C GAUGING THE EFFECTIVENESS OF CROSS-SECTIONAL MACRO-PRUDENTIAL TOOLS THROUGH THE LENS OF INTERBANK NETWORKS[1]

This special feature examines various macro-prudential tools through the lens of recent advances in the study of interbank contagion. The specific set of tools analysed are those designed to contain the "cross-sectional" dimension of systemic risk – that is, those designed to limit the systemic risk stemming from factors such as correlations and common exposures across financial institutions. These include tools such as large exposure limits and other regulatory requirements designed to limit the spread of systemic risk between banks. The analysis rests on the basic notion that interbank network structures, and hence the risk of contagion across the banking system in response to shocks, are influenced by banks' optimising behaviour subject to regulatory (and other) constraints.

Changes in macro-prudential policy parameters, such as large exposure limits, capital charges on counterparty exposures and capital and liquidity requirements more generally, will affect the contagion risk because of their impact on banks' asset allocation and interbank funding decisions. This in turn implies that well-tailored macro-prudential policy can help reduce interbank contagion risk by making network structures more resilient.

The analysis shows that to capture the full extent of potential interbank contagion, all of the different layers of bank interaction should be taken into account. Hence, if the regulator only focuses on one segment of interbank relationships (e.g. direct bilateral exposures), the true contagion risks are likely to be grossly underestimated. This finding has clear policy implications and flags the importance of micro- and macro-prudential regulators having access to sufficiently detailed data so as to be able to map the many interactions between banks.

INTRODUCTION

Shocks to individual financial institutions may spread across the market depending on the network structure of the system

A key lesson to have emerged from the recent financial crisis is that shocks hitting specific financial institutions have the potential to spread quickly across the entire financial system, with potentially disastrous consequences. Such experiences have led to a wealth of studies on financial contagion, many of which apply network theory, to better understand the risk built in to the financial system as a result of the interconnectedness of financial institutions. A key finding in the literature is that an important determining factor of contagion risks in, for instance, the interbank market is the structure of the networks through which banks are connected to each other. In other words, the scope for contagious losses following an idiosyncratic or system-wide shock depends on the number of connections and the centrality of the affected institutions within the network.

The financial network formation process is not well understood

However, so far, little is known about how financial networks are formed and about their sensitivity to changes in key bank parameters (for example, common exogenous shocks or regulatory initiatives) and how the many different layers of bank networks affect each other. A more comprehensive knowledge of these elements is, however, important so as to be able to better calibrate macro-prudential policies that will contribute to making interbank networks more resilient.

Two recently developed ECB network tools are presented…

Against this background, and drawing on recent ECB research, this special feature presents two analytical network tools that capture behavioural patterns of interbank relationships and the dynamic implications of multi-layered network structures.[2] Both approaches rely on "agent-based"

1 Prepared by Grzegorz Hałaj, Christoffer Kok and Mattia Montagna.

2 For a general description of network modelling for financial stability purposes, see ECB, "Evaluating interconnectedness in the financial system on the basis of actual and simulated networks", *Financial Stability Review*, June 2012.

modelling, which imposes certain behavioural assumptions on the banks in the system subject to pre-specified budget (and regulatory) constraints.

… and their potential for analysing macro-prudential policies demonstrated

The article first presents the methodology and macro-prudential implications of a modelling framework that focuses on how interbank networks are formed and in particular how they can be affected by certain macro-prudential policy actions. Second, the methodology and macro-prudential implications of a multi-layered interbank network model are presented. This framework illustrates the importance from a macro-prudential perspective of taking full account of all the different layers of banks' interactions. The final section concludes.

THE EMERGENCE OF INTERBANK NETWORKS[3]

This model is related to research on network formation, which has only recently become a topic of study within the field of finance. Understanding how interbank networks emerge can be critical to controlling and mitigating the related risks. Endogenous networks (and their dynamics) are a difficult problem since the behaviour of the agents (banks in particular) is very complex. The emergent literature on network formation therefore considers game theory and portfolio optimisation.[4] The network formation model presented here adds to this strand of the literature by feeding a firm-level data set of European banks into a model based on portfolio-optimising banks.

