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MULTIPLE LENDING, CREDIT LINES AND FINANCIAL CONTAGION

by Giuseppe Cappelletti* and Paolo Emilio Mistrulli**

Abstract

Multiple lending has been widely investigated from both an empirical and a theoretical perspective. Nevertheless, the implications of multiple lending for the stability of the banking system still need to be understood. By lending to a common set of borrowers, banks are interconnected and then exposed to financial contagion phenomena, even if not directly. In this paper, we investigate a specific type of externality that originates from those borrowers that obtain liquidity from more than one bank. In this case, contagion may occur if a bank hit by a liquidity shock calls in some loans and borrowers then pay them back by drawing money from other banks. We show that, under certain circumstances that make other sources of liquidity unavailable or too costly, multiple lending might be responsible for a large liquidity shortage.

JEL Classification: G21, G28.
Keywords: financial contagion, multiple lending, credit lines.

Contents

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1 Introduction[1]

Multiple lending, i.e. the practice of firms or households of borrowing from more than one lender at the same time, has been investigated by several papers, from both an empirical and theoretical perspective (Degryse, Kim and Ongena, 2009). The literature has highlighted both pros (diversification of risk, mitigation of hold-up phenomena) and cons (less monitoring incentives, coordination failures) of it but only from a microeconomic point of view. To our best knowledge we are the first to consider the link between multiple lending and financial stability.

In this paper we take a different perspective as we look at the implications of multiple lending in terms of financial contagion within the banking system. To this aim we rely on very detailed data obtained from the supervisory reports and from the Italian Credit Register both collected by the Bank of Italy. Since the seminal paper by Allen and Gale (2000), many papers have investigated the role of direct financial interlinkages among banks (e.g. interbank lending, share holdings) as a potential source of financial contagion. No paper has stressed yet the importance of relatively less direct financial interlinkages among banks arising from multiple lending in the market for credit to the real sector and, in particular, stemming from the existence of multiple credit lines.

In a micro-economic perspective Detragiache, Garella and Guiso (2000) argued one reason why firms and households borrow from more than one lender is that in this way they mitigate the risk of a premature liquidation of the project financed once a lender falls short of liquidity. Indeed, in case one of the banks lending to a borrower falls short of liquidity other lenders may easily step in as they are already lending to that borrower and then asymmetric information problems are highly mitigated (Bolton et al., 2016). What has been overlooked so far is that in case the liquidity shock that hits a bank is large enough also many borrowers would be hit and the liquidity shock may propagate to other lenders. This may easily occur in particular when a firm or an household has obtained credit lines from more than one bank (Gobbi and Sette, 2013). Indeed, it is reasonable to assume that a borrower that has to pay back part of its debt to the illiquid bank draws money from other banks that have granted a credit line, up to the line ceiling.

Credit lines are an important source of liquidity for firms around the world (Lins, Servaes and Tufano, 2010) and have two crucial features. First, they are a pre-committed source of liquidity, meaning that borrowers are entitled to draw cash from banks up to a pre-specified limit, at mutually agreed-upon terms. Second, banks may have the option of cutting credit lines if circumstances change (Sufi, 2009; Acharya et al., 2014). This implies that banks hit

[1] The views expressed in the paper are those of the authors and do not necessarily reflect those of the Bank of Italy or the European Central Bank. We thanks participants in a seminar given at the Bank of Italy and European Central Bank, Paolo Angelini, Giorgio Gobbi, Philipp Hartmann, Victoria Ivashina, Carmelo Salleo and Aurea Ponte Marques for their comments on a previous version of the paper.

by a liquidity shock may call back credit lines and firms whose lines have been called may in turn draw money from the credit lines they had been granted by other lenders and the initial shock propagates to other lenders.

In this paper, we show that the consequences of this channel for contagion might be quite severe when other sources of bank funding are not available or are too costly and banks are hit by large liquidity shocks, as it occurred during the last financial crisis. Indeed, the recent crisis showed that banks were hit by severe liquidity shocks they were unable to overcome by tapping the interbank market since that market dried up. In a financial turmoil then banks might have an incentive to obtain liquidity from their borrowers by asking them to reduce the amount of credit drawn on the credit lines they have been granted. This is of course a quite costly source of cash in normal times since the interest rate banks charge on the credit lines granted to their customers are usually much higher than those at which they are able to borrow in the interbank market. However, in a crisis, banks may be severely rationed in the interbank market or being able at borrowing only at very high costs. In a situation of this kind, calling credit lines back might then represent a reasonable way out of a liquidity shortage.

For these reasons, it should be emphasized that this channel for contagion operates once the interbank market is already not working smoothly and the central bank is absent or can not intervene. This latter hypothesis, that is common to related papers, is useful in order to highlight the crucial role of central banks in a crisis from a new angle.

Following the approach widely used in related papers (see Upper, 2011 for a survey) we simulate the impact of contagion by letting each bank fall short of liquidity one at a time. We assume that once a bank becomes illiquid it calls back some loans in order to get liquidity from its borrowers. This may solve the liquidity problem of the bank hit by a shock but at the cost of propagating it within the banking system in case borrowers pay back their loans by drawing money from credit lines they have been granted by other banks. Those banks may in turn become illiquid and possibly rely on the same strategy, i.e. calling back some loans, thus propagating further the contagion mechanism. We show that, under certain circumstances, this kind of mechanism may represent a major contagion channel threatening the financial stability of the economy. Moreover, the initial liquidity shock might be amplified by both the behaviour of banks and borrowers.

As far as the former is concerned, some papers have shown that during a crisis the interbank market collapses because banks "hoard" liquidity for precautionary reasons and are not willing to lend even to other banks (Heider, Hoerova and Holthausen, 2010). Indeed, in a crisis, when the risk for a bank not being able to roll over its debt increases, banks "hoard" liquidity by lending less and more expensively at longer term maturities (Acharya and Skeie, 2011). In our setup, this may entail that, once a bank faces a massive overdraft on the credit lines granted to its borrowers, it may overreact and tend to hoard liquidity and to this aim it may call back credit lines by an amount which is well far beyond what it would be needed in order to restore the pre-shock liquidity holdings.

Similarly, also firms may "hoard" liquidity once they are asked to pay back come of their credit lines. As shown by Ivashina and Scharfstein (2010) during the crisis, firms tend to draw money as much as they could from their credit lines so that to mitigate the risk of a premature liquidation of their investment projects. If this happens, then we may identify another source for the amplification of the initial liquidity shock. Indeed, firms would draw money from credit lines beyond what strictly required to compensate for the reduction of lending due to the initial shortage of liquidity occurred to a lending bank.

Naturally, this channel may be triggered not only by a liquidity shock but also by a shock that hits the regulatory capital of a bank. If this occurs, then a relative easy way to improve the regulatory ratios is to reduce the level of risky assets. Credit lines, which can be called back by banks at a relative short notice, might be quite suitable for making a fast deleveraging.

Once one is aware of this possible alternative triggering mechanism then it is easy also to understand how this channel for contagion may interact with a more standard and already well investigate one. In particular, many papers have analyzed how financial inter-linkages among banks may give rise to financial contagion in the banking system stemming from losses on different interbank claims (see Mistrulli, 2011 and Cappelletti and Guazzarotti, 2017 for an analysis on the Italian banking system).

One has to bear in mind the known limitations of this approach that are common to papers related to ours. Indeed, we do not provide a micro-foundation of the behaviour of banks and borrowers. We simply assume some hypotheses about a reasonable behaviour on the base of the existent empirical evidence supported to empirical evidence from the recent financial crisis. Furthermore, our results crucially depends on the value used for the parameters used for the simulations. For these reasons, we run alternative scenarios, assuming different values. We are aware of the difficulty of measuring the exact impact of this channel for contagion. However, we are at least confident that by this way we can assess whether this type of contagion may exist and how it propagates within the banking system.

The analysis relies on the assumption that banks, in reaction to a liquidity shock, ask for pay back of exposures at least partially. Some evidence seems to support our view that this a potentially important channel for contagion. In December 2011 the twelve-month rate of growth in lending by banks belonging to the five largest groups turned negative (by 1.0 per cent), with no significant difference between firms and households. Lending by the other large banks and by smaller banks continued to expand but its annual growth slowed from 6.0 to 2.0 per cent for the former and from 5.4 to 2.3 per cent for the latter. During the same period loans granted by branches of foreign banks accelerated sharply (to growth of 7.9 per cent) and in December accounted for 5.6 per cent of total lending and 5.9 per cent of loans to households and firms. The disparities in the growth in lending by category of bank reflect the different level of constraints encountered in fund-raising. The largest banks were more affected by the turmoil generated by the sovereign debt crisis, mainly because they make greater recourse to international markets for wholesale funding. The slowdown in lending by all categories of Italian banks was partly due to the cyclical deterioration in credit quality (Bofondi et al., 2013).

