
Simulation results: different liquidity thresholds (liquidity channel).

α	α'	δ	Contagion (%) (1)	Average number of banks (2)	Delta loans (%) (3)	Delta loan (mln) (4)	Delta margin (%) (5)	Delta margin (mln) (6)
10%	0%	30%	1.9%	3.8	−0.002%	−4.0	−0.1%	−343
20%	0%	30%	4.6%	5.4	−0.007%	−17.9	−0.2%	−488
30%	0%	30%	8.1%	5.1	−0.015%	−36.9	−0.3%	−636
10%	0%	10%	5.3%	5.2	−0.002%	−4.1	−0.2%	−473
20%	0%	10%	15.2%	5.0	−0.007%	−18.5	−0.3%	−813
30%	0%	10%	20.6%	6.0	−0.016%	−40.2	−0.5%	−1136
10%	0%	**0%**	78.5%	601.1	−0.008%	−19.2	−71.8%	−176,056
20%	0%	**0%**	78.5%	601.1	−0.024%	−59.8	−71.8%	−176,067
30%	0%	**0%**	78.5%	601.1	−0.041%	−102.1	−71.8%	−176,076

Note: (1) Share of cases where the number of illiquid banks is strictly higher than 1, that is, the percentage of cases where more than one (including the initial one) bank became illiquid. (2) Average number of banks that became illiquid due to the multiple lending channels after a bank experiences an initial liquidity shock. Notably, (3) and (4) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and millions of euros), and (5) and (6) show the change in outstanding available margin on credit line gross of the initial idiosyncratic shock (percentage points and millions of euros).

(CRRs), and the capital requirements directive (CRD IV), exposure value related to the committed but unused credit lines are computed as granted but not used. It is then multiplied by a conversion factor (art 166 CCR) denoted as θ. The conversion factor ranges between 0 and 100 percent, depending on the risk of exposure. Once borrowers withdraw liquidity from their credit lines, banks face higher capital requirements because risk-weighted assets (RWAs) increase by $(1-\theta)$ times the drawn amount. An increase in RWAs implies a decrease in the capital ratio, which could lead the bank to call back credit lines to restore the initial capital ratio.

To assess the importance of this additional motive for becoming illiquid, we run a few simulations where we assume that banks call back credit lines not only when they fall short of liquidity, as in our previous analysis, but also when their capital is γ percentage points lower than the initial level (refer to Table 6). Overall, two distinct values were adopted for the conversion factor: unused credit lines (θ), 20 and 50 percent, and two similar values for the threshold for capital depletion (γ), 1 and 5 percent. The first pair of parameters correspond to a more severe contagion propagation. Based on the Supervisory Banking Statistics at the end of 2017, the average CET1 ratio for significant institutions in the Single Supervisory Mechanism (SSM) was around 14.50 percentage points, implying that the average excess capital compared to the required value was, on average, higher than 5 percentage points, and the conversion factor of 50 percentage points was associated with medium risk exposure (CCR art. 166(10)).

The results obtained for these simulations (Table 6) indicate that once we consider both liquidity and capital buffers, the impact of contagion is, ceteris paribus, greater. Fig. 2 shows that the percentage of scenarios wherein at least one bank is illiquid is always greater when we consider both liquidity and capital requirements compared to the case wherein only liquidity buffers are considered.

4.2. Banks' and borrowers' liquidity hoarding

In this section, we depart from the baseline scenario and assume that banks and firms may hoard liquidity when they are shocked. Until now we have assumed that infected banks that become illiquid proportionally reduce all outstanding loans to restore the initial outstanding loan amount credit lines. In this subsection, we assume that banks call back amounts of credit lines necessary to restore pre-shock liquidity plus share α' for all the credit lines. This corresponds to the bank liquidity hoarding scenario, which is consistent with the prudent behavior of banks trying to reach a level of liquidity that is higher compared to the pre-shock case (see Heider et al., 2015). Regulatory capital continues to have a role in the propagation of the contagion because we assume here that banks call back credit lines by a certain amount whether they run out of both liquidity and regulatory capital.

Once we assume that banks hoard liquidity, we find that the impact of the contagion is not necessarily more severe than the one obtained when banks do not accumulate extra liquidity. When we compare the results reported in Table 6 with those obtained when we assume banks' liquidity hoarding (Tables 7 and 8), we find that the percentage of contagious scenarios when banks do not hoard liquidity is smaller than that obtained when banks hoard liquidity and are less sensitive to liquidity shocks, that is, for higher values of δ (δ = 50 percent; refer to Table 7). Otherwise, we obtain the opposite result when banks are sensitive to liquidity shocks, that is, for lower values of δ (δ = 10%; refer to Table 8). However, it is still confirmed that when banks hoard liquidity, the percentage of simulations where contagion occurs is greater when banks are more sensitive to liquidity shocks with respect to the case wherein they are less sensitive, as it occurs when we compare the simulations obtained in the case wherein banks strictly restore their initial liquidity buffers. We also see that, on average, the number of banks that become illiquid increases significantly when they react more promptly to liquidity shocks.

The reason why the percentage of contagious scenarios is lower in the case wherein banks are quite sensitive to liquidity shocks and also hoard liquidity, compared to the case wherein banks are quite sensitive to liquidity shocks but they do not hoard liquidity, is because, following the initial shock, the contagion process stops earlier than