Model description

The interbank network emerges from a sequential, four-round game played by banks

The interbank network formation model looks at the banking system from the perspective of investment portfolio theory. The emerging linkages are the outcome of a sequential game played by banks trying to invest in the interbank market and borrow interbank funding. Banks optimise their interbank assets taking into account risk and regulatory constraints as well as the demand for interbank funding and propose their preferred portfolio allocation among the interbank counterparties.[5] As regards the funding side, banks define their most acceptable structure of funding sources with the objective of limiting refinancing risk. Banks meet in a bargaining game in which the supply and demand for interbank lending is matched.

In order to account for the complexity of interbank markets, a sequential optimisation process encompassing four distinct rounds is assumed (see Figure C.1).

In the first round, banks formulate their preferred structure of interbank assets

In the *first* round, banks specify the preferred allocation of interbank assets by maximising the risk-adjusted return from the interbank portfolio. In this optimisation process, each bank first draws a sample of banks according to a predefined probability that a bank is related to another bank.[6] On this basis, banks make offers of interbank placements at a current market rate corrected

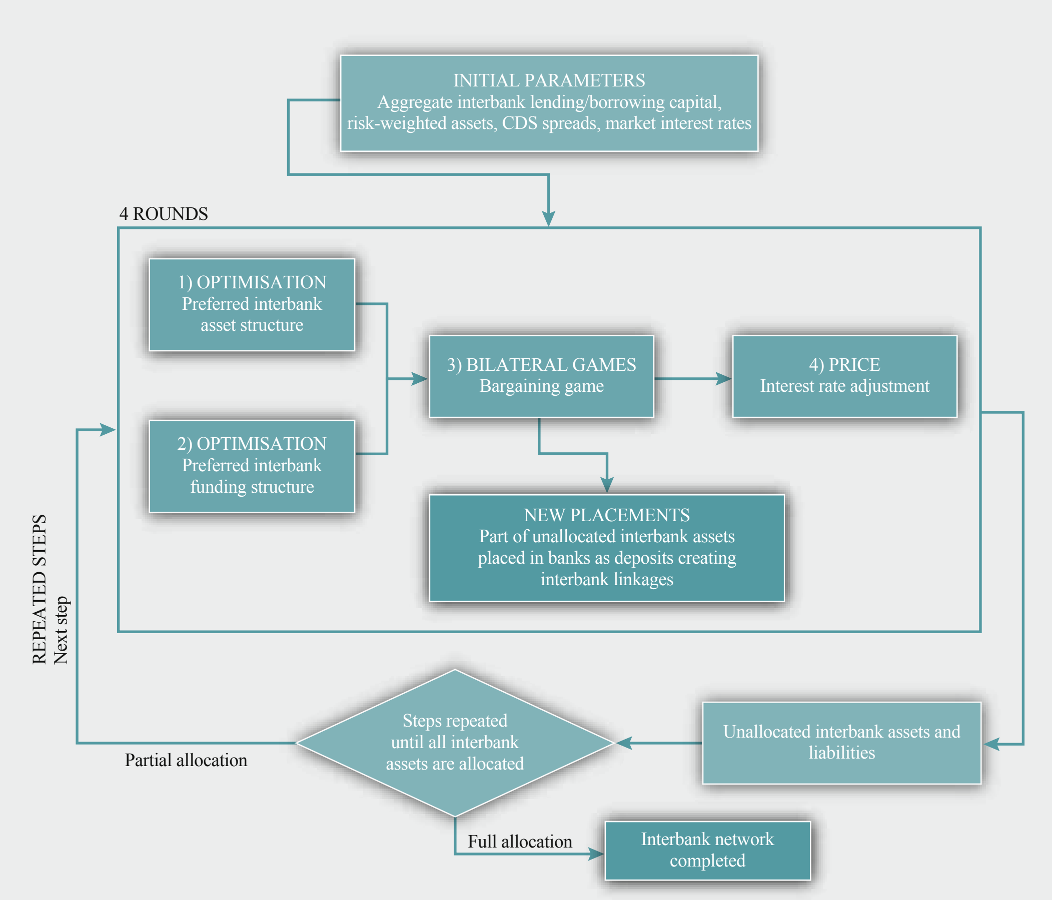
3 This sub-section is based on Hałaj, G. and Kok, C., "Modelling the emergence of interbank networks", *Working Paper Series,* ECB, forthcoming.