Figure 1 shows that during the crisis and, in particular, after the Lehman collapse, the interest rates on the overnight interbank deposits traded in the e-Mid rose spectacularly and the volumes traded declined sharply. On the other hand, according to a survey run by the Bank of Italy (INVIND) the percentage of firms that were asked by banks for reducing their bank debt exposures also sharply increased in 2011 and kept increasing in the following years. Moreover, between the end of 2011 and 2012 firms borrowing from more than one bank recorded a decrease of around 90 billions on credit lines outstanding at the end of 2011. This reduction was partially compensated by an increase in the drawing on existing credit lines (around 40 billions) and by new credit lines (30 billions). The request of reducing the loan exposures was more frequent for smaller firms (Table 1). All in all, this seems to suggest that the channel we investigate in this paper might have effectively been working during the crisis. In December 2011 ECB decided on additional enhanced credit support measures to support bank lending and liquidity in the euro area money market. In particular, the ECB's Governing Council has decided to conduct two longer-term refinancing operations (LTROs) with a maturity of 36 months and the option of early repayment after one year.

Yet, in this paper we do not aim to perform a structural estimation (see Keane, Todd and Wolpin, 2011) of the effect of a liquidity shock on the credit supply. This would require a completely different approach which would not allow us to use all the information provided by the credit register, due to computational intractability.[2] The simulation approach (see Upper; 2011) adopted aims to provide a counterfactual assessment of the potential risk of contagion through interbank' linkages related to existing multiple lending relations for a range of possible parameter values. It remains to be estimate which value of the parameters is the correct one.

Multiple lending is present in the major European countries. For example loans to borrowers with credit lines outstanding with more than one banks represents more than two third of the total loans in France, Germany and Spain.

To assess the potential importance of this channel for contagion we rely on very detailed data from the Italian credit register and supervisory reports allowing us to observe all

[2] Following a causal estimation approach, Bofondi, Carpinelli and Sette (2013), exploiting the lower impact of sovereign risk on foreign banks operating in Italy than on domestic banks, estimate that the lending of Italian banks grew by about 3 percentage points less than that of foreign banks, and their interest rates were 15-20 basis points higher.

Table 1: Percentage of firms reporting that they were asked by banks for reducing their bank debt exposures

	Firm with less than 50 employees	Firm with less than 100 employees	Firm with more 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

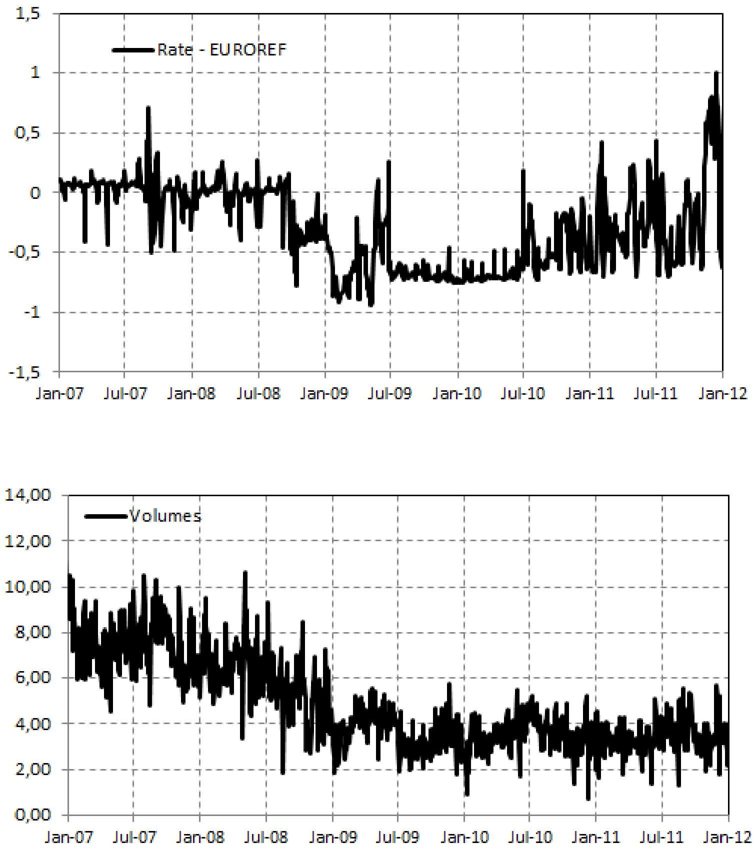
the financial interlinkages between banks, at the bilateral level, and all the indirect links between banks originated by the existence of multiple lending relationships between banks and their non-bank customers. Many supervisory regulations and public facilities, such as liquidity regulations (LCR, NFSR), emergency liquidity assistance, have been set up to prevent situations that illiquid banks cannot fulfill their business and have to resort to fire sales or ask repayment of loans. The results of the simulation could be framed as potential counterfactual impact of lacking of this facilities. It remains open for future research to assess whether additional measures are needed.

We obtain data on individual bank-firm relationships from the Italian Credit Register (CR) at the end of 2011. This source lists all outstanding loan amounts above 30,000 Euros that each borrower (both firms and households) has with banks operating in Italy. Intermediaries are required by law to report this information. Loans are distinguished into three classes: revolving credit lines, term loans, and loans backed by account receivables. The dataset includes both granted and drawn amounts. Therefore, we can use in our simulations the effective drawable amount from credit lines on which a firm can rely once some of its other credit lines have been called back.

We find that, by simulating contagion in the Italian banking system, multiple lending may be an important source of contagion especially when we allow for an interaction between the multiple lending channel and that based on direct financial interlinkages between banks. Therefore, this paper shows that the benefits from diversification of funding sources may come at the cost of an increasing systemic risk.

This paper contributes to the vast literature on financial contagion. Indeed, since the paper by Rochet and Tirole (1996) much attention has been paid to financial contagion in the interbank market. Theoretical works (Allen and Gale, 2000; Freixas, Parigi and Rochet, 2000) have then highlighted that the propagation of shocks within the interbank market is dependent on the exact pattern of banks' financial linkages and many papers have empirically supported this view (see Upper, 2011, for a survey). More recently, the

Figure 1: E-MID market between January 2007 and January 2012 (percentage points, billions Euro).



literature has gone beyond the interbank lending market and has taken into account also cross holdings of share and bonds and fire-sales on assets (Gai and Papadia, 2010). Karaas and Schoors (2012), in addition, model bank runs as a response of depositors to significant losses on assets. However, to our best knowledge, no paper has investigated the possibility that systemic risk may arise not only from direct financial linkages among banks but also from indirect ones involving non-bank borrowers. This allows us to model a bank run triggered not by panic episodes (Diamond and Dybvig, 1983) or by informational cascades, but by some liquidity shock that hit a bank and then propagates through a network of indirect linkages arising from multiple lending relationships.

The rest of the paper is structured as follows: Section 2 describes the data and their main characteristics. In Section 3 we outline the contagion channels and we report the results of the simulations. Section 4 concludes.

2 The data

We rely on very detailed data obtained from the Italian Credit Register. The Credit Register (CR) maintained by the Bank of Italy, contains detailed information on those loans granted to each borrower whose total debt from a bank is above 75,000 euros (30,000 euros since January 2009; no threshold is required for bad loans). The CR collects end-of-month stocks broken down by maturity, currency, type of contract (mortgage, advances against receivables and overdrafts) and 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. We obtain information on all types of interbank bilateral exposures by supervisory reports. Italian banks have to report to the Bank of Italy the outstanding amount of end-of-month gross bilateral exposures relative to different interbank claims (loans, bonds, shares).[3] The data allow distinguishing between different maturities (overnight, up to 18 months and over 18 months), seniorities, currencies of denomination, counterpart nationalities and it is also possible to distinguish between secured and unsecured claims.

We match interbank exposures with information, obtained from the Italian Credit Register, referred to credit lines granted to non-bank customers.[4] For each outstanding credit line we look at the amount granted and actually used by the borrower. All information are referred to the end of 2011. In all the simulations, banks are considered on a solo (unconsolidated) basis. From a theoretical perspective a consolidated perspective could imply smaller or to larger effects than those shown in our simulation. On one hand, the initial shock would impact all the subsidiaries in a group. On the other hand, the subsequent con-

[3] Supervisory reports cover all Italian banks, locally incorporated and branches of foreign banks.