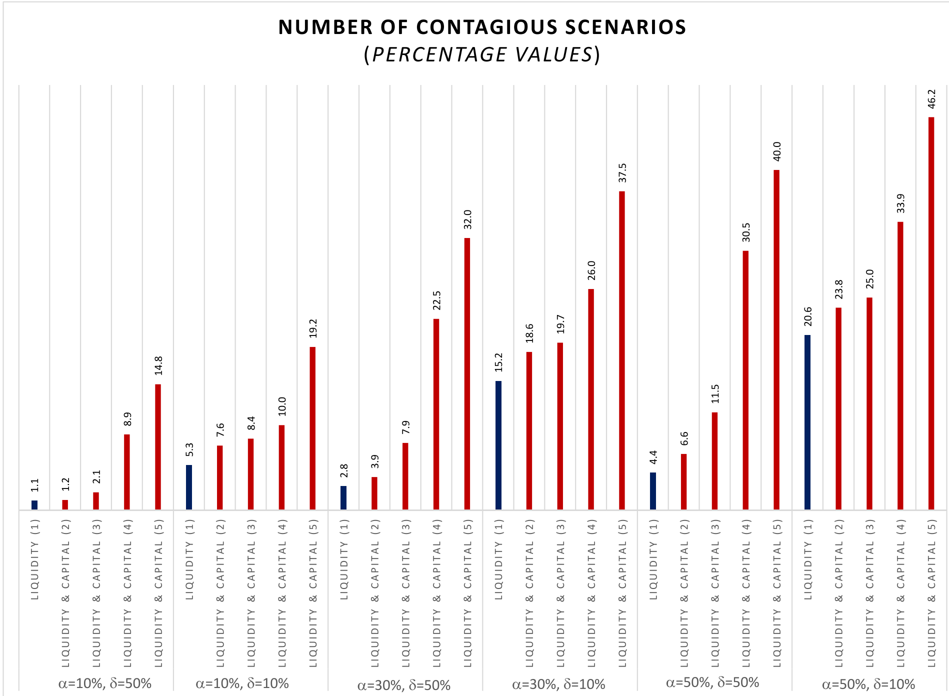

Fig. 2. Contagion based on different parameterizations. Note: Share of cases where the number of illiquid banks is strictly higher than 1.
(1) Only the liquidity shock is considered. (2) Liquidity and capital shocks are considered. The threshold for capital shock (γ) is equal to 5% and the conversion factor is equal to 50%. (3) Liquidity and capital shocks are considered. The threshold for capital shock (γ) is equal to 5% and the conversion factor is equal to 20%. (4) Liquidity and capital shocks are considered. The threshold for capital shock (γ) is equal to 1% and the conversion factor is equal to 20%. (5) Liquidity and capital shocks are considered. The threshold for capital shock (γ) is equal to 1% and the conversion factor is equal to 50%.

Table 6
Simulation results: liquidity and solvency channels.

α	α'	δ	γ	Conversion factor	Contagion (%) (1)	Delta loans (%) (2)	Delta loan (mln) (3)	Delta margin (%) (4)	Delta margin (mln) (5)
10%	0%	50%	5%	50%	1.2	−0.002%	−3.93	−0.121%	−298
10%	0%	50%	5%	20%	2.1	−0.159%	−3.95	−0.128%	−313
30%	0%	50%	5%	50%	3.9	−0.007%	−17.46	−0.141%	−345
30%	0%	50%	5%	20%	7.9	−0.890%	−22.09	−0.120%	−610
50%	0%	50%	5%	50%	6.6	−0.015%	−38.04	−0.197%	−483
50%	0%	50%	5%	20%	11.5	−1.848%	−45.85	−0.119%	−784
10%	0%	50%	1%	50%	8.9	−0.002%	−5.69	−0.226%	−554
10%	0%	50%	1%	20%	14.8	−0.252%	−6.24	−0.305%	−747
30%	0%	50%	1%	50%	22.5	−0.001%	−30.06	−0.524%	−1285
30%	0%	50%	1%	20%	32.0	−1.367%	−33.91	−0.297%	−1905
50%	0%	50%	1%	50%	30.5	−0.002%	−60.83	−0.755%	−1851
50%	0%	50%	1%	20%	40.0	−2.715%	−67.35	−0.296%	−2755
10%	0%	10%	5%	50%	7.6	0.098%	2.43	−0.216%	−530
10%	0%	10%	5%	20%	8.4	0.098%	2.43	−0.217%	−532
30%	0%	10%	5%	50%	18.6	−0.229%	−5.67	−0.198%	−1112
30%	0%	10%	5%	20%	19.7	−0.285%	−7.07	−0.199%	−1187
50%	0%	10%	5%	50%	23.8	−0.896%	−22.22	−0.197%	−1391
50%	0%	10%	5%	20%	25.0	−1.022%	−25.35	−0.198%	−1698
10%	0%	10%	1%	50%	10.0	−0.238%	−5.90	−0.287%	−702
10%	0%	10%	1%	20%	19.2	−0.072%	−1.78	−0.528%	−1293
30%	0%	10%	1%	50%	26.0	−1.229%	−30.50	−0.275%	−1647
30%	0%	10%	1%	20%	37.5	−0.864%	−21.43	−0.509%	−2915
50%	0%	10%	1%	50%	33.9	−2.474%	−61.37	−0.274%	−2253
50%	0%	10%	1%	20%	46.2	−1.941%	−48.16	−0.507%	−4154

Note: (1) Share of cases where the number of illiquid banks is strictly higher than 1, that is, the percentage of cases where more than one (including the initial one) bank became illiquid. Notably, (2) and (3) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and millions of euros), and (4) and (5) show the change in outstanding available margin on credit line net of the initial idiosyncratic shock (percentage points and millions of euros).

in our previous simulations. Indeed, first-round infected banks react more aggressively and accumulate more liquidity, denoting that in the subsequent rounds of the contagion, banks react more to the shock, and a greater number of credit lines are zeroed. Consequently, the overall market for this particular type of liquidity shrinks faster than in the absence of banks' liquidity hoarding, and connections among banks are reduced, leaving less room for the contagion to propagate.

However, when we consider the impact of the contagion on overall lending or available credit line margins, we observe that the impact is larger when we assume that banks hoard liquidity, independent of the sensitivity of banks to liquidity shocks. To make sense of this impact, let us consider the case wherein a high liquidity hoarding parameter (i.e. $\alpha' = 50\%$) and a high sensitivity of banks to liquidity shocks (i.e., $\delta = 10\%$) are assumed. In this case, the impact on overall lending ranges

Table 7
Simulation results: banks' liquidity hoarding ($\delta = 50\%$).

α	α'	δ	γ	Conversion factor	Contagion (%) (1)	Average number of banks (2)	Delta loans (%) (2)	Delta loan (mln) (3)	Delta margin (%) (4)	Delta margin (mln) (5)
10%	10%	50%	5%	50%	1.6%	2.7	−0.002%	−4	−0.13%	−312
10%	30%	50%	5%	50%	1.6%	3.2	−0.002%	−5	−0.13%	−316
10%	50%	50%	5%	50%	1.6%	42.4	−0.045%	−112	−0.23%	−559
30%	10%	50%	5%	50%	5.1%	12.7	−0.015%	−37	−0.25%	−614
30%	30%	50%	5%	50%	5.1%	39.5	−0.072%	−179	−0.44%	−1088
30%	50%	50%	5%	50%	5.1%	68.8	−0.237%	−589	−0.70%	−1715
30%	10%	50%	5%	50%	7.6%	13.0	−0.026%	−64	−0.25%	−765
50%	30%	50%	5%	50%	7.6%	44.2	−0.154%	−383	−0.44%	−1741
50%	50%	50%	5%	50%	7.6%	94.0	−0.525%	−1303	−0.70%	−3358

Note: (1) Share of cases where the number of illiquid banks is strictly higher than 1, that is, the percentage of cases where more than one (including the initial one) bank became illiquid. (2) Average number of banks that became illiquid due to the multiple lending channels after a bank experiences an initial liquidity shock. Notably, (3) and (4) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and millions of euros), and (5) and (6) show the change in outstanding available margin on credit line gross of the initial idiosyncratic shock (percentage points and millions of euros).