4 For a few recent studies, see Acemoglu, D., Dahleh, M.A., Lobel, I. and Ozdaglar, A., "Bayesian learning in social networks", *Review of Economic Studies*, Vol. 78, pp. 1201-1236, 2011; Cohen-Cole, E., Petacchini, E. and Zenou, Y., "Systemic risk and network formation in the interbank market", *CEPR Discussion Papers*, No 8332, 2011; Bluhm, M., Faia, E. and Krahnen, J.P., "Endogenous banks' networks, cascades, and systemic risk", *SAFE Working Paper*, Goethe University, 2013; Georg, C.-P., "The effect of the interbank network structure on contagion and common shocks", *Journal of Banking and Finance*, Vol. 37(7), 2013.

5 The model abstracts from the presence of a central bank that can act as a lender of last resort for banks unable (or unwilling) to fund themselves in the interbank market. Hence, the interbank contagion effects derived from the model would reflect the impact without any central bank intervention. While not the focus of this article, the modelling framework could easily account for exogenous central bank liquidity injections.

6 The probability of interbank relationships is based on the "probability map" constructed by Hałaj and Kok (2013), which is derived from information about banks' total interbank assets and liabilities, the geographical breakdowns of those assets and information about whether banks are internationally active or not; see Hałaj, G. and Kok, C., "Assessing interbank contagion using simulated networks", *Working Paper Series*, No 1506, ECB, 2013.

Figure C.1 Sequential game: the four-round procedure behind the formation of the interbank network



Source: Hałaj and Kok (op.cit.).

for a premium based on the counterparty's default probability. They try to maximise the return adjusted by investment risk, taking into account the volume of total interbank lending, the expected interest income accounting for the counterparty risk, the volatility of the interbank lending rates and regulatory and other constraints.[7]

In the second round, banks define their optimal interbank funding structure

Obviously, the recipients of the interbank funding will have their own preferences regarding funding sources. Therefore, in the *second* round of the model, after the individual banks' optimisation of interbank assets, banks calculate their optimal funding structure among banks that have offered placements. They decide on the preferred structure based on the funding risk of the resulting interbank liabilities. The funding decision is based on the objective of minimising the rollover (refinancing) risk of interbank deposits.

7 The regulatory constraints imposed on the banks include a "minimum risk-weighted capital ratio" of 8% and a "large exposure limit" on the maximum size of an exposure to a given counterparty relative to the capitalisation of the bank creditor. In addition to the regulatory constraints, capital is also assumed to be constrained by a "credit valuation adjustment (CVA) surcharge" reflecting the additional capital required in banks' internal economic capital models for changes in the riskiness of interbank exposures gauged by market-based default probabilities for banks. This CVA element is not to be mistaken for the CVA capital charge on changes in the credit spread of counterparties on over-the-counter derivatives transactions.

In the third round, banks try to match optimally determined interbank deposits in a bargaining game…

The offers of interbank placements may diverge from the funding needs of the other side of the interbank market. In the *third* round, it is therefore assumed that pairs of banks negotiate the volume of interbank deposits. These negotiations are modelled by means of a bargaining game in which banks may be more or less willing to deviate from their preferred and optimisation-based structures of assets and liabilities.[8]

… and in the fourth round, banks that still do not have sufficient funding adjust their offered interest rate upwards

After the first three rounds, a full allocation of interbank assets may still not be achieved, with some banks remaining short of their desired interbank funding. To increase the chance of attracting the missing interbank funding, in the *fourth* round banks in need of additional funding are assumed to change the offered interest rate for new deposits. Intuitively, it follows that the bigger the funding gap with respect to the assumed interbank funding needs, the higher the increase in the offered interest rate.

The rounds are repeated until all interbank assets and liabilities are matched

The four consecutive rounds are repeated with a new drawing of banks to be included into subsamples of banks with which each bank prefers to trade. Consequently, each bank enlarges the group of banks considered to be their counterparties in the interbank market and proposes a new preferred structure of interbank assets and liabilities for the part unallocated in the previous step. In this way, interbank assets and liabilities are incrementally allocated among banks. All in all, the network formation algorithm ensures a swift convergence of network structures. After a handful of iterations, the algorithm yields an allocation of above 80% of total interbank assets. After 20 such steps, more than 95% of interbank assets are allocated.