[4] The Credit Register includes information on all outstanding loan amounts above 75,000 euros (30,000 since January 2009) granted by banks operating in Italy, including branches and subsidiaries of foreign banks.

tagion could be lower since the effects could be absorbed more easily with mutual support within a banking group. There is some empirical evidence (see Mistrulli, 2011; JBF) that contagion could be more or less severe, depending on the value of the parameters used in the simulation. Yet from a regulatory perspective, liquidity requirements apply both on an individual and consolidated basis (Regulation (EU) No 575/2013 (Capital Requirements Regulation), art. 6).

In order to define the multiple lending network we go through different steps. First, let $c_{j,h}$ be the amount of credit line of bank j used by borrower h and $g_{j,h}$ the amount granted, then the available margin is $m_{j,h}$ that is equal to the difference between the amount granted and the amount used ($m_{j,h} = g_{j,h} - c_{j,h}$). Then, assume that borrower h has also been granted a credit line by bank i and that this bank is hit by a liquidity shock and calls back at least partially the credit line granted to borrower h. In case borrower h has no other source of liquidity he may rely on the margin available on the credit line granted by bank j, i.e. $m_{j,h}$ to pay back the loan granted by bank i.

Second, for each pair of bank i and j we can identify the set of common borrowers, i.e. those debtors that have been granted a credit line from both bank i and bank j at the same time. We denote the set of borrower in common between i and j as $H_{i,j}$. Therefore, reducing the loans granted by α the maximum amount of liquidity bank i may obtain from borrowers through the credit lines granted to $H_{i,j}$ from bank j is equal to:

$$L_{i,j} = \sum_{h \in H_{i,j}}^{M} \max\left(\alpha \times c_{i,h}, m_{j,h}\right)$$

where $h = 1, ..., M$. Then each $L_{i,j}$ is the (i,j)-entry of a matrix L of all bilateral "exposures" between each pair of bank i and j. The matrix L represents the network arising from the existence of multiple credit lines that we can compare with other networks generated by the existence of direct links among banks (i.e. interbank loans, bonds and shares cross holdings) that are already well known to researchers.

Third, in case borrower h has been granted credit lines by more than two banks, for each bank i we can identify a set B_i of all banks that are connected to bank i, that is all the intermediaries that have granted a credit line to bank i borrowers:

$$B_i = \{j : L_{i,j} > 0\}$$

Fourth, the maximum amount that bank i may obtain by calling back the credit lines it has granted to all borrowers is:

$$L_i = \sum_{j \in B_i}^{\mathcal{B}} \sum_{h \in H_{i,j}}^{\mathcal{M}} \max\left(\alpha \times c_{i,h}, m_{j,h}\right)$$

where $\mathcal{B}$ is the total number of banks, and $\mathcal{M}$ is the total number of borrowers.

At the end of 2011, the total amount of margins available on credit lines granted to non-banks was equal to 352 billions, of which 230 billions were referred to borrowers with multiple lending relations. Figure 2 represents the network generated by multiple lending relations and the amount of liquidity that is at risk, meaning that it may be potentially transferred from one bank to another in case the latter is hit by a liquidity or capital shock.

The network originated from multiple lending relations seems not to be very concentrated. The first 5 banks accounted for around one third of the total potential usage of credit lines of other banks. In order to reach at least the 90 per cent of all usable credit lines we have to consider more than 100 banks. The number of links is more than 60.000. With respect to the interbank markets' network the multiple lending network is much more dispersed. For unsecured interbank deposits the first 5 banks account for almost the 50 per cent of total position at the June of 2011. As a result the network base on multi-lenders loans seems more disperse but with a higher volume with respect the interbank unsecured market[5].

At the end of 2011, the multiple-lending relationship network amounted to 230 billions euro while the total value of interbank' unsecured exposures in which either the borrower or the lender is an Italian bank was around 750 billions euro, of which more than 70 per cent was between banks affiliated with the same group. Focusing only on intermediaries headquartered in Italy, the value reduces to around 250 billion euro, of which around 190 within the same banking group. The network between Italian banks related to cross-holding of assets amounts to around to 120 billions. Table 2 show commonly used index for describing network topology[6], Montagna and Kok (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 if we look at the network related to multiple lending and the monetary market, instead it is much less diffuse if we consider only the cross-holding of bonds and shares. Instead, if we consider the number of banks connected the network related to multiple lending is much more dense with an higher number of relation for each bank.

Borrowers with more than one credit lines can have generally less than 5 outstanding credit lines, although some borrowers can have a much higher number of available credit sources. The median borrowers has two credit lines with a total value of 160.000 euro and with one of banks having a majority share (Table 3).

[5] Until the recent Long Term Refinancing Operation the unsecured segment has represented the most relevant part of interbank positions (see Cappelletti et al., 2011).

[6] See Acemoglu et al. (2013), Cont et al. (2012), Degryse and Nguyen (2007), Iori, et al. (2006), Kares et al. (2008), Furfine (2003) and Sheldon and Maurer (1998).

Figure 2: Network based on multiple lending relations.

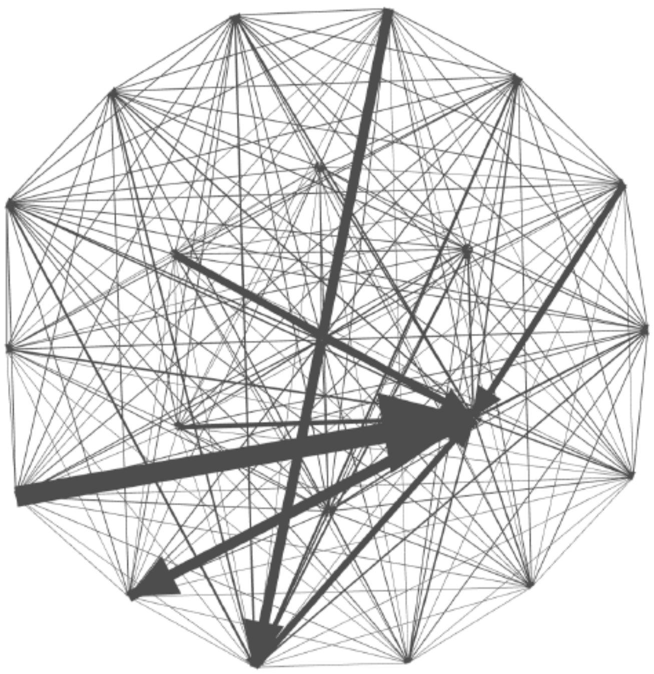


Figure 3: Unsecured interbank network

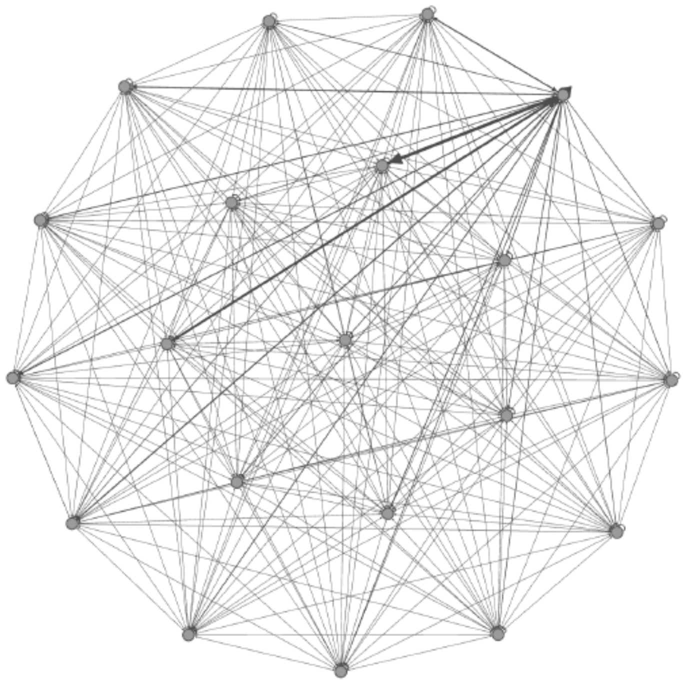


Table 2: Statistics on plan participants

	Interbank market	Cross-assets Network	Multiple relations network
Number of nodes	782	299	646
Number of relations	3,988	3,231	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	0.19	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: In order to have comparable figures we consider only Italian banks.

3 Multiple lending and the contagion mechanism in a crisis

In this section we describe how contagion propagates within the banking system because of indirect financial linkages stemming from multiple lending to non-banks. It is worthwhile to emphasize that this contagion mechanism has very limited scope in "normal" times. On the contrary, we argue that it might be quite harmful in a crisis by amplifying the effects of an already on-going crisis.

As it is generally assumed in many papers relying on simulations in order to investigate financial contagion phenomena, we assume that a bank is hit by an idiosyncratic shock which then may propagate to other banks financially linked to the former. This is justified by the fact that we tried to take a quite conservative perspective although the conditions under which the contagion mechanism can be relevant could imply the presence of a systemic shock hitting more than one bank contemporaneously.