Table 8
Simulation results: banks' liquidity hoarding ($\delta = 10\%$).

α	α'	δ	γ	Conversion factor	Contagion (%) (1)	Average number of banks (2)	Delta loans (%) (2)	Delta loan (mln) (3)	Delta margin (%) (4)	Delta margin (mln) (5)
10%	10%	10%	5%	50%	5.5%	9	−0.003%	−8	−0.25%	−619
10%	30%	10%	5%	50%	5.5%	241	−0.579%	−1435	−2.55%	−6260
10%	50%	10%	5%	50%	5.5%	330	−1.321%	−3276	−3.36%	−8248
30%	10%	10%	5%	50%	16.0%	12	−0.021%	−53	−0.55%	−1356
30%	30%	10%	5%	50%	16.0%	254	−1.822%	−4519	−7.77%	−19,049
20%	50%	10%	5%	50%	16.0%	337	−4.015%	−9959	−9.99%	−24,478
50%	10%	10%	5%	50%	21.5%	16	−0.047%	−118	−0.81%	−1978
50%	30%	10%	5%	50%	21.5%	251	−2.428%	−6022	−10.27%	−25,171
50%	50%	10%	5%	50%	21.5%	312	−5.005%	−12,416	−12.39%	−30,382

Note: (1) Share of cases where the number of illiquid banks is strictly higher than 1, that is, the percentage of cases where more than one (including the initial one) bank became illiquid. (2) Average number of banks that became illiquid due to the multiple lending channels after a bank experiences an initial liquidity shock. Notably, (3) and (4) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and millions of euros), and (5) and (6) show the change in outstanding available margin on credit line gross of the initial idiosyncratic shock (percentage points and millions of euros).

between −3276 million euros when $\alpha = 10\%$, to −12,416 million euros, in case $\alpha = 50\%$, which is quite larger than the correspondent values (i.e., +2,43 and −22,22 million euros, respectively) obtained when banks do not hoard liquidity. In general, margins on lines of credit shrink by even a greater amount compared to the overall lending, that is, the amount of lending used by borrowers. This association reflects the behavior of banks that, once infected, reduce the amount granted on credit lines, such that available margins are zeroed. Therefore, after the shock, borrowers can no longer count on this buffer of liquidity anymore.

An additional possible amplification driver of the contagion mechanism comes from borrowers' behavior. Following Ivashina and Scharfstein (2010), we assume that borrowers draw their credit lines down, aiming to hoard liquidity up to β percent of the liquidity called back by banks. As an extreme case, we assume that borrowers draw down all liquidity available on their credit lines. Table 9 presents the results of the new simulations obtained when banks are assumed to be slightly sensitive to liquidity shocks (i.e., $\delta = 50\%$). Table 11 reports the results for banks with a higher sensitivity to liquidity shocks (i.e., $\delta = 10\%$). We see that, ceteris paribus, the percentage of contagious scenarios is larger when borrowers hoard liquidity than when they do not, conditional on banks being relatively insensitive to liquidity shocks (Table 9). In contrast, when we consider a higher sensitivity to liquidity shocks (i.e., $\delta = 10\%$), it seems that unless we assume a very high propensity of borrowers to hoard liquidity, liquidity hoarding does not amplify the propagation of the contagion, at least in terms of the percentage of contagious scenarios (Fig. 3). The main reason for this result is that not only do banks zero credit line margins when shocked but also borrowers, when asked to pay back their loans to infected banks, tend to reduce the margins available at banks not already shocked. This tendency leads to a faster contraction of the liquidity available on credit lines, thus dampening the diffusion of the contagion. Notably, the impact of the contagion is quite different when borrowers hoard liquidity compared with our previous simulations in terms of lending. Consistent with Detragiache et al. (2000) and Ivashina and Scharfstein (2010), borrowers react more promptly by hoarding more liquidity than needed and, consequently, are less affected by bank liquidity shocks. Hence, the lending amount mostly increases, contrary to our previous results.

Finally, we simulated the impact of bank idiosyncratic shocks on the banking system when both banks and borrowers hoard liquidity. In this case, we assume that banks are quite sensitive to liquidity shocks (i.e., $\delta = 10$ percent) and once they are shocked, they overreact to hold more liquidity than the pre-shock level. Similarly, borrowers also draw down more money than needed from credit lines to pay back loans to infected banks. The findings in Table 11 indicate that, while we cannot detect an amplification of the contagion in terms of the percentage of contagious scenarios, we see that when both types of liquidity hoarding are considered, the negative impact on lending is, ceteris paribus, much greater compared to the case wherein only banks hoard liquidity. This relationship reflects that the negative impact of banks lending behavior prevails over the positive impact associated with borrowers' liquidity hoarding (see Table 10).

5. A comparison among contagion channels

In this section, we compare the contagion mechanism due to multiple lending relationships with alternative contagion mechanisms. In particular, we run simulations that consider bank losses in the interbank market due to defaults of other banks (e.g., Mistrulli, 2011; Eisenberg and Noe, 2001; Elsinger et al., 2006). Namely, all banks raising funds in the interbank market are allowed to fail one at a time; the losses suffered by lending to failed banks are then computed. If the

