EUROPEAN CENTRAL BANK

EUROSYSTEM

Working Paper Series

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No 2883

Financial Contagion within the Interbank Network

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Abstract

The analysis of contagion in financial networks has primarily focused on transmission channels operating through direct linkages. This paper develops a model of financial contagion in the interbank market featuring both direct and indirect transmission mechanisms. The model is used to analyse how shocks originating from outside sectors impact the functioning of the interbank market and investigates the emergence of instability in this setting. We conduct simulations on actual interbank bilateral exposures, constructed manually from a supervisory dataset reported by the largest euro area banks. We find that while the impact of direct contagion increases gradually with the shock intensity, the effect of indirect contagion is subject to threshold effects and can increase abruptly when the threshold is exceeded. In addition, the risk posed by indirect contagion has a higher upper bound compared to direct contagion. Finally, we find that in terms of overall impact, the shocks to the value of sovereign debt and non-bank financial institutions represent the most significant risk to the functioning of the interbank market.

Keywords: Banking sector, Funding concentration risk, Contagion, Network analysis

JEL classification codes: G01, G21, G23, D85

Non-technical summary

In the aftermath of the 2008-2009 financial crisis, the presence of multiple links between the financial institutions is viewed not only as a sign of a well-functioning and diversified financial system but also as a potential risk to financial stability. Risk can be transmitted within an interconnected financial system through both direct contagion channels, i.e., due to contractual obligations present between economic agents, and indirect mechanisms such as fire sales leading to depressed asset values and impacting banks' balance sheets, risk realisation in correlated portfolios, asymmetric information and the updating of imperfect information or beliefs. In addition, risk transmission depends significantly on the topology of the network formed by the contractual links between financial institutions.

This paper builds a model of financial contagion that incorporates both direct and indirect contagion mechanisms and is calibrated on actual interbank data. Specifically, the model features sector-specific shocks both on the asset and the liability side, the hoarding of existing interbank funding as a response to liquidity strains while also featuring pro-cyclical haircuts and time-varying risk aversion that operate across the banking network. The analysis is grounded on an actual network of liquidity interconnections constructed based on supervisory data reported by all significant institutions (SIs) of the euro area countries as these institutions are designated by the European Central Bank (ECB), i.e., mainly large and interconnected credit institutions.

Overall, we find that the impact of indirect contagion features a relatively large additional impact for a relatively small increase in the shock intensity, for example in the case of shocks to the government sector. Furthermore, the relative contributions of direct and indirect contagion are negatively correlated, with that of indirect contagion exceeding direct contagion for large values of the shock intensity. In addition, the upper bound of impact due to indirect contagion is significantly higher compared to that of direct contagion and can potentially affect the whole network. Overall, indirect contagion has the potential to substantially dominate the contagion phenomenon, especially during most severe shocks. This conclusion casts doubt in the focus on transmission channels propagating only through contractual connections that features in much of the existing literature. In addition, our results have important implications for the design of macro-prudential policy pointing to the need for focusing on indirect contagion channels.

1. Introduction

In the aftermath of the 2008-2009 financial crisis, the interconnectedness of the financial institutions is viewed not only as a sign of a well-functioning and diversified financial system but also as a potential risk to financial stability. Theoretical models have been used to analyse the benefits of interconnectedness as well as vulnerabilities emerging due to a dense interbank market. A consensus seems to have emerged that tipping-point effects exist so that as the strength of the impinging shock increases there is a threshold beyond which interconnectedness could lead to wide spreading and amplification of risk rather than enabling the absorption of the initial shock. Seminal papers in this literature include Allen and Gale (2000), Gai et al. (2011) and Acemoglu et al. (2015) while analyses calibrated through empirical data have also appeared (see Chinazzi et al., 2013; Silva et al., 2017; Bardoscia et al., 2019, among others).

The literature examining the emergence of instability within an interconnected financial system has so far focused mainly on direct contagion channels, i.e., due to contractual obligations present between economic agents. Usually, the risk is not found to be significant when only direct channels are considered, as the initial triggering shock can be contained, either through its absorption within the network or policy interventions (Sheldon and Maurer, 1998; Allen and Gale, 2000; Freixas et al., 2000; Furfine, 2003; Wells, 2004; Upper, 2011; Summer, 2013; Elliott et al., 2014). However, the transmission and amplification of stress through an interconnected financial system was evident during the global financial crisis that erupted in 2008 and the various waves of the European debt crisis after 2010.