In the first step, we assume that a bank i is hit by a shock and as a consequence bank i calls back a share of all credit lines by an amount that depends on the size of the shock

Table 3: Statistics on loans by borrower

	Min	p10	Median	p90	Max
Loan by borrower (number)	2	2	2	5	125
Loan by borrower (value)	0.001	16	62	299	327,400
Total loans by borrower	0.002	35	160	1,166	1,617,000
Max loan by borrower	0.001	24	96	578	1,118,000
Maximum loan over total	9%	37%	60%	89%	100%

(α).[7] We run different scenarios one for each bank in the banking system and for each bank by assuming different sizes of the idiosyncratic shock.

We can think of two possible types of shock: a) liquidity shocks such that bank i falls short of high-quality liquid assets (HQLA); b) capital shocks such that bank i falls short of regulatory capital. In both cases, in a situation in which the financial markets are impaired and banks are not able to tap them, bank i can restore its liquidity or regulatory capital pre-shock endowments by selling their assets. However, selling assets, both directly or by securitizing them, might be of little help in a crisis since this would entail severe losses with little liquidity inflows and also a capital drop too (Glasserman and Young, 2016).

Alternatively, banks may ask their borrowers to pay back at least part of their debt exposure thus providing liquidity and lowering regulatory capital needs at the same time. This is possible for at least those loans that banks may unilaterally call back at a short notice as it occurs for credit lines. Of course this is not costless for banks since they have to give up loan interest rates, calling back loans at a very short notice may imply a lot of effort from loan officers and, finally, this may also be harmful to the bank-firm relationships since borrowers may then switch to other banks. In that case, incumbent banks waste part of the efforts (mostly implying relation specific sunk costs) they have exerted to build up the relationship with the borrower, since they might have not reaped all the benefits yet. However, we maintain that during a severe crisis, banks might have little room for maneuvering and then resort to even quite costly strategy to overcome a liquidity or capital shock.

Once bank i relies on this strategy then contagion may propagate to other banks. This may happen whether the shock is so severe that bank i has to call back a great amount of credit lines in order to restore the pre-shock level of liquidity and, at the same time, in order to avoid any further outflows of liquidity, it zeros all the unused margins available on credit lines granted to its borrowers. Indeed, once this happens, all borrowers of banks i, named H_i, will draw money from the available unused credit lines granted by other banks to pay

[7] Customers can not draw on credit lines after a liquidity shock or after request for repayment.

back the loans granted by bank i.[8] As a consequence, all other banks lending to borrowers in H_i will record an increase in their lending activity and also a outflow of liquidity from them to bank i.

This in turn may have two consequences on shocked banks. The unwanted growth in their lending may lead to a shortage of regulatory capital; the outflows of liquidity to bank i might be so large that they fall short of liquidity. As a consequence those banks may in turn call back at least part of the credit lines granted and, similarly to bank i, propagate contagion further to banks that were not hit in the first round. Obviously this process may go even further in case these other banks face a regulatory capital or a liquidity shortage and they have to call back at least part of the credit lines they have granted. The contagion mechanism stops only once no bank faces any liquidity and regulatory shortage or once all banks have been infected and as a consequence they have zeroed all the available credit lines margins. Indeed in this latter case it is impossible to draw liquidity from other banks.

The propagation of the initial liquidity shock depends on a condition that triggers subsequent withdrawals from other banks that have not been infected yet. Since it is not easy to empirically define such a triggering condition we simulate different scenarios with different liquidity thresholds. Specifically, we assume that a bank becomes illiquid if the total liquidity outflow is such that their high-quality liquid assets (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 with Basel 3 Liquidity Coverage Ratio (LCR) rules. Let $L = \delta' \times HQLA$ be the amount of liquidity outflows that bank j suffered because of the bank i illiquidity, bank j is illiquid if $\delta' > \delta$. The liquidity coverage requirement provides for the maintenance of a minimum liquidity buffer over a 30-day horizon to cover any net cash outflows occurring in the event of market-wide, idiosyncratic stress scenarios.[9] If the liquidity requirements δ were already in place, δ represents the distance distance of banks from the minimum requirement. Based on EBA results of the CRDIV-CRR/Basel III monitoring exercise as of end 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%).

Alternative, new drawn from available credit lines could imply an increase in the capital requirement of banks which is another reason why bank may decide to reduce their loan exposures. According to the Capital Requirements Regulation (CRR; Article 166(8)) "for credit lines that are unconditionally cancellable at any time by the institution without prior notice, or that effectively provide for automatic cancellation due to deterioration in a borrower's creditworthiness, a conversion factor (c) of 0% shall apply". Indeed, a rise

[8] We do not consider the possibility that borrowers can ask banks for new credit lines or, in general, an increase in the amount of lending granted.

[9] 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.

in the drawn amount would increase bank capital requirements and consequently reduce regulatory capital relative to regulatory requirements (the actual solvency ratio goes down). Undrawn 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. Therefore, as a consequence of an increase in drawn credit lines (which corresponds to a fall in the undrawn amount of credit lines), due to the liquidity shock, banks would also suffer an increase in capital absorption that could propagate contagion even if infected banks meet their liquidity requirements.

If this effect is big enough then banks would reduce lending and, as for the case of liquidity shortage, a possible way to this is to call back credit lines. In order to explore this additional mechanism of contagion we simulate different scenarios with different capital thresholds. Specifically, we assume that a bank capital falls short of regulatory capital if the total liquidity outflow and the consequent increase in the drawn amount of credit is such that the ratio between the total capital and risk weighted assets (RWA)[10] decreases more than certain γ percentage points. Let D_j be the amount of liquidity outflows that bank j register because of the other banks becoming illiquid. RWA will increase by $(c - 0\%)\, D_j$, where c is the conversion factor of the additionally drawn liquidity.[11] The ratio between the total capital and risk weighted assets will decrease by $\frac{Capital}{RWA} - \frac{Capital}{(c-0\%)D_j + RWA} = \gamma'$. We assume that the bank j will become illiquid if $\gamma' > \gamma$.

If a bank become illiquid it will call back credit lines in order to restore the pre-shock level of liquidity, there could be contagion across banks but there is no amplification of the initial shock. The overall decrease of credit in the economy is limited by the initial idiosyncratic shock. Still, at each round of the contagion mechanism, the amount of liquidity available on credit lines in the banking system shrinks since we assume that infected banks zero credit line margins in order to avoid other borrowers' runs. This implies that, even without assuming liquidity hoarding by banks and borrowers, the initial shock is amplified by the prudent behaviour of banks. This is what we define as the baseline scenario (see Section 4.1). We simulate other scenarios in which we allow for banks' and borrowers' liquidity hoarding. Consistently, in line with Heider, Hoerova and Holthausen (2009), we assume that banks call back the amount of credit lines that is necessary to restore their pre-shock liquidity plus a share α' of all credit lines (Section 4.2). Similarly, borrowers, once they are asked to pay back the credit lines granted by illiquid banks, draw more money than needed from other banks (Ivashina and Scharfstein, 2010; Ippolito et al., 2016). Formally, borrowers may withdraw $(1 + \gamma)$ of the credit line called back by illiquid banks, up to the amount available on their credit lines (Section 4.3).

[10] Capital and risk weighted assets are those reported in supervisory data

[11] In gerneral, the increase in RWA is equal to $(c - c_0)L$ where c_0 is the conversion factor of the undrawn credit lines.

In section 4.4 we report the results for some worst case scenarios where parameters are set at a very harmful level. Section 5 compares the multiple lending contagion mechanism (indirect contagion mechanism) with that based on losses on interbank assets (direct contagion mechanism). Finally, we allow the multiple lending contagion mechanism to interact with other contagion channels (Section 6). In particular, since the multiple lending mechanism may be triggered also by a capital shock we simulate the former together with the channel based on losses on interbank assets (see Upper, 2011 for a survey).

Within each section, corresponding to alternative behavioral assumptions, we simulate alternative scenarios corresponding to different values for the parameters involved. This approach reflects the difficulty to identify the "true" values for parameters. Our ambition is to assess the potential impact of the aforementioned contagion mechanism and to identify a reasonable range of possible measures of it, or at least to assess whether the channel for contagion we are investigating does exist or not.

4 Results

In this section we report the results of the simulation based on the contagion mechanism outlined in the previous section. The main aim is to assess whether the multiple lending network is a source of contagion in the Italian banking system. We simulate different scenarios starting from the baseline one, which is the more conservative one, and subsequently augmenting the contagion mechanism by alternatively allowing for banks' and borrowers' liquidity hoarding. It is worthwhile to stress that in our scenarios we do not take the existence of a central bank into the account and that, as already argued, the multiple lending contagion mechanism assumes that the markets for liquidity and capital are not working or at least they do not allow banks to restore fast enough their liquidity or capital endowments, as it happened during the last crisis.