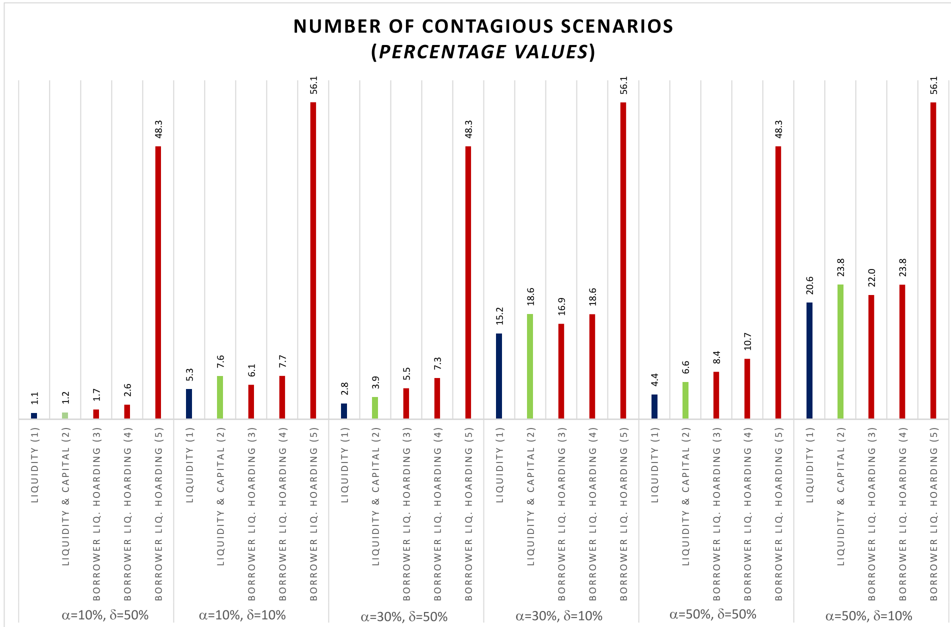

Fig. 3. Contagion based on different parameterization. Note: Share of cases where the number of illiquid banks is strictly higher than 1, that is, the percentage of cases where more than one (including the initial one) bank became illiquid.
(1) Only the liquidity shock is considered. (2) Liquidity and capital shocks are considered. The threshold for capital shock (γ) is equal to 5% and the conversion factor is equal to 50%. (3) Liquidity hoarding by the borrowers is considered with $\beta = 10\%$. (4) Liquidity hoarding by the borrowers is considered with $\beta = 30\%$. (5) Liquidity hoarding by the borrowers is considered with $\beta = \infty$.

Table 9
Simulation results: borrowers' hoarding of liquidity ($\delta = 50\%$).

α	α'	δ	γ	Conversion factor	β	Contagion (%) (1)	Average number of banks (2)	Delta loans (%) (3)	Delta loan (mln) (4)	Delta margin (%) (5)	Delta margin (mln) (6)
10%	0%	50%	5%	50%	10%	1.7%	2.79	−0.08%	−1.89	−0.13%	−314
10%	0%	50%	5%	50%	20%	2.1%	3.24	0.09%	2.23	−0.14%	−331
10%	0%	50%	5%	50%	30%	2.5%	3.33	0.26%	6.36	−0.14%	−347
10%	0%	50%	5%	50%	∞	48.3%	508.51	341.35%	8467.62	−43.41%	−106,415
30%	0%	50%	5%	50%	10%	5.5%	4.69	−0.50%	−12.41	−0.18%	−438
30%	0%	50%	5%	50%	20%	6.3%	5.46	−0.07%	−1.65	−0.20%	−492
30%	0%	50%	5%	50%	30%	7.3%	10.67	0.17%	4.30	−0.27%	−673
30%	0%	50%	5%	50%	∞	48.3%	508.51	339.28%	8416.10	−43.41%	−106,415
50%	0%	50%	5%	50%	10%	8.4%	10.04	−1.46%	−36.33	−0.30%	−728
50%	0%	50%	5%	50%	20%	10.2%	10.36	−0.89%	−22.02	−0.33%	−809
50%	0%	50%	5%	50%	30%	10.7%	11.22	−0.30%	−7.45	−0.35%	−868
50%	0%	50%	5%	50%	∞	48.3%	508.51	337.20%	8364.59	−43.41%	−106,415

Note: (1) Share of cases where the number of illiquid banks is strictly higher than 1, that is, the percentage of cases where more than one (including the initial one) bank became illiquid. (2) Average number of banks that became illiquid due to the multiple lending channels after a bank experiences an initial liquidity shock. Notably, (3) and (4) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and millions of euros), and (5) and (6) show the change in outstanding available margin on credit line gross of the initial idiosyncratic shock (percentage points and millions of euros).

amount of losses is greater than the lenders' Tier-1 capital (i.e., capital and reserves), lenders default. Formally, when we consider only interbank loans a bank i defaults if the following condition holds:

$$Capital_i - \lambda_U \sum_{j \text{ in default}} unsec_{i,j} - \lambda_S \sum_{j \text{ in default}} sec_{i,j} < 0 \tag{4}$$

where $unsec_{i,j}$ and $sec_{i,j}$ are respectively the amount of unsecured and secured loans granted by bank i to bank j.

More recently, di Iasio et al. (2013) also consider losses due to cross-holdings of shares and bonds. We then run simulations to understand the propagation of the contagion due to losses related to all interbank cross-holdings, that is, interbank loans, bonds, and shares (refer to Appendix B for further details). Formally, when we consider only interbanks cross-holding of financial assets one bank i defaults if the following condition holds:

$$Capital_i - \lambda_E \sum_{j \text{ in default}} Shares_{i,j} - \lambda_B \sum_{j \text{ in default}} Bonds_{i,j} < 0 \tag{5}$$

where $Shares_{i,j}$ and $Bonds_{i,j}$ are respectively the amount of shares and bonds of bank j held by bank i. The simulation was then repeated by verifying whether banks that failed after the first iteration let other banks to fail as well. At each iteration, the banks that failed in the previous iteration are dropped from the set of banks, which may have been affected by the contagion. The simulation continues until at least one bank defaults.

Table 12 summarizes the parameters used in the baseline simulation. Once a bank becomes illiquid, it will reduce its loans by 10 percentage points, and the threshold for the outflow of liquidity that causes a bank to become illiquid (δ) is set at 50 percentage points. To evaluate other sources of the contagion already studied in the literature, we assume that the loss given default for unsecured and secured loans is respectively 40 and 80 percent, and the recovery rate for stocks and bonds is respectively 0 and 40 percent. These values are in line with those of previous studies (Bargigli et al. and 2015). The recovery rate is differentiated between shares and bonds but is independent of the issuer.

Table 10
Simulation results: borrowers' hoarding of liquidity ($\delta = 10\%$).