The model calibration is based on publicly available aggregate data on banks' balance sheet structures, in particular total interbank lending and borrowing. The proposed algorithm that matches banks on the interbank market utilises risky returns from interbank investment related to the general level of interbank interest rates and bank-specific counterparty default risk, proxied by banks' CDS spreads. Asset diversification can be controlled by a set of regulatory rules related to large exposure limits and minimum capital requirements. The effectiveness of the rules can be assessed by comparing the magnitude of contagion initiated by defaults of groups of banks following adverse economic scenarios in the stress-testing context and transmitted across the networks emerging from the model for different measures of the regulatory rules.

Macro-prudential policy implications

The sensitivity of the interbank network structure to large exposure limits is verified

On the basis of the network formation modelling approach, various policy questions can be addressed. For example, the approach can be employed to detect the impact of different macro-prudential policy measures on the formation of network structures and the related contagion risks.

An obvious avenue for using the model is to assess the effects of different regulatory instruments aimed at limiting banks' risk in terms of counterparty exposures, such as the large exposure limits already embedded in current regulatory frameworks[9] as well as systemic risk capital surcharges and changes in risk weights on exposures to other financial institutions to be introduced in the context of the implementation of the Basel III framework in the EU.

By lowering the large exposure limits, interbank connectivity increases…

First of all, more stringent large exposure limits (i.e. lowering the threshold below 25%) could trigger substantial changes to the structure of banks' network connections. Chart C.1 illustrates that,

8 The game portrays an agreement between banks about the volume of the interbank placement in a given step of the interbank matching algorithm. Banks' willingness to engage in negotiations with direct counterparties depends on the trade-off between their disutility of adapting somewhat their optimised asset-liability structure and the costs of having to find a completely new counterparty (if they do not want to accept the offers from their existing counterparties).

9 See Article 111 of Directive 2006/48/EC which states that the interbank exposure of each bank cannot exceed 25% of its regulatory capital and that the sum of the interbank exposures of a bank, individually exceeding 10% of its capital, cannot be higher than 800% of its capital.

on average, across the sample of banks, the number of network connections increases when large exposure thresholds are lowered. Such action also results in a lower degree of concentration of interbank connections (as measured by the "betweenness" measure). This is intuitive: as limits on large exposures become more binding, banks have to reduce the size of individual exposures and as a result spread their interbank business across a wider range of counterparties.

… but the implications for contagion risk under adverse market conditions are a priori ambiguous

Going beyond this simple illustration, it is instructive to use the model by imposing an adverse shock on the banking sector and assessing the interbank contagion for different settings of the macro-prudential instruments. More specifically, the interbank network is first subjected to a common adverse macroeconomic scenario, which induces banks to re-optimise the structure of their asset allocation[10] and leads to the emergence of a new interbank network of bilateral exposures. In the second step, the impact of the adverse shock on bank solvency resulting from interbank contagion is observed and the impact across different settings of macro-prudential parameters (i.e. large exposure limits) is compared.

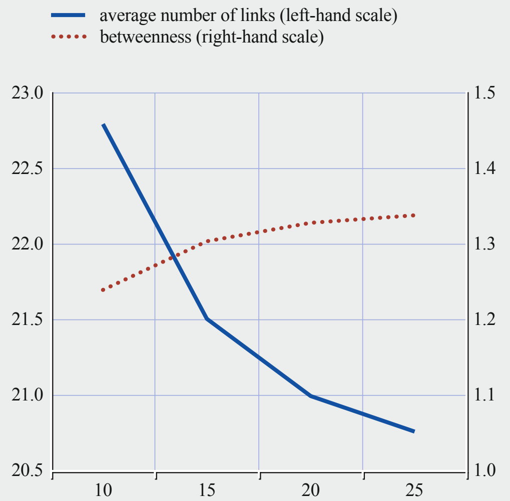
The model suggests that contagion losses fall as the large exposure limit is lowered