4.1 Baseline scenario

We start from an idiosyncratic shock that hits bank i . The shock is such that bank i has to call back, in order to restore the initial liquidity condition, a percentage α of the outstanding credit lines granted to its borrowers. Assuming that these borrowers have no other source of liquidity to pay back the credit lines they have been granted by bank i they draw cash from the credit lines they have been granted by other banks that consequently will suffer a liquidity outflow. We then assume that these banks would then call back the credit lines to restore their initial liquidity conditions in case the amount of their high-quality liquid assets (HQLA) is δ percentage points lower than the pre-shock level.

In the baseline scenario we set all the parameters at a quite conservative level, assuming that δ is set at 50 percentage points, meaning that banks react to a liquidity shock once the amount of their high-quality liquidity assets drops by more than a half. Since this seems quite a very conservative hypothesis, i.e. banks react only to quite large liquidity shocks, we simulate less conservative scenarios assuming lower values for δ. Since the average LCR was 133.7% at end June 2016 (EBA, 2016) the value for the simulation seems quite conservative. We assume that infected banks do not hoard liquidity, i.e. α' is equal to 0. And the reference value of the initial reduction in the credit supply is 10% which is in line with the evidence from the survey run by the Bank of Italy (INVIND; see Table 1) and the observed changes in the credit supply between the end of 2011 and 2012.

Table 4 shows the results for different values of the idiosyncratic shock, i.e. for different values of α. The number of cases in which contagion occurs and the change in outstanding credit lines, net of the initial idiosyncratic shock, is quite limited. This reflects the hypothesis that banks react and call back the credit lines granted to their borrowers only in case the liquidity shock is huge (50 per cent of total HQLA) and that they just want to restore the initial amount of liquidity. Based

Table 4: Simulation results: baseline

α	α'	δ	Contagion (%) (1)	Delta loans (%) (2)	Delta loan (mln) (3)	Delta available margin (%) (4)	Delta margin (mln) (5)
10%	0%	50%	1.1%	0.00%	-3.86	-0.126%	-269
20%	0%	50%	1.7%	0.00%	-6.67	-0.141%	-267
30%	0%	50%	2.1%	0.00%	-9.84	-0.149%	-266
40%	0%	50%	3.9%	-0.01%	-26.59	-0.192%	-471
50%	0%	50%	4.4%	-0.01%	-36.56	-0.210%	-515

Note: (1) Share of cases where the number of illiquid banks is strictly higher than 1. (2) and (3) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and milions Euro). (4) and (5) show the change in outstanding available margin on credit line gross of the initial idiosyncratic shock (percentage points and milions Euro).

Once we assume a lower threshold that triggers the reaction of banks we obtain a larger effect for the multiple lending contagion. In particular, we run same simulation for lower values for δ. Table 5 reports the new results indicating a greater impact for this channel of contagion. The percentage of cases in which contagion occurs rises, reaching 20.6 per cent in the worst scenario and also lending drops up to 1.62 per cent.

In order to compare these results with those that take into account the potential role of alternative sources of propagation related to capital requirement, we run the simulations where we assume that banks would call back the credit lines to restore their initial liquidity conditions in case the amount of their capital is γ percentage points lower than the pre-shock level. We let the parameters, the conversion factor of undrawn credit lines and the threshold of capital, at a quite conservative level, assuming that γ is set at 5 percentage points, meaning that banks react to a liquidity shock once the amount of their capital drops by more than a 5 percentage points and the conversion factor is 50 per cent. Since this seems quite conservative hypothesis, i.e. banks react only to quite relevant liquidity shocks,

Table 5: Simulation results: different liquidity thresholds

α	α'	δ	Contagion (%) (1)	Delta loans (%) (2)	Delta loan (mln) (3)	Delta available margin (%) (4)	Delta margin (mln) (5)
10%	0%	50.0%	1.1%	-0.002%	-3.86	-0.126%	-268.79
10%	0%	30.0%	1.9%	-0.002%	-3.99	-0.140%	-342.54
10%	0%	10.0%	5.3%	-0.002%	-4.10	-0.193%	-473.04
30%	0%	50.0%	2.8%	-0.714%	-17.71	-16.984%	-17.71
30%	0%	30.0%	4.6%	-0.721%	-17.88	-19.910%	-17.88
30%	0%	10.0%	15.2%	-0.744%	-18.46	-33.150%	-812.59
50%	0%	50.0%	4.4%	-1.474%	-36.56	-21.005%	-36.56
50%	0%	30.0%	8.1%	-1.486%	-36.86	-25.962%	-36.86
50%	0%	10.0%	20.6%	-1.619%	-40.17	-46.360%	-1136.39

Note: (1) Share of cases where the number of illiquid banks is strictly higher than 1. (2) and (3) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and milions Euro). (4) and (5) show the change in outstanding available margin on credit line net of the initial idiosyncratic shock (percentage points and bilions Euro).

we simulate less conservative scenarios assuming lower values for γ and conversion factor. We keep assuming that infected banks do not hoard liquidity, i.e. α' is equal to 0.

Table 6: Simulation results: different liquidity thresholds

α	α'	γ	Conversion factor	Contagion (%) (1)	Delta loans (%) (2)	Delta loan (mln) (3)	Delta available margin (%) (4)	Delta margin (mln) (5)
10%	0%	5%	50%	0.8	0.00	-4	-0.12	-298
30%	0%	5%	50%	3.9	-0.01	-17	-0.14	-345
50%	0%	5%	50%	6.6	-0.02	-38	-0.20	-483
10%	0%	1%	50%	8.9	0.00	-6	-0.23	-554
30%	0%	1%	50%	22.5	-0.01	-30	-0.52	-1285
50%	0%	1%	50%	30.5	-0.02	-61	-0.76	-1851
10%	0%	5%	20%	1.7	0.00	-4	-0.12	-300
30%	0%	5%	20%	7.2	-0.01	-19	-0.20	-487
50%	0%	5%	20%	11.0	-0.02	-45	-0.28	-684
10%	0%	1%	20%	14.8	0.00	-6	-0.30	-746
30%	0%	1%	20%	32.0	-0.01	-34	-0.78	-1901
50%	0%	1%	20%	39.9	-0.03	-67	-1.12	-2751

Note: (1) Share of cases where the number of illiquid banks is strictly higher than 1. (2) and (3) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and milions Euro). (4) and (5) show the change in outstanding available margin on credit line net of the initial idiosyncratic shock (percentage points and bilions Euro).

4.2 Liquidity hoarding by banks

Until now we have assumed that the infected banks that become illiquid reduce proportionally all outstanding loans in order to restore the initial amount of outstanding credit lines. In this sub-section, we assume that banks call back the amount of credit lines that is necessary to restore their pre-shock liquidity plus a share α' of all credit lines. This corresponds to what we name bank liquidity hoarding scenario and it is consistent with a prudent behaviour of banks that try to restore a level of liquidity that is higher compared to the pre-shock one.

In this case, the impact of contagion is quite severe. Following the initial idiosyncratic shock we observe contagion in 5.3 to 20.6 per cent of the cases, depending on the value set for α'. At the same time, assuming a high liquidity hoarding parameter (i.e. $\alpha' = 30\%$) the impact on lending ranges between -1,132 millions euro, when we have $\alpha = 10\%$, to -5,303 millions, in case $\alpha = 50\%$. Correspondingly, overall lending shrinks by 5,341 and 23,466 millions. It is also worthwhile to observe that margins on lines of credit shrink by even a greater amount. This reflects the behaviour of banks that once infected reduce the amount granted on credit lines. This means that borrowers, after the shock, can not count anymore on this buffer of liquidity and they might be quite in trouble.

Table 7: Simulation results: banks' liquidity hoarding

α	α'	δ	Contagion (%) (1)	Delta loans (%) (2)	Delta loan (mln) (3)	Delta available margin (%) (4)	Delta margin (mln) (5)
10%	10%	10%	5.3%	-0.003	-8	-0.3	-617
10%	20%	10%	5.3%	-0.019	-46	-0.4	-1,005
10%	30%	10%	5.3%	-0.456	-1,132	-2.2	-5,341
30%	10%	10%	15.2%	-0.017	-42	-0.5	-1,219
30%	20%	10%	15.2%	-0.073	-182	-0.9	-2,323
30%	30%	10%	15.2%	-1.489	-3,693	-6.8	-16,551
50%	10%	10%	20.6%	-0.033	-82	-0.7	-1,694
50%	20%	10%	20.6%	-0.109	-271	-1.3	-3,076
50%	30%	10%	20.6%	-2.138	-5,303	-9.6	-23,466

Note: (1) Share of cases where the number of illiquid banks is strictly higher than 1. (2) and (3) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and milions Euro). (4) and (5) show the change in outstanding available margin on credit line net of the initial idiosyncratic shock (percentage points and bilions Euro).