α	α'	δ	γ	Conversion factor	β	Contagion (%) (1)	Average number of banks (2)	Delta loans (%) (3)	Delta loan (mln) (4)	Delta margin (%) (5)	Delta margin (mln) (6)
10%	0%	10%	1%	50%	10%	6.1%	5.2	0.00%	−1.93	−0.20%	−489
10%	0%	10%	1%	50%	20%	6.9%	5.0	0.00%	0.24	−0.21%	−505
10%	0%	10%	1%	50%	30%	7.6%	5.0	0.00%	2.43	−0.22%	−530
10%	0%	10%	1%	50%	∞	56.1%	564.9	4.34%	10,776	−55.40%	−135,791
30%	0%	10%	1%	50%	10%	16.9%	5.6	−0.01%	−13.06	−0.36%	−893
30%	0%	10%	1%	50%	20%	17.4%	6.6	0.00%	−8.63	−0.42%	−1,019
30%	0%	10%	1%	50%	30%	18.6%	7.4	0.00%	−5.67	−0.45%	−1,112
30%	0%	10%	1%	50%	∞	56.1%	564.9	4.32%	10,724	−55.40%	−135,791
50%	0%	10%	1%	50%	10%	22.0%	7.9	−0.02%	−37.38	−0.52%	−1,282
50%	0%	10%	1%	50%	20%	22.9%	8.2	−0.01%	−29.52	−0.55%	−1,344
50%	0%	10%	1%	50%	30%	23.8%	8.5	−0.01%	−22.22	−0.57%	−1,391
50%	0%	10%	1%	50%	∞	56.1%	564.9	4.30%	10,673	−55.40%	−135,791

Note: (1) Share of cases where the number of illiquid banks is strictly higher than 1, that is, the percentage of cases where more than one (including the initial one) bank became illiquid. (2) Average number of banks that became illiquid due to the multiple lending channels after a bank experiences an initial liquidity shock. Notably, (3) and (4) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and millions of euros), and (5) and (6) show the change in outstanding available margin on credit line gross of the initial idiosyncratic shock (percentage points and millions of euros).

Table 11
Simulation results: banks and borrowers' hoarding of liquidity ($\delta = 10\%$).

α	α'	δ	γ	Conversion factor	β	Contagion (%) (1)	Average number of banks (2)	Delta loans (%) (2)	Delta loan (mln) (3)	Delta margin (%) (4)	Delta margin (mln) (5)
10%	10%	10%	5%	50%	10%	1.70%	3.0	0.00%	−1.98	−0.13%	−318
10%	30%	10%	5%	50%	20%	1.82%	65.3	−0.04%	−108.26	−0.32%	−772
10%	50%	10%	5%	50%	30%	2.06%	61.7	−0.08%	−203.22	−0.33%	−804
30%	10%	10%	5%	50%	10%	5.46%	13.8	−0.01%	−33.08	−0.27%	−655
30%	30%	10%	5%	50%	20%	5.70%	60.4	−0.14%	−341.56	−0.70%	−1,705
30%	50%	10%	5%	50%	30%	6.31%	150.0	−0.68%	−1683.37	−1.80%	−4422
50%	10%	10%	5%	50%	10%	8.37%	13.3	−0.02%	−56.53	−0.27%	−812
50%	30%	10%	5%	50%	20%	9.71%	64.7	−0.26%	−642.12	−0.70%	−2919
50%	50%	10%	5%	50%	30%	10.19%	149.8	−1.11%	−2742.90	−1.80%	−6966

Note: (1) Share of cases where the number of illiquid banks is strictly higher than 1, that is, the percentage of cases where more than one (including the initial one) bank became illiquid. (2) Average number of banks that became illiquid due to the multiple lending channels after a bank experiences an initial liquidity shock. Notably, (3) and (4) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and millions of euros), and (5) and (6) show the change in outstanding available margin on credit line gross of the initial idiosyncratic shock (percentage points and millions of euros).

Table 12
Simulation parameters: recovery rates and liquidity threshold.

Simulation parameters	
α = initial idiosyncratic shock	10%
α' = share of credit lines called back by banks	10%
δ = threshold of $HQLA$	50%
λ_U = LGD unsecured interbank loans	90%
λ_S = LGD secured interbank loans	40%
λ_B = LGD bonds holdings	40%
λ_E = LGD share holdings	100%

Note that we cannot determine whether one mechanism is stronger than the other because the network structure is specific to each channel. To evaluate the relevance of different contagion mechanisms, we consider the default and the illiquidity of every Italian bank. Moreover, the metrics on which different channels should be assessed cannot show a decrease in credit because the default and the illiquidity of a bank have different effects on loan supply. Therefore, in this section, we focus only on the number of banks that default or that become illiquid.

A contagion based only on interbank loans is quite limited because it does not occur in 98 percent of the cases (Fig. 4). Besides, the inclusion of the cross-holdings of bonds and shares increases the probability of contagion by only 1.2 percent. Instead, banks share a relevant number of borrowers, implying that in almost one to 10 cases, at least one other bank becomes illiquid. Even if cross-holdings of assets exist, it does not dramatically change the total number of banks that default. The possibility that a bank becomes illiquid because of drawdowns on existing credit lines implies a relevant increase in the total number of banks that run out of liquidity because of the multiple lending network. All three mechanisms of the contagion imply that in 90 percent of cases, there was no evidence of contagion. In 3.3 percent of the cases (almost one-third of the total contagion cases), the number of illiquid or defaulted banks is higher than 10.

Different channels of contagion can interact and reinforce each other. Losses related to banks' default can reduce capital and make it more likely that drawing from credit lines can make banks illiquid due to a capital shortage (refer to the previous section). Table 13 shows that the first interaction between the possible contagion channels has a very limited impact. This result reflects two facts. Contagions related to defaults are significantly limited and the interdependence related to cross-bank holdings and multiple lending does not overlap.