Indirect mechanisms have also been investigated, such as fire sales leading to depressed asset values and impacting banks' balance sheets (Cifuentes et al., 2005; Caccioli et al., 2015; Caballero and Simsek, 2013; Anand et al., 2013), risk realisation in correlated portfolios (Lagunoff and Schreft, 2011), asymmetric information (Heider et al., 2015) and the updating of imperfect information or beliefs (Arinaminpathy et al., 2012; Benzoni et al., 2015; Ahnert and Georg, 2018). Some studies have examined the interplay of both direct and indirect transmission channels either in theory (Elliott et al., 2014) or in networks generated by algorithms that complement aggregate data (Aldasoro and Faia, 2016; Roncoroni et al., 2021). See also Clerc et al. (2018) for a discussion on the policy implications of indirect contagion channels. This literature however has not compared the impact of direct and indirect transmission channels, nor the qualitative differences in the risk profile attributed to the respective channels.

Understanding the risk posed by the various transmission mechanisms is also complex because real world networks present significantly more sources of heterogeneity compared to the networks usually examined in theoretical analysis, such as for example different balance sheet size and composition of each institution present in the network. Furthermore, the limitations of datasets used in existing empirical analyses do not usually allow an investigation of the main sources of risk e.g. through exposures to outside sectors (see Glasserman and Young, 2016, for a review) while in the majority of cases the networks to be analysed are reconstructed using partial data on aggregate exposures (using e.g. algorithms like the maximum or minimum entropy, see e.g. Halaj and Kok, 2013) or are based on real data of interbank connections only for very specific types of exposures (e.g. syndicated loans). Assuming away heterogeneity or imposing an arbitrary network structure can significantly impact the assessment of the contagion potential within a network, due to the different stability properties between homogeneous networks and networks featuring power law distributions, the sensitivity of the stability properties of heterogeneous networks and, in general, the complex properties emerging from the interplay between banks' size and balance sheet composition and the network topology (see e.g. Iori et al., 2006; Mistrulli, 2011; Banwo et al., 2016; Roncoroni et al., 2021).

This paper contributes to the literature in the following ways. First, we extend the modelling framework presented in Gai et al (2011) to examine both direct and indirect contagion mechanisms and their interplay. Our analysis incorporates the hoarding of existing interbank funding as a response to liquidity strains while also featuring pro-cyclical haircuts and time-varying risk aversion that operate across the banking network. We run simulations conditional on the operation of different transmission mechanisms and quantify the relative contributions of direct and indirect channels to the total impact of each shock scenario and to the robust-yet-fragile property of the network.

Second, our analysis is grounded on an actual network of liquidity interconnections constructed based on supervisory data reported by all significant institutions (SIs) of the euro area countries as these institutions are designated by the European Central Bank (ECB) i.e. large and interconnected credit institutions.[3] Given the intended use of these supervisory data for micro-prudential supervision, a significant amount of manual work was required to construct the financial network from the raw data. The use of this dataset allows us to avoid a number of simplifying assumptions used in the literature and to consider realistically heterogeneous networks, e.g., encompassing multiple types of bilateral links,[4] and avoid imposing an arbitrary network structure by reconstructing bilateral links from the aggregates exposures, as is common in the literature. As far as we are aware, this is one of the first papers that investigates contagion within an extended interbank network that is constructed from real bilateral linkages, therefore featuring a realistic degree of heterogeneity, under the simultaneous operation of direct and indirect contagion channels.[5]

This paper also investigates the impact of shocks originating from non-financial sectors, e.g. non-financial corporations (NFCs), or other segments of the financial system, e.g. central clearing counterparties (CCPs). In other words, we consider not only interconnectedness within the interbank network but also between the interbank network and outside sectors. The examination of the different impact of shocks originating from these external sources enables the identification and ranking of the risks to the SI interbank network. This is critical for macro-prudential policy and contributes to the existing literature which usually investigates contagion starting from random, unspecified shocks impinging on a set of banks.

Our analysis points to a significantly different relationship between the impact of direct or indirect transmission channels on the one hand and the shock intensity on the other. The impact of indirect contagion is subject to strong cliff effects, whereby the additional impact for a relatively small increase in the shock intensity may be substantial, much more so than the impact originating from direct contagion, which exhibits a relatively proportional relationship with the shock size. The risk contribution of indirect contagion tends to exceed that of direct contagion. Additionally, the impact due to indirect contagion exhibits a higher upper bound

[3] Specifically, the set of 'significant institutions' comprises credit institutions that are directly supervised by the ECB and are mainly characterised by their size (total value larger than €30 billion), economic importance, cross-border activities and whether the entity has received funding from the European Stability Mechanism.