4.3 Possible runs by borrowers

In this sub-section we explore another amplification driver of the contagion mechanism. Following Ivashina and Scharfstein (2010) we assume that borrowers draw down their credit lines, aiming to hoard liquidity up to β per cent of the liquidity called back by the banks. At the limit case we assume that borrowers draw down all the liquidity that is available on their lines of credit. Table 8 reports the results of these new simulations. Allowing borrowers to hoard liquidity has two effects. On the one hand, it propagates contagion more widely across banks. On the other hand, consistently with Detragiache, Garella and Guiso (2000) and Ivashina and Scharfstein (2010), borrowers are less affected by the liquidity shock and the amount of lending increases, in case they draw down cash up to the line ceiling. In these scenarios we observe a huge reduction in the available margins. Differently, from the results reported in the previous sub-section this is also partly harmful to borrowers since it also reflects the behaviour of borrowers themselves, not only that of infected banks, that tend to hoard liquidity too.

Table 8: Simulation results: borrowers' hoarding of liquidity

α	α'	δ	β	Contagion (%) (1)	Delta loans (%) (2)	Delta loan (mln) (3)	Delta available margin (%) (4)	Delta margin (mln) (5)
10%	0%	10%	10%	5.8%	-0.001	-2	-0.2	-489
10%	0%	10%	30%	7.3%	0.001	2	-0.2	-529
10%	0%	10%	50%	8.3%	0.003	7	-0.2	-578
10%	0%	10%	oo	55.3%	4.908	12,174	-54.7	-134,057
30%	0%	10%	10%	16.0%	-0.005	-13	-0.4	-869
30%	0%	10%	30%	17.7%	0.000	-1	-0.4	-997
30%	0%	10%	50%	18.7%	0.004	10	-0.5	-1,130
30%	0%	10%	oo	55.3%	4.908	12,174	-54.7	-134,057
50%	0%	10%	10%	21.0%	-0.013	-32	-0.5	-1,192
50%	0%	10%	30%	22.9%	-0.008	-19	-0.5	-1,333
50%	0%	10%	50%	24.3%	-0.003	-6	-0.6	-1,506
50%	0%	10%	oo	55.3%	4.908	12,174	-54.7	-134,057

Note: (1) Share of cases where the number of illiquid banks is strictly higher than 1. (2) and (3) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and milions Euro). (4) and (5) show the change in outstanding available margin on credit line net of the initial idiosyncratic shock (percentage points and bilions Euro).

4.4 Worst case scenarios

Finally, we run a quite extreme scenarios where we set simulation parameters at a very harmful level. In particular, in Table 6 we report some results obtained for large initial liquidity shocks (alpha=90%), banks' liquidity hoarding, for the case in which banks react to relatively small shocks to their liquidity endowments (delta=50%). We run these worst case scenarios for 2 alternative behaviors of borrowers. In one case, borrowers are passive and then just draw the amount of money necessary to pay back the loans to banks that have called them back. At the other extreme, we assume that they are quite reactive to the shock and draw money from their lines of credit up to the credit line ceiling.

Table 9: Simulation results: stressed scenarios

α	α'	δ	β	Contagion (%) (1)	Delta loans (%) (2)	Delta loan (mln) (3)	Delta available margin (%) (4)	Delta margin (mln) (5)
90%	10%	10%	0%	20.6%	-0.03	-82	-0.69	-1694
90%	30%	10%	0%	20.6%	-2.14	-5303	-9.57	-23466
90%	50%	10%	0%	20.6%	-4.72	-11706	-12.12	-29703
90%	10%	10%	50%	47.0%	-0.79	-1,970	-42	-103,468
90%	30%	10%	50%	47.0%	-7.92	-19,646	-43	-104,497
90%	50%	10%	50%	47.0%	-15.36	-38,106	-44	-107,116

Note: (1) Share of cases where the number of illiquid banks is strictly higher than 1. (2) and (3) show the change in outstanding credit line net of the initial idiosyncratic shock (percentage points and milions Euro). (4) and (5) show the change in outstanding available margin on credit line net of the initial idiosyncratic shock (percentage points and bilions Euro).

In this case we obtain the most severe impact of contagion on lending. In the worst scenario reported in Table 6, lending shrinks by more than 15 per cent.

5 A comparison among contagion channels

In this section we compare the contagion mechanism due to multiple-lending relations with alternative mechanism. In particular, we run simulations which take into the account bank losses on interbank market due to defaults of other banks (see, among others, Mistrulli, 2011). Namely, all banks raising funds in the interbank market are allowed to fail one at a time; the losses suffered by banks lending to the failed bank are then computed. If the amount of the losses is greater than lenders' Tier-1 capital (i.e. capital and reserves) then lenders default. The simulation is then iterated by verifying if banks that fail after the first iteration make other banks fail as well. At each iteration banks that failed in the previous one are dropped from the set of banks which may be affected by contagion. The simulation continues until at least one bank default occurs. More recently, Battiston et al, 2013 consider also losses due to cross-holding of shares and the possibility of near defaulting banks. Limiting ourselves to the first aspect we can run the same simulations considering contagion due to losses related to shares and bonds holding of defaulted banks (see Appendix).

Table 10 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 to cause a bank to become illiquid (δ) is set at 50 percentage points. For evaluate other source of contagion, already studied in the literature we assume that the loss given default for unsecured and secured loans is respectively 40 and 80 per cent, and the recovery rate for stocks and bonds is respectively the 0 and 40 per cent. These values are in line with previous paper in the literature (Bargigli et al, 2015). The recovery rate is differentiated between shares and bonds but it is independent from the issuer and from the holder.

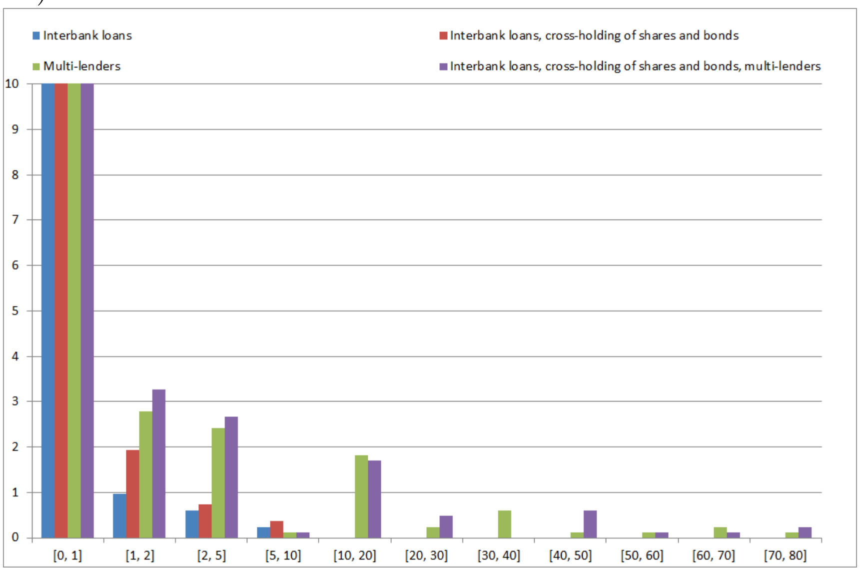
Table 10: Simulation parameters: recovery rates and liquidity threshold

Simulation parameters	
$\alpha =$ initial idiosyncratic shock	0.10
$\alpha' =$ share of credit lines called back by banks	0.10
$\delta =$ threshold of $HQLA$	0.50
$\lambda =$ LGD unsecured interbank loans	0.90
$\phi =$ LGD secured interbank loans	0.40
$\beta =$ LGD bonds holdings	0.40
$\sigma =$ LGD share holdings	1.0

Note that generically we can not say whether one mechanism is stronger than another since only the network structure related to each channel determine which one is more relevant. In order to evaluate the relevance of different contagion's mechanisms, we consider the default and the becoming illiquid of every single Italian bank and see what is the effect according to different contagion mechanism.

Contagion based on a pure interbank interlinkages is quite limited since in 98 per cent of the cases it does not occur (Figure 1). Including the cross holding of bonds and share increase the probability of contagion by only 1.2 per cent. Instead, the fact that banks share a relevant number of borrowers implies alone that in almost 1 over 10 cases at least another bank become illiquid. Even if the cross holding of assets does not change dramatically the total number of banks defaulting the possibility that a bank become illiquid due to new draws on existing credit lines implies a relevant increase in the total number of banks becoming illiquid. Considering all three mechanisms of contagion implies that in 90 per cent of cases there is not contagion. In 3.3 per cent of the cases (almost one third of the total case of contagion) the number of illiquid or defaulted banks is higher than 10.