We enrich the contagion mechanism by including direct linkages among banks related to interbank lending and the cross-holding of financial assets within the banking system. This channel of interconnectedness across banks has been investigated in the literature (refer to Mistrulli, 2011; Cappelletti and Guazzarotti, 2019) for an analysis of the Italian banking system). In particular, we allow the credit line contagion mechanism described above to interact with that triggered by losses in different interbank claims. In particular, we consider the possibility that banks could call back the granted credit lines because they suffer losses that reduce their capital and make it difficult to meet regulatory capital requirements. If the market for capital is not working, as it happens in a crisis, the only way to meet solvency requirements is by reducing lending. Therefore, the losses due to the default of other banks and the increase in RWA related to drawing on available credit lines are summed, leading to a greater number of banks facing solvency difficulties (without defaulting) and the need to reduce lending. Table 13 shows that this second type of interaction between different contagion channels could increase the propagation of shocks across the banks. If we assume that banks may become infected

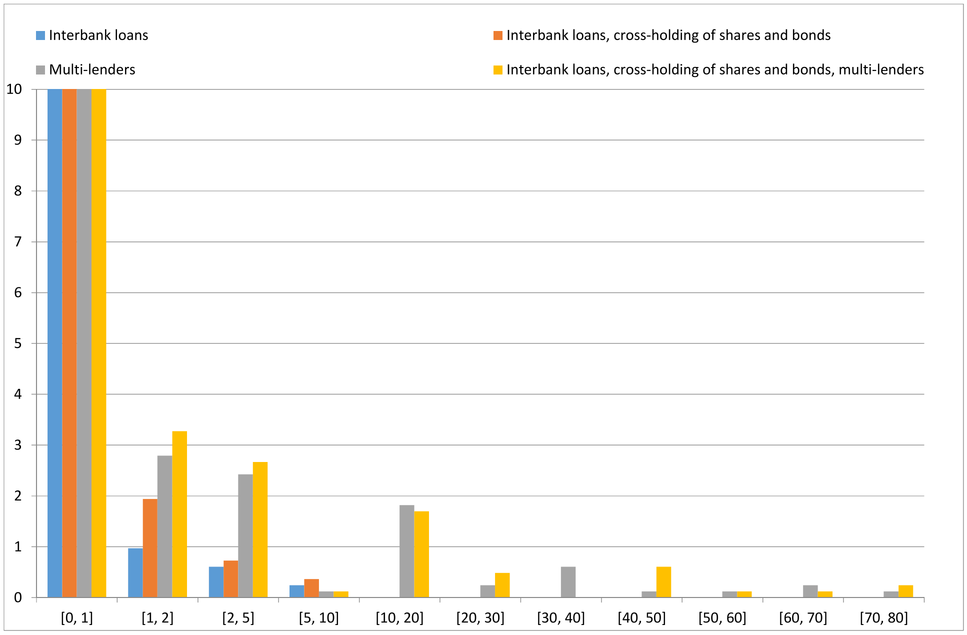

Fig. 4. Contagion mechanisms: buckets of the number of defaulting or illiquid banks (percentage points).

Table 13
Simulation results: different channels of contagion and possible interaction between them.

	α	α'	δ	γ	Conversion factor	β	Contagion defaults (%) (1a)	Contagion liquidity (%) (1b)	Delta loans (%) (2)	Delta loan (mln) (3)	Delta margin (%) (4)	Delta margin (mln) (5)
	10%	0	50%	5	50%	0%	–	1.2%	−0.002%	−3.93	−0.121%	−298
Baseline	20%	0	50%	5	50%	0%	–	3.9%	−0.007%	−17.46	−0.141%	−345
	30%	0	50%	5	50%	0%	–	6.6%	−0.015%	−38.04	−0.197%	−483
Interaction between	10%	0	50%	5	50%	0%	3.5%	6.8%	−0.159%	−3.95	−0.137%	−337
Liquidity and default	20%	0	50%	5	50%	0%	3.5%	9.1%	−0.717%	−17.79	−0.184%	−450
Contagion channels	30%	0	50%	5	50%	0%	3.5%	11.4%	−1.649%	−40.89	−0.278%	−681
Interaction adding	10%	0	50%	5	50%	0%	3.5%	7.3%	−0.002%	−3.96	−0.138%	−339
Illiquidity due to drawn	20%	0	50%	5	50%	0%	3.5%	11.4%	−0.009%	−22.13	−0.260%	−637
On capital	30%	0	50%	5	50%	0%	3.5%	14.6%	−0.019%	−45.89	−0.331%	−811

Note: (1a, 1b) Share of cases where the number of defaulted (1a) or illiquid (1b) banks is strictly higher than 1. Notably, (2) and (3) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and millions of euros), and (4) and (5) show the change in outstanding available margin on credit line net of the initial idiosyncratic shock (percentage points and millions of euros).

if they suffer losses equal to 50 percent of their capital, the share of cases wherein the contagion occurs increases from 1.2% to 7.3%, with a sizable increase in the number of banks potentially hit by the shock.

6. Conclusion

A wide literature, starting from the seminal papers by Allen and Gale (2000) and Freixas et al. (2000), has shown, both at the empirical and theoretical level, that contagion within the banking system may propagate as banks are financially interconnected. Indirect linkages may have a role due to banks' common asset holdings, as documented in the literature on asset fire sales. This study shows for the first time that commonalities in asset holdings may also originate in the credit market because banks lend to a common set of borrowers due to the existence of multiple lending. However, the propagation of contagion through these indirect links among banks does not hinge on loan fire sales, given that loans cannot be easily sold. The contagion mechanism rests on the existence of a special loan contract, that is, credit lines that, on the one hand, allow banks to call back the loan both unilaterally and at a short notice, and, on the other, allow borrowers to draw down cash whenever they want, up to a predefined limit. These characteristics enable the contagion to propagate within the banking system and impact, through changes in lending, the real economy.

By using simulation techniques, we find that in the baseline scenarios, for highly conservative parameters, the contagion may be limited. Once we consider the possibility of amplifying factors, namely the hoarding of liquidity by banks or borrowers, the effects of the initial liquidity shock are sizable both in terms of the total volume of credit and total available credit lines.

Our results highlight the trade-off between the benefits of diversification of liquidity risk that borrowers may pursue by establishing multiple lending relationships, especially when they are granted credit lines, and the cost of propagating liquidity shocks within the banking system. This trade-off depends on the structure of the network and the severity of the liquidity shock that hits a bank or a part of the banking system. In particular, multiple lending, in line with Detragiache et al. (2000), may mitigate the impact of banks' liquidity shocks on borrowers'' economic activities. However, this holds in normal times, when the liquidity market works smoothly. In contrast, in a crisis, when financial markets are impaired, the dark side of multiple lending may emerge because, as we have shown, it may give rise to contagion and threaten financial stability.