Chart C.2 shows the results of such an analysis. The y-axis depicts the difference between networks formed under a 10%, 15% and 20% large exposure limit, respectively, and under the standard 25% large exposure limit, taking into account the capital loss following an adverse shock. A negative value implies that contagion losses decline when the large exposure limit is lowered. On the x-axis, the banks' riskiness (as measured by individual bank CDS spreads) is plotted. Contagion losses under an adverse scenario are reduced when making large exposure limits more binding by lowering them from the current regulatory threshold of 25% to 20%, 15% and 10%. Interestingly,

The implications of more stringent large exposure limits are more pronounced for the soundest banks

Chart C.1 Topological measures of networks emerging under different large exposure thresholds

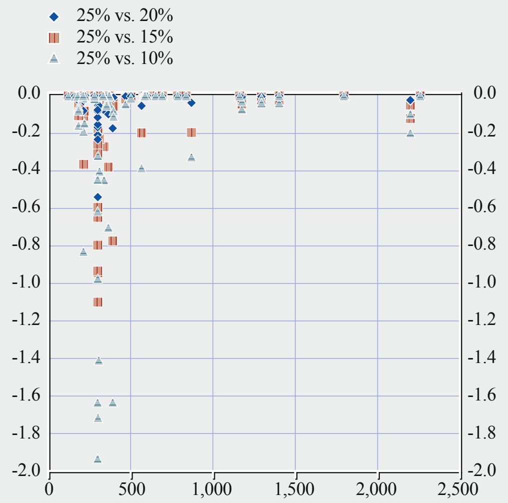
(percentages; x-axis: large exposure thresholds; y-axis: topological measures of networks)



Source: Hałaj and Kok (op.cit.).
Note: Averages across all banks.

Chart C.2 Impact of large exposure limits on total capital ratio under an adverse macroeconomic scenario vs. bank credit quality

(x-axis: impact of large exposure limits on total capital ratio under an adverse macroeconomic scenario in basis points; y-axis: bank CDS spread in percentage points)



Source: Hałaj and Kok (op.cit.).

10 The assumed asset allocation optimisation process follows Hałaj, G., "Optimal asset structure of a bank – bank reactions to stressful market conditions", *Working Paper Series*, No 1533, ECB, 2013.

this effect is especially pronounced for the group of banks perceived (by the markets) to be the soundest. In other words, the forced reduction of counterparty concentration risk seems to benefit in particular the safest part of the banking system, whereas the more vulnerable segments are found to be less affected by changes in the large exposure limits. This could suggest that, in this sample, the weaker banks have less scope for diversification, whereas stricter limits on interbank exposures could induce some of the stronger banks to diversify more, to the benefit of the system's overall resilience to contagion effects. This notwithstanding, caution is required in adopting measures that limit interbank funding and such actions should be weighed against potential unintended consequences on the overall liquidity and functioning of the money market.

While acknowledging that these results are contingent on the simulated networks, the relevance of the imposed asset and funding optimisation problem and the particular adverse scenarios considered, the results suggest that the tool can provide a useful benchmark for the calibration of the optimal configuration of such macro-prudential and regulatory instruments. An important way forward would be to extend the model set-up in order to be able to assess the effectiveness of macro-prudential instruments more explicitly in terms of their impact on the real economy (e.g. via the effect on banks' non-interbank assets).

A HOLISTIC APPROACH TO INTERBANK CONTAGION[11]

Similar to the model presented in the previous section, this second approach is also based on a model of dynamic bank behaviour. In addition, a multi-layered network structure is modelled to account for the various layers of interbank relationships. This more holistic approach to studying interbank contagion is distinct from the traditional network-based contagion literature, which typically focuses on single segments of interbank relationships.[12]

Model description

Banks are connected via multiple channels that may amplify contagion

Financial entities are usually connected to each other through several kinds of financial products that link banks' balance sheets in several dimensions and may transfer idiosyncratic risks from one institution to its counterparties. While this mechanism is beneficial in normal times, enabling banks to pool their risks, in bad times the many different interbank connections can become channels of contagion that may amplify the overall effect.[13]