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



6 Interactions among contagion channels

The different channels of contagion can interact and reinforce each other. Banks could call back the credit lines granted not only because they fall short of liquidity but also because they suffer losses that reduce their capital and make difficult to meet regulatory capital requirements. Indeed, in case the market for capital is not working, as it happens in a crisis, the only way to meet solvency requirements is by a deleveraging process.

Table 11 shows that the interaction of different channels of contagion could significantly increase the propagation of the shock across banks. If we assume that banks may become illiquid if they suffer losses equal to X per cent of their capital, the share of cases in which contagion occurs increases from 2.2% to 6.8% with a sizeable increase in the number of banks potentially hit by the shock.

Table 11: Number of illiquid bank for different value of X (Alpha = 0.10 and K=50).

		X				X			
		No Interaction	10	20	50	No Interaction	10	20	50
Number of illiquid banks	[1]	806	550	664	768	97,8	66,7	80,7	93,2
	[2]	8	183	102	29	1,0	22,2	12,4	3,5
	(2, 5]	5	57	37	11	0,6	6,9	4,5	1,3
	(5, 10]	3	20	8	8	0,4	2,4	1,0	1,0
	(10, 20]	1	5	3	3	0,1	0,6	0,4	0,4
	(20, 30]	0	0	2	2	0,0	0,0	0,2	0,2
	(30, 40]	1	1	1	0	0,1	0,1	0,1	0,0
	(40, 50]	0	3	2	1	0,0	0,4	0,2	0,1
	(50, 60]	0	1	2	0	0,0	0,1	0,2	0,0
	(60, 70]	0	0	0	1	0,0	0,0	0,0	0,1
	(70, 80]	0	1	0	1	0,0	0,1	0,0	0,1
	(80, 100]	0	1	0	0	0,0	0,1	0,0	0,0
	(100, 450]	0	2	2	0	0,0	0,2	0,2	0,0
	Totale	824	824	823	824	100	100	100	100

Finally, we explore a possible feed-back from the multiple lending channel to the loss on interbank assets one. Once banks call back credit lines it has not necessarily true that all borrowers would be able to pay back their loans. If we do not allow for borrowers to rely to internal liquidity and therefore become insolvent if the available liquidity is not sufficient to replace the calls backs from illiquid banks than banks would suffer some losses even in the multiple lending mechanism. As consequence, the interaction among different channels of contagion would be reinforced.

7 Conclusions

A wide literature, starting from the seminal paper by Allen and Gale (2000), has shown, both at the empirical and theoretical level, that contagion within the banking system may propagate since banks are financially interconnected. However, the extant literature has focused on direct financial exposures among banks (i.e. interbank lending, bank bonds and shares cross holdings) that give rise to a quite interconnected network of relationships.

We explore another source of interconnectedness that has not being investigated yet which originates from the existence of multiple credit lines. A quite common characteristics of lending relationships is that debtors, especially firms, borrow from many lenders at the same time (multiple lending). There are many reasons for that. Lenders diversify credit risk, borrowers diversify the risk of premature liquidations (Detragiache et al., 2000) and avoid or at least mitigate hold-up problems (Rajan, 1992; Sharpe, 1992). We argue that this may hold in normal times. In this paper we have shown that, during a crisis, multiple lending may be an important channel for contagion.

When the typical markets for liquidity are impaired, banks may call back credit lines in order to obtain cash from borrowers. However, a reasonable reaction of the latter is that of drawing money from credit lines available at other banks thus propagating the liquidity shocks within the banking system. We find that this channel of contagion might have a significant impact on the stability of the banking system, in particular when that channel interacts with other channels for contagion related to direct interbank exposures. Our paper is the first to show that while multiple lending is beneficial to banks and borrowers (Detragiache et al., 2000) in normal times, it may amplify and propagate liquidity shocks in a crisis.

Based on the results of the simulations, we find that in the baseline scenario contagion may be limited for very conservative calibration of the parameter. Once we consider the possibility of amplifying factors, namely hoarding of liquidity by banks or borrowers, the effects of initial liquidity shock are sizeable both in term of total volume of credit and total available credit lines.

In section 5 we have provided a tentative comparison among different channels, showing that multiple lending may be a major factor of contagion. However, this result has to be considered with caution since the severity of contagion, as Allen and Gale (2000) have shown, highly depends on the structure of financial interlinkages and, reasonably, this affects in a different way alternative channels. Moreover, we have shown (Section 6) that what we call direct linkages (i.e. interbank financial assets) and the indirect ones, arising from the existence of multiple lending, may make both channels for contagion interact and reinforce each other.

All in all, our paper identify the trade-off between the benefits of diversification of the 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 part of the banking system. In particular, multiple lending, in line with Detragiache, Garella and Guiso (2000), may mitigate the impact of banks' liquidity shocks on the economic activity of borrowers. However, this holds in normal times when the market for liquidity works smoothly. On the contrary, in a crisis, when interbank market are impaired, a dark side of multiple lending may emerge since, as we have shown, it may give rise to contagion and financial instability.

Appendix

A Contagion mechanisms through multiple lending relation

Formally, Given the set of the banks $\mathcal{B}$and the set of 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 drawn by bank i (Table **??**). The margin usable is denoted as $m_{i,h} = g_{i,h} - c_{i,h}$.

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

$$\begin{aligned} ILS^n &= \left\{ j \in \mathcal{B} : d_j^n > \delta \times HQLA_j^{Tier\ 1} \right\} \\ LS^n(i) &= \mathcal{B} \backslash ILS^n(i) \end{aligned}$$

where d_j^n is the total amount of credit lines drawn by borrowers at the nth step of contagion from bank j and $HQLA_j^{Tier\ 1}$ is Tier 1 high-quality liquid assets, defined following Basel 3 recommendations. Conditional on resulting new loans draws from surviving banks we assume that banks facing an excessive flow of liquidity become illiquid due to an increase in the illiquidity risk or equivalently to an increase in the volatility of liquidity needs. Namely we assume that if the ratio between total drawing and high-quality liquid assets is higher than δ the bank becomes illiquid. The amount of liquidity drawn at stage n from bank j is equal to:[12]

$$d_j^n = d_j^{n-1} + \sum_{h \in \mathcal{D}} d_{j,h}^n$$

In the baseline scenario, once a bank i becomes illiquid at stage n of the simulation, it reduces proportionally the outstanding loans in order to return to the initial total value of loans, that is:

$$c_{i,h}^{n+1} = \frac{c_{i,h}^n}{\sum\limits_{h \in \mathcal{D}} c_{i,h}^n} \sum_{h \in \mathcal{D}} c_{i,h} \text{ for each borrower } h \text{ and } i \in ILS_{ML}^n(i) \qquad \text{(Behavior 1)}$$

where for each borrower h, where $\sum\limits_{k \in \mathcal{D}} c_{i,h}$ is the value of credit lines outstanding before the shock. Alternatively, we can assume that all the banks becoming illiquid reduce propor-

[12] In the simulation bank j can register a drawn on its credit lines only by borrowers that having outstanding loans from banks become illiquid at stage $n-1$

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

tionally all outstanding loans formally:[13]

$$c_{i,h}^{n+1} = \alpha c_{i,h} \text{ for all borrower } h \text{ and bank } i \text{ such that } i \in ILS_{ML}^{n}(i) \qquad \text{(Behavior 2)}$$

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 each borrower h will try to compensate the reduction in its banks' funding with the existing credit lines, drawing the unused granted loans, that is for borrower h and liquid bank j at stage n of the simulation. Let us define the desired level of new loans by borrower h at the nth step of the contagion path as:

$$c_h^{*n} = (1+\beta)\, cb_h^n$$

the resulting withdraw on available credit lines will be equal to:

$$d_{j,h}^{n} = \begin{cases} \min\left(0, g_{j,h}^{n} - c_{j,h}^{n}\right) \frac{cb_h^n}{cl_h^n} \\ \qquad\qquad \text{if } cl_h^n > cb_h^n \\ \\ \min\left(0, g_{j,h}^{n} - c_{j,h}^{n}\right) \\ \qquad\qquad \text{if } cl_h^n \leq cb_h \end{cases}$$

where $cb_h^n = \sum\limits_{j \in ILS^{n-1}(i)} c_{j,h}^{n} - c_{j,h}^{n-1}$ and $cl_h^n = \sum\limits_{j \in LS^{n-1}(i)} \min\left(0, g_{j,h} - c_{j,h}\right)$. If the unused margins are more than sufficient for the substitution we assume that the borrower draws proportionally the available credit lines, instead if this is not the case the borrower simply uses all the available credit lines.[14] Alternatively, we allow that borrowers asked to reduced their loan exposure by a bank want to draw funds in an higher amount for precautionary reasons ($\beta > 0$).