In this study, we show that the consequences of this specific channel of contagion among banks might be quite severe when other sources of bank funding are not available or are too costly and banks are hit by large liquidity or capital shocks, as seen during the 2008 global financial crisis.[19] This channel for contagion might threaten the financial stability of the economy, in particular, whether banks and borrowers overreact to shocks, thus amplifying them. Moreover, this mechanism can provide a rationale for the existence of network spillovers across loans, as Gupta et al. (2023) highlights for loan rates charged on syndicated loans.[20]

Our study contributes to the literature on financial contagion and to a very recent one that focuses on the role of credit lines in the propagation of macroeconomic shocks (Greenwald et al., 2020), such as the outbreak of COVID-19.

Furthermore, our results also reinforce the view that banking crisis management schemes must incorporate an evaluation of the impact of bank resolution on the banking system as a whole. We have shown that the liquidation of a defaulting bank must be carefully evaluated because it can trigger, under certain circumstances, a systemic event. This event does not necessarily depend solely on the size of the bank, which is an important characteristic to be considered, and on the direct linkages among banks, but also on common exposures in the credit market. To our knowledge, this study is the first to identify this specific channel for contagion.

Appendix A. Contagion mechanisms through multiple lending relations

Formally, given the set of banks $\mathcal{B}$ and borrowers $\mathcal{D}$, let $c_{i,h}$ denote the credit line of bank i that borrower h has already outstanding and $g_{i,h}$ is the maximum credit line that borrower h can draw from bank i. Margin that can be drawn by the borrower h from bank i is denoted by $m_{i,h} = g_{i,h} - c_{i,h}$.

Let i be the first bank that becomes illiquid because of an idiosyncratic shock, and define $ILS^n(i) \subseteq \mathcal{B}$ and $LS^n(i) \subseteq \mathcal{B}$ as a set of banks, illiquid or liquid at the nth step of the contagion path initiated by bank i:

$$ILS_1^n(i) = \left\{ j \in \mathcal{B} : d_j^n > \delta \times HQLA_j^{Tier\ 1} \right\} \tag{A.1}$$

$$ILS_2^n(i) = \left\{ j \in \mathcal{B} : \partial \times d_j^n > \gamma \times Capital \right\} \tag{A.2}$$

$$ILS^n = ILS_1^n(i) \cup ILS_2^n(i) \tag{A.3}$$

$$LS^n(i) = \mathcal{B} \backslash ILS^n(i) \tag{A.4}$$

where d_j^n is the total number of credit lines drawn by the borrowers at the nth step of the contagion from bank j and $HQLA_j^{Tier\ 1}$ is Tier 1 HQLA defined following Basel 3 recommendations and ∂ is the conversion factor for off-balance-sheet exposures. Conditional on the resulting new loans drawn from the surviving banks, we assume that banks facing an excessive flow of liquidity become illiquid because of increase in illiquidity risk or, equivalently, to an increase in the volatility of liquidity needs. In other words, we assume that if the ratio between total drawings and HQLA are higher than δ, the bank becomes illiquid. The amount of liquidity drawn at stage n from the bank j is equal to:[21]

$$d_j^n = d_j^{n-1} + \sum_{h \in D} d_{j,h}^n \tag{A.6}$$

[19] Indeed, the Lehman crisis revealed that banks were hit by severe liquidity shocks, which they were unable to overcome by tapping into the interbank market since that market dried up (Cappelletti et al., 2011).

[20] Cai et al. (2018) show that syndication increases the overlap of bank loan portfolios and makes them more vulnerable to contagious effects.

[21] In the simulation, bank j can register the credit lines drawn by borrowers with outstanding loans from banks that become illiquid in stage $n-1$

$$H^{n-1}(i) = \left\{ h \in \mathcal{H} : \sum_{j \in ILS^{n-1}(i)} l_{j,h} > 0 \right\} \tag{A.5}$$

.

In the baseline scenario, bank i becomes illiquid in stage n of the simulation; it proportionally reduces the outstanding loans to return to the initial total value of loans; that is, (Behavior 1):

$$\begin{aligned} c_{i,h}^{n+1} &= \frac{c_{i,h}^n}{\sum_{h \in D} c_{i,h}^n} \sum_{h \in D} c_{i,h} \text{ for each borrower } h \text{ and } i \in ILS_{ML}^n(i) \\ g_{i,h}^{n+1} &= c_{i,h}^{n+1} \\ m_{i,h}^{n+1} &= 0 \end{aligned} \tag{A.7}$$

for each borrower h, where $\sum_{k \in D} c_{i,h}$ is the value of credit lines outstanding before the shock. Alternatively, we can assume that all banks that become illiquid proportionally reduce all outstanding loans (Behavior 2).[22]

$$\begin{aligned} c_{i,h}^{n+1} &= \alpha c_{i,h} \text{ for all borrower } h \text{ and bank } i \\ &\quad \text{such that } i \in ILS_{ML}^n(i) \\ g_{i,h}^{n+1} &= c_{i,h}^{n+1} \\ m_{i,h}^{n+1} &= 0 \end{aligned} \tag{A.8}$$

where $c_{i,k}$ is the original value of the borrowing position of h with respect to bank i.

Similarly, in the baseline scenario, we assume that borrower h will try to compensate for the reduction in bank funding ($\Delta b_h^n = \sum_i c_{i,h}^n - c_{i,h}^{n-1}$) with the existing credit lines, drawing unused granted loans; that is, for borrower h and the liquid bank j at stage n of the simulation. Let us define the desired level of new loans by borrower h in the nth step of the contagion path as:

$$c_h^{*n} = (1+\beta)\,\Delta b_h^n \tag{A.9}$$

the resulting withdrawal of available credit lines will be equal to

$$d_{j,h}^n = \begin{cases} \min\left(0, g_{j,h}^n - c_{j,h}^n\right) \frac{c_h^{*n}}{\sum_{j \in \mathcal{B}} g_{j,h}^n - c_{j,h}^n} & \text{if } M_h^n > c_h^{*n} \\ \min\left(0, g_{j,h}^n - c_{j,h}^n\right) & \text{if } M_h^n \le c_h^{*n} \end{cases} \tag{A.10}$$

where $\Delta b_h^n = \sum_{j \in \mathcal{B}} c_{j,h}^n - c_{j,h}^{n-1}$ and $M_h^n = \sum_{j \in \mathcal{B}} \min\left(0, g_{j,h}^n - c_{j,h}^n\right) = \sum_{j \in \mathcal{B}} m_{j,h}^n$. If the unused margins are more than sufficient for reach replacing the reduction in credit, we assume that the borrower draws proportionally the available credit lines. Instead, if this is not the case, the borrower simply uses all available credit lines.[23] We allowed borrowers to ask for a reduction of their loan exposure by a bank wanting to draw funds at a higher rate for precautionary reasons ($\beta > 0$).