The proposed model of contagion includes three layers of connections: long-term, short-term and common exposures

To embody the different nature of the possible financial products connecting banks, it is useful to introduce a multi-layered framework, where each layer of the network represents a particular kind of link between banks. In order to account for the most common risks in banking activities, the model includes three layers: (i) long-term direct bilateral exposures, reflecting the lending-borrowing network, *L1*; (ii) short-term direct bilateral exposures, representing the liquidity network, *L2*; and (iii) common exposures to financial assets, representing the network of overlapping portfolios, *L3*. The networks on each of the three layers can have very different topological properties, such that each node (bank) may have different neighbouring nodes across different layers (see Figure C.2).

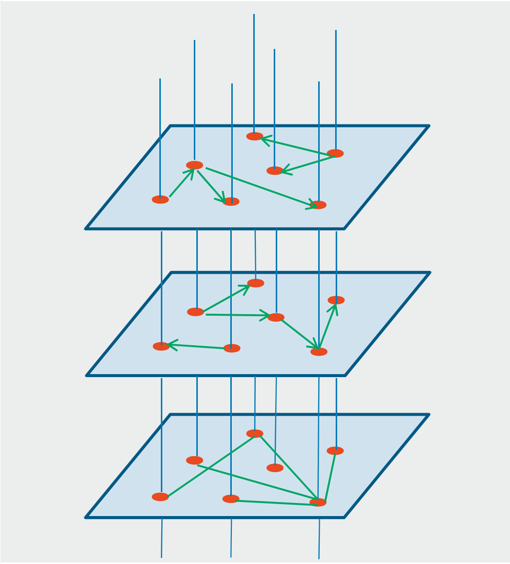
11 This subsection is based on Montagna, M. and Kok, C., "Multi-layered interbank model for assessing systemic risk", *Working Paper Series*, ECB, forthcoming and *Kiel Working Papers*, No 1873, Kiel Institute for the World Economy, 2013.

12 A couple of recent studies likewise highlight the importance of considering the various dimensions of interbank linkages (direct and indirect) for capturing the true contagion risk; see, for example, Gomez, S., Diaz-Guilera, A., Gomez-Gardeñes, J., Pérez-Vicente, C.J., Moreno, Y. and Arenas, A., "Diffusion dynamics on multiplex networks", arXiv: 1207.2788 [physics.soc-ph], 2013; Caccioli, F., Farmer, J.D., Foti, N. and Rockmore, D., "How interbank lending amplifies overlapping portfolio contagion: a case study of the Austrian banking network", arXiv: 1306.3704v1 [q-fin.GN].

13 See also Battiston, S., Delli Gatti, D., Gallegati, M., Greenwald, B. and Stiglitz, J.E., "Default cascades: when does risk diversification increase stability?", *Journal of Financial Stability*, Vol. 8, pp. 138-149, 2010; Fourel, V., Héam, J., Salakhova, D. and Tavolaro, S., "Domino effects when banks hoard liquidity: the French network", *Banque de France Working Paper Series*, No 432, 2013.

Importantly, the interbank network layers are assumed to interact in the sense that shocks are transmitted between layers via balance sheet adjustment mechanisms as banks respond to the shocks in a heterogeneous optimising manner.

Figure C.2 An illustration of a triple-layered network structure



Source: Montagna and Kok (op.cit.).

Interactions between network layers are defined using an agent-based approach

In addition to the multi-layered network structure, an agent-based model is also imposed in this modelling approach to account for the fact that the structure of the network can change owing to banks' reactions to idiosyncratic or system-wide shocks. It is assumed that banks have to comply with minimum risk-weighted capital ratios and that they face liquidity constraints. If a certain shock results in banks' not fulfilling one or both of these predefined (regulatory) constraints, action is taken following a given pecking order.

First, they can decide to withdraw liquidity from the short-term interbank market, thus triggering funding shocks for other banks in the system.

Second, banks can liquidate part of their securities portfolios, which in turn may give rise to "fire sale" losses, also affecting the solvency position of other banks holding similar securities.[14] Banks which cannot fulfil the requirements following these actions are declared to be in default and are liquidated, potentially transmitting losses to their creditors.