Formally, we define a set of illiquid banks due to defaulting banks and implied reduction in the value of their capital as:

$$ILS_{LBS}^{n}(i) = \left\{ j \in \mathcal{B} : Capital_j - \sum_{d \in D_{LBS\_ML}^{n-1}(i)} \left(\lambda unsec_{j,d} + \phi sec_{j,d}\right) - \sum_{d \in D_{LBS\_ML}^{n-1}(i)} \left(s_{j,d} + \varepsilon b_{j,d}\right) < X \right\}$$

Therefore the set of illiquid banks is defined as:

$$ILS_{LBS\_ML}^{n}(i) = ILS_{ML}^{n}(i) \cup ILS_{LBS}^{n}(i)$$

[13] One should note that the results are equivalent if we assume that illiquid banks zero the drawable credit lines and the existing credit positions naturally grows at the rate of α per cent.

[14] We do not consider the default of borrowers in case of impossibility of fully substituting the closed loans. This fact could enhance the contagion mechanism due to multi-lending relationships.

Another source of interaction comes from the fact that firms could not drawn liquidity from banks that have defaulted. Since the condition of illiquidity due to losses is stricter than the condition of defaulting, the equation that defines the drawing of credit lined does not change, apart from replacing $ILS^n_{LBS}(i)$ with $ILS^n_{LBS\_ML}(i)$.[15]

Formally, in each step n of the simulation we compute the value of possible problematic loans as:

$$NPL^n_{i,k} = \begin{cases} 0 \text{ if} \sum\limits_{j \in LS^n_{LBS\_ML}(i)} \min(0, g_{j,k} - c_{j,k}) \geq \sum\limits_{j \in ILS^n_{LBS\_ML}(i)} \alpha c_{j,k} \\ \alpha c_{i,k} - \frac{\alpha c_{i,k}}{\alpha \sum\limits_{j \in ILS^{n-1}_{LBS\_ML}(i)} c_{j,k}} \left(\sum\limits_{j \in LS^{n-1}_{LBS\_ML}(i)} d^n_{j,k} \right) \text{ otherwise} \end{cases}$$

for each borrower h that experience a reduction in the outstanding loans (formally for every $h \in H^{n-1}(i)$). We assume that problematic loans are distributed across all the illiquid banks, that have reduced their loans, in a proportional manner.

When we want to consider contagion due to losses suffered by banks we could include losses due to non performing loans. Hence, we define the set of insolvent banks as:

$$D^n_{LBS\_MAFF}(i) = \left\{ z \in \mathcal{B} : Capital_z - \sum_{j \in D^{n-1}_{LBS\_ML}(i)} (s_{z,j} + \varepsilon b_{z,j} + s_{z,j} + \varepsilon b_{z,j}) - \rho \sum_{k \in H^{n-1}_{LBS\_ML}(i)} NPL^n_{z,k} < 0 \right\}$$

Note that $D^n_{LBS\_MAFF}(i) \supseteq D^n_L(i) \cup D^n_{BS}(i)$ for every bank i and for every step n of the simulation.

B Contagion mechanisms through inter-banks exposures

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

Let i be the first bank that defaults because of some idiosyncratic shock, and define $D^n_m(i) \subseteq \mathcal{B}$ and $S^n_l(i) \subseteq \mathcal{B}$ as the set of banks, respectively, defaulted and surviving at the nth step of the contagion process initiated by bank i under mechanism m.[16] We allow for

[15] Formally, for each bank i and n we the set of illiquid banks $ILS^n_{LBS}(i)$ includes the set of defaulted banks $D^n_{BS}(i)$ where $D^n_{BS}(i) = \{z \in \mathcal{B} : c_z - \gamma s_{z,i} - \phi b_{z,i} < 0\}$.

[16] In general $B = S^n_l(i) \cup D^n_m(i)$.

Table 12: Unsecured and secured interbank positions

Unsecurd deposits

		Banks					
		B_1	B_2	...	B_i	...	B_I
Banks	B_1	$unsec_{1,1}$	$unsec_{1,1}$				
	B_2	$unsec_{2,1}$	$unsec_{2,2}$				
	...						
	B_i				$unsec_{i,j}$		
	...						
	B_I						$unsec_{I,J}$

Secured deposits

		Banks					
		B_1	B_2	...	B_i	...	B_I
Banks	B_1	$sec_{1,1}$	$sec_{1,1}$				
	B_2	$sec_{2,1}$	$sec_{2,2}$				
	...						
	B_i				$sec_{i,j}$		
	...						
	B_I						$sec_{I,J}$

three main sources of contagion: interbank loans losses, interbank loans and cross-holdings losses.

Under a first mechanism the set of defaulting banks is defined as:

$$D_L^n(i) = \left\{ z \in \mathcal{B} : C_z - \sum_{j \in D_L^{n-1}(i)} (\lambda unsec_{z,j} + \phi sec_{z,j}) < 0 \right\}$$

where C_z is the Tier 1 capital of bank z, and λ, ϕ are respectively the recovery rate for unsecured and secured deposits. That is the set of banks that suffer losses from interbank loans sufficient to deplete their Tier 1 capital.

If we consider also the fact that banks own shares and bonds of other banks, the contagion could occur because banks suffer losses on their interbank loans and on cross-holdings of shares and bonds that deplete their capital, and the defaulting banks are:

$$D_{BS}^n(i) = \left\{ z \in \mathcal{B} : C_z - \sum_{j \in D_{LBS}^{n-1}(i)} (\sigma s_{z,j} + \beta b_{z,j}) < 0 \right\}$$

where σ and β are, respectively the recovery rate on stocks and bonds' holding.

The contagion mechanism can be formally summarized, describing the contagion paths.

Table 13: Interbank cross-holding of bonds and shares

Bonds

		Banks					
		B_1	B_2	…	B_i	…	B_I
	B_1	$b_{1,1}$	$b_{1,1}$				
	B_2	$b_{2,1}$	$b_{2,2}$				
Banks	…						
	B_i				$b_{i,j}$		
	…						
	B_I						$b_{I,J}$

Shares

		Banks					
		B_1	B_2	…	B_i	…	B_I
	B_1	$s_{1,1}$	$s_{1,1}$				
	B_2	$s_{2,1}$	$s_{2,2}$				
Banks	…						
	B_i				$s_{i,j}$		
	…						
	B_I						$s_{I,J}$

Given the initial default of a single bank i the initial sets of defaulted banks are trivial:

$$D_L^0(i) = D_{BS}^n(i) = ILS^n(i) = \{i\} \tag{1}$$

then the infection spreads according to different channel considered:

$$\begin{aligned}
D_L^n(i) &= \{z \in \mathcal{B} : c_z - \lambda unsec_{z,i} - \phi sec_{z,i} < 0\} \\
D_{BS}^1(i) &= \{z \in \mathcal{B} : c_z - \sigma s_{z,i} - \beta b_{z,i} < 0\} \\
ILS_{ML}^1(i) &= \left\{ z \in \mathcal{B} : \frac{\sum\limits_{k \in H_{ML}^0(i)} drawn_loans_{j,k}^n}{HQLA_z^{Tier\ 1}} > K \right\} \\
\text{where } H_{ML}^0(i) &= \{h \in \mathcal{H} : l_{i,h} > 0\}
\end{aligned}$$

Iterating the exercise we derive the relevant set of defaulted and illiquid banks.

$$
\begin{aligned}
D_L^n(i) &= \left\{ z \in \mathcal{B} : \sum_{j \in D_L^{n-1}(i)} \left(c_z - \lambda unsec_{z,j} - \phi sec_{z,j} \right) < 0 \right\} \\
D_{BS}^n(i) &= \left\{ z \in \mathcal{B} : \sum_{j \in D_{LBS}^{n-1}(i)} \left(c_z - \sigma s_{z,j} - \beta b_{z,j} \right) < 0 \right\} \\
ILS_{ML}^n(i) &= \left\{ z \in \mathcal{B} : \frac{\sum\limits_{k \in H_{ML}^{n-1}(i)} drawn\_loans_{z,k}^n}{HQLA_z^{Tier\ 1}} > K \right\} \\
\text{where } H_{ML}^{n-1}(i) &= \left\{ h \in \mathcal{H} : \sum_{j \in ILS_{ML}^{n-1}(i)} l_{j,h} > 0 \right\}
\end{aligned}
$$

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