Appendix B. Contagion mechanisms through inter-bank exposures and interaction with contagion related to credit lines

Let us recall the different channels of contagion already studied in literature and the conditions that lead to default. Let $\mathcal{B}$ be the set of banks. Lending positions between banks and cross-holding assets within the banking system can be represented in a matrix form. Let $unsec_{i,j}$ denote the unsecured loans that bank $j \in \mathcal{B}$ borrows from bank $i \in \mathcal{B}$, and let $sec_{i,j}$ denote secured loans that bank $j \in \mathcal{B}$ borrows from bank $i \in \mathcal{B}$ and let $s_{i,j}$ denotes the value of the shares of bank j held by bank i. Finally, consider $b_{i,j}$ as the value of bonds of bank j held by bank j.

Let i be the first bank that defaults because of idiosyncratic shocks, and define $D_m^n(i) \subseteq \mathcal{B}$ and $S_l^n(i) \subseteq \mathcal{B}$ as a set of banks that defaulted

[22] Notably, the results are equivalent if we assume that illiquid banks' zero drawable credit lines and existing credit positions grow naturally at a rate of α percent.

[23] We do not consider borrowers' defaults in the case of the impossibility of fully substituting closed loans as it could enhance the contagion. mechanism owing to multi-lending relationships.

and survived at the nth step of the contagion process initiated by bank i under mechanism m.[24] We allow for three main sources of contagion: interbank loan losses, interbank loans, and cross-holding losses.

In the first mechanism, the set of defaulting banks is defined as

$$D_L^n(i) = \left\{ z \in \mathcal{B} : Capital_z - \sum_{j \in D_L^{n-1}(i)} \left(\lambda_U unsec_{z,j} + \lambda_S sec_{z,j} \right) < 0 \right\} \quad \text{(B.1)}$$

where C_z is the Tier 1 capital of bank z and λ and ϕ are the recovery rates for unsecured and secured deposits, respectively (i.e., set of banks that suffer losses due to interbank loans that are sufficient to deplete their Tier 1 capital).

If we also consider that banks own shares and bonds with other banks, The contagion can occur because banks suffer losses in their interbank loans and cross-holdings of shares and bonds that deplete their capital and the defaulting banks are

$$D_{BS}^n(i) = \left\{ z \in \mathcal{B} : Capital_z - \sum_{j \in D_{BS}^{n-1}(i)} \left(\lambda_E Shares_{z,j} + \lambda_B Bonds_{z,j} \right) < 0 \right\} \quad \text{(B.2)}$$

where σ and β are the recovery rate of stocks and bonds' holding.

The contagion mechanism can be formally summarized by describing the contagion paths. Given the initial default of a single bank i, the initial sets of defaulted banks are trivial:

$$D_L^0(i) = D_{BS}^0(i) = ILS^0(i) = \{i\} \quad \text{(B.3)}$$

Then, the infection spreads according to the different channels considered:

$$D_L^1(i) = \left\{ z \in \mathcal{B} : Capital_z - \lambda_U unsec_{z,i} - \lambda_S sec_{z,i} < 0 \right\} \quad \text{(B.4)}$$

$$D_{BS}^1(i) = \left\{ z \in \mathcal{B} : Capital_z - \lambda_E Shares_{z,i} - \lambda_B Bonds_{z,i} < 0 \right\} \quad \text{(B.5)}$$

$$ILS_1^1(i) = \left\{ z \in \mathcal{B} : \sum_{k \in H_{ML}^0(i)} drawn\_loans_{z,k}^n > \delta HQLA_z^{Tier\ 1} \right\} \quad \text{(B.6)}$$

$$\text{where } H_{ML}^0(i) = \left\{ h \in \mathcal{D} : l_{i,h} > 0 \right\} \quad \text{(B.7)}$$

By iterating, we derive the relevant set of defaulted and illiquid banks.

$$D_L^n(i) = \left\{ z \in \mathcal{B} : \sum_{j \in D_L^{n-1}(i)} \left(Capital_z - \lambda_U unsec_{z,j} - \lambda_S sec_{z,j} \right) < 0 \right\}$$

$$D_{BS}^n(i) = \left\{ z \in \mathcal{B} : \sum_{j \in D_{BS}^{n-1}(i)} \left(Capital_z - \lambda_E Shares_{z,j} - \lambda_B Bonds_{z,j} \right) < 0 \right\}$$

$$ILS_1^n(i) = \left\{ z \in \mathcal{B} : \sum_{k \in H_{ML}^{n-1}(i)} drawn\_loans_{z,k}^n > \delta HQLA_z^{Tier\ 1} \right\}$$

$$\text{where } H_{ML}^{n-1}(i) = \left\{ h \in \mathcal{H} : \sum_{j \in ILS_{ML}^{n-1}(i)} l_{j,h} > 0 \right\}$$

We also investigate the interaction of different contagion channels. First, losses on cross-bank exposure reduce banks" capital. Therefore, losses could strengthen the condition for banks to become illiquid, owing to solvency reasons (condition $ILS_2^n(i)$ see Appendix A):

$$ILS_{2'}^n(i) = \left\{ z \in \mathcal{B} : (1-\theta) \times \sum_{k \in H_{ML}^{n-1}(i)} drawn\_loans_{z,k}^n > \gamma \times \left(Capital_z - Losses_z \right) \right\} \quad \text{(B.8)}$$

where θ is the conversion factor and γ is the threshold for becoming illiquid due to solvency reasons and $Losses_z = \sum_{j \in D_L^{n-1}(i)} \left(\lambda_U unsec_{z,j} - \lambda_S sec_{z,j} \right) + \sum_{j \in D_{BS}^{n-1}(i)} \left(\lambda_E Shares_{z,j} + \lambda_{UB} Bonds_{z,j} \right)$.

Therefore, the set of illiquid banks was defined as

$$ILS^n(i) = ILS_1^n(i) \cup ILS_2^n(i) \quad \text{(B.9)}$$

As firms cannot draw liquidity from banks that have defaulted and because the condition of illiquidity due to losses is stricter than the condition of default, the equation that defines the drawing of credit line does not change in addition to replacing $ILS_{BS}^n(i)$, where $ILS_{LBS\_ML}^n(i)$.

[24] In general, $B = S_l^n(i) \cup D_m^n(i)$.

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