Network structures prone to contagion risk are identified by randomly selecting various possible structures of the layers

The model is calibrated using bank balance sheet data for a sample of 50 large EU banks. Bank-level balance sheet information includes data on capital, short-term (maturity of less than three months) and longer-term (more than three months) interbank borrowing and lending, customer deposits, aggregate securities holdings and cash holdings. Information regarding individual banks' bilateral exposures is, however, not available.

In order to identify configurations of the system which are particularly prone to a systemic breakdown in case of an initial local shock, a large number of plausible interbank networks and portfolio structures are generated and the financial resilience of the system under different scenarios is assessed. Networks in layers *L1* and *L2* are generated according to a probability matrix *P,* whose entries represent the probability of a link between two nodes based on existing lending relationships (see Hałaj and Kok, 2013, op.cit.).[15] The network in layer *L3* is derived from a random generation of banks' securities portfolios, where each security belongs to a bank portfolio with a fixed probability *p*.

14 Since the price of the securities is endogenously driven by the amount of securities sold by the banking system, withdrawing liquidity is the cheapest way for banks to improve their capital and liquidity ratios. This implies that, as long as a bank has some short-term interbank assets to liquidate, it will prefer to do this than sell securities.

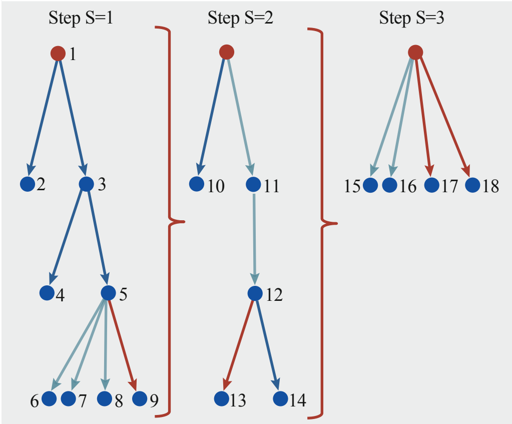
15 Also in this case, a large exposure limit is imposed on the size of bilateral interbank exposures.

Less contagion is observed for networks when considered in isolation

Macro-prudential policy implications

An interesting feature of the model is the possibility to disentangle the effects stemming from the different layers. In other words, the model makes it possible to study how interbank counterparty risk, funding risk and liquidity risk materialise and interact with each other after an initial shock to the system. In this set-up, the idiosyncratic risk of single institutions is shared not only with its direct counterparties, which are likely to be aware of the risks taken, but also with other players not directly connected to the institution, which are unlikely to be fully aware of the potential risk transfers.

Figure C.3 An illustration of the propagation mechanism across different network layers



Source: Montagna and Kok (op.cit.).
Note: The blue arrows indicate layer L1, the light green arrows indicate layer L2 and the red arrows indicate layer L3.

Simulations performed on a model of a real banking system show that an idiosyncratic shock to a bank on one layer can be transmitted between layers, increasing the overall number of defaults

Figure C.3 provides an illustration of how the transmission of shocks across the different layers is likely to amplify the impact compared with a situation where only shocks within single network segments are considered. In the left-hand panel, an initial shock to bank *1* results in the default of four additional banks via their direct bilateral counterparty exposures. If only this segment of the multi-layered interbank relationships is analysed (as is typically the case in network-based contagion literature), the shock propagation would be assumed to stop at this point. However, in the example, it can be seen that the default of bank *5* results in further bank defaults owing to contagion via the short-term funding channel and via the common exposure channel. The joint defaults of the nine banks (reflected in the red "super-node" in the middle panel of Figure C.3) result in the default of five additional banks. This process continues until no further defaults are triggered. In this example, a total of 18 banks default (compared with five if only the direct bilateral exposures are considered).

The amplification of interbank contagion effects when considering the shock propagation across multiple layers of bank interrelations is further illustrated in Charts C.3 and C.4 which show the results of 1 million simulations of the multi-layered network model.