[4] As the global financial crisis that erupted in 2008 showed, the initial shock that triggered multiple contagion mechanisms originated outside the banking sector and was transmitted through multiple channels and markets e.g. the repo market (Copeland et al., 2014), the CDS market (Caporin et al., 2018) or the syndicated loans market (Hale 2012).

[5] Another paper is Anderson et al. (2019) who use data on US bilateral interbank exposures in two years, 1862 and 1867, to examine the stability properties of the interbank network. In the 19th century banks had bilateral exposures only through deposits while in our analysis we consider also repos and other types of securities financing transactions which feature prominently in a modern interbank market.

compared to that attributed to direct linkages. Overall, we find that indirect contagion has the potential to substantially dominate the contagion phenomenon, a conclusion which casts doubt in the focus on transmission channels propagating only through physical connections that features in much of the existing literature. In addition, our results have important implications for the design of macro-prudential policy pointing to the need for focusing on indirect contagion channels.

Finally, we find that shocks to shadow banks, central clearing counterparties and other financial institutions besides banks could have a strong impact to the large banks' interbank network, pointing to the potential of contagion in the banking system through liabilities towards the non-banking financial sector. Furthermore, risk stemming from the sovereign bond holdings of banks seems to also represent a primary source of risk. These results also have important implications for the design of appropriate micro- and macro-prudential regulation and policy tools to address liquidity and contagion risks in the interbank market.

The remainder of the paper is organized as follows. In Section 2, we specify the modelling framework and the underlying banks' behavioural assumptions. Section 3 presents the compilation of network data from the underlying supervisory data and elaborates on the salient features of the reconstructed financial network. Section 4 provides a discussion of our results. Finally, Section 5 concludes.

2. Model

Our modelling framework builds upon Gai et al (2011) but with a number of enhancements. We incorporate mechanisms of both direct and indirect contagion for which there is empirical evidence that they played a significant role in the propagation of the global financial crisis that erupted in 2007-2008 (see Clerc et al. 2018 for a literature review). Therefore, we can capture a wide spectrum of dynamics emerging from the interplay between the various transmission channels that propagate and amplify an initial shock through the interbank network. Specifically, shock transmission channels are distinguished in our model across two dimensions. First, we consider both direct contagion, due to banks' contractual obligations with each other, and indirect contagion, which manifests through the externalities generated by banks' actions on prices and on risk aversion, even in the absence of direct links. Second, contagion is caused by the realisation of both funding liquidity risk and market liquidity risk

(Brunnermeier and Pedersen 2009). We populate the network using a real dataset of mutual exposures for the interbank market in the euro area and thus take into account the effect of heterogeneity in balance sheet composition, especially of the funding sources and high quality assets (HQLAs) that can be used to address funding shocks.

The model considers a set of banks indexed by $i = 1,..N$ which have bilateral exposures to each other, by means of contractual agreements through various financial instruments (e.g. both secured and unsecured loan contracts). In addition, there are $s = \{1, \dots, S\}$ outside sectors, such as households, non-financial corporations, central banks etc, to which banks are also linked, either on the asset or on the liability side, thus forming a set of external links. [6] The banks hold liquid instruments as a buffer to address unexpected liquidity shortfalls. Consequently, the financial network is characterized by a tuple $G = (V, E)$ comprising a set $V = \{1, \dots, N + S\}$ of nodes (banks and outside sectors) and a set $E \subseteq V \times V$ of edges (exposures). Each link e_{ij} represents a financial contract (or a portfolio of financial contracts in case one of the edges refers to a sector), such as loans, repos, holding of securities etc, which represents an asset for bank (or outside sector) i and a liability for bank (or outside sector) j.[7]

2.1 Banks' liquidity position

Our model focuses on contagion through liquidity shocks and therefore it assumes a short-term horizon, e.g., a 30-day order of magnitude as featured in the liquidity coverage ratio (LCR), which was introduced as part of the post-2007 crisis regulatory reforms. The LCR is defined as the ratio of unencumbered high-quality liquid assets (HQLAs) to the net outflows during a 30-day time window and requires that banks should hold an adequate amount of HQLAs that is sufficient to counterbalance funding disruptions in a liquidity distress scenario.