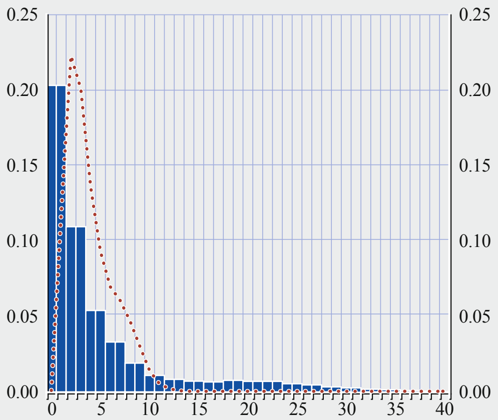
Strong non-linear effects emerge from the interactions between the layers

The key point to notice is the non-linear effects that emerge when dynamic interactions across different network layers are taken into account. Chart C.3 shows the contagion effects when one large bank defaults, comparing the situation when network layers are considered in isolation (red dotted line in the chart) and the situation when all three layers are considered simultaneously, allowing for interactions between them (blue columns). While in the majority of network configurations there are no substantial differences between the two dimensions, in the tails of the distributions the number of defaults triggered when all three layers are considered at the same time substantially exceed those triggered when the three network segments are considered in isolation.

Chart C.4 shows the dynamics of the contagion process for one specific network configuration of the multi-layered network (based on the default of the same bank as in Chart C.3). Again, the amplifying effects of having a multi-layered network structure is clearly visible given that the cumulated number of defaults when considering the full system of interbank layers largely exceeds the number of defaults resulting when only accounting for contagion effects in parts of the system.

Chart C.3 Number of defaults triggered by one bank defaulting – with and without multi-layered network interactions

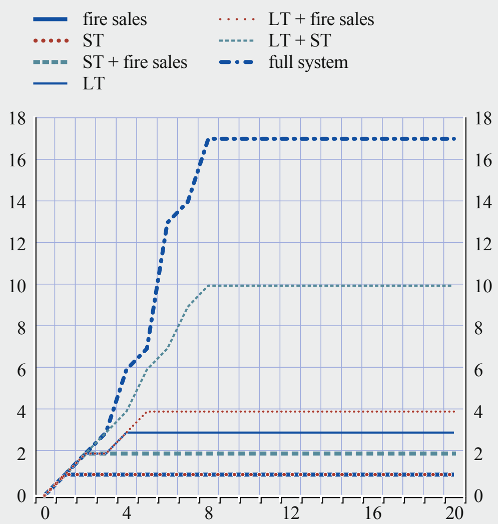
(x-axis: number of bank defaults; y-axis: density)



Source: Montagna and Kok (op.cit.).
Notes: Distribution of defaults across 1 million simulated network configurations. The blue bars represent the number of defaults when all three layers are considered simultaneously. The red dotted line reflects the sum of the number of defaults across the three layers when they are seen in isolation.

Chart C.4 The amplifying effects of multi-layered networks

(x-axis: time periods; y-axis: number of bank defaults)



Source: Montagna and Kok (op.cit.).
Note: "LT" refers to long-term direct bilateral exposures (layer L1), "ST" refers to short-term bilateral exposures (layer L2) and "fire sales" refer to common securities exposures (layer L3).

CONCLUDING REMARKS

Identifying the critical links in interbank networks and reducing their strength using dedicated macro-prudential policy instruments should help make the financial system safer. The interbank network models presented in this special feature focus especially on this dimension of prospective macro-prudential policies. More specifically, the article shows that certain macro-prudential policy instruments, available to the ECB in the context of the single supervisory mechanism (SSM), could potentially be effective in pulling interbank network structures in a direction which makes the overall system more resilient.

The strengthening of capital and liquidity buffers should, all things being equal, make the risk of contagion less probable, as individual banks would be more resilient and less prone to transmitting shocks to their counterparties.

In addition, efforts should be made to avoid triggering contagion. This requires the mitigation of systemic risks before they reach tipping point, for example, by preventing the build-up of financial imbalances.

Looking forward, in order for the ECB's macro-prudential policy function, in cooperation with national macro-prudential authorities, to be able to tailor its policy actions along the lines highlighted in this article, it will be of crucial importance that the macro-prudential regulator has proper access to the relevant data so as to be able to map the most important elements of interbank relationships. In addition, further work is needed on the analytical tools for modelling interbank networks and on the impact of macro-prudential tools on complex financial systems.