Consequently, in our analysis we focus on the parts of the balance sheet that are critical for short-run liquidity crisis. On the asset side, HQLAs can be utilised at short notice to secure liquidity (either by selling them for cash or by pledging them as collateral) while collateral that has been received under reverse repo transactions can be re-hypothecated with liquidity

[6] Each outside sector is considered as a single entity.

[7] A link e_{ij} can be also a sum of financial contracts in the case that bank i is connected to bank j through more than one financial contract, e.g., bank i has both purchased a debt security issued by bank j and has a reverse repo with bank j.

providers (i.e. used as collateral to secure funding in a new transaction).[8] On the liabilities side, we concentrate on wholesale funding, specifically on repos and unsecured liabilities, which can disappear swiftly in the presence of negative news. The HQLAs and wholesale funding instruments determine the formation of the directed edges e_{ij} that represent the interbank linkage between bank (or an outside sector) i and bank (or an outside sector) j in the financial network G.[9] Figure 1 depicts the balance-sheet structure for the asset and liability side indicating the financial instruments that are relevant for liquidity.

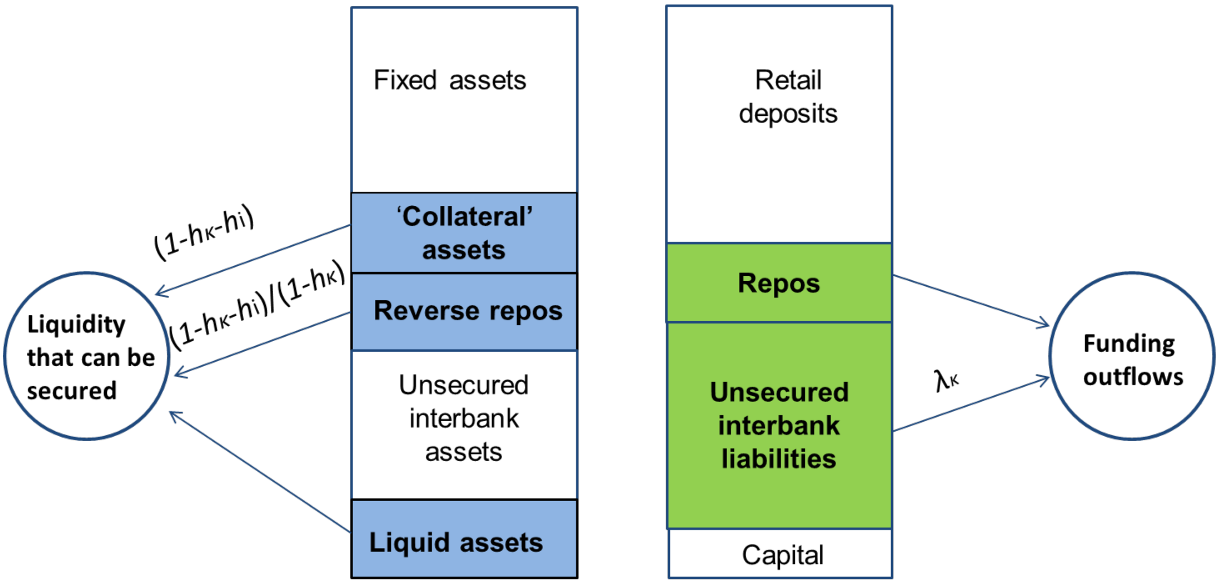


Figure 1: Components of the banks' balance sheet that are used to determine banks' liquidity ratio. The h parameters refer to haircuts on the amount of funding that can be obtained by the corresponding assets while λ refers to the rate of outflows.

In more detail, we distinguish on the asset side between collateral assets, reverse repo contracts and off-balance sheet assets. Collateral assets A_{ik}^{C} held by bank i could refer to different instruments either with a bank or an outside sector as a counterparty, i.e., $k \in \{1 \dots N, 1 \dots S\}$ or with no counterparty in the case, e.g., of commodities such as gold. Collateral assets could be bonds of various seniority degrees (covered, senior or subordinated bonds), commercial paper, shares in an investment fund, asset-backed securities, credit claims, shares of a listed

[8] Our dataset does not contain information on loans or unsecured assets which are not HQLAs, however these instruments are not especially relevant during liquidity shocks and under the considered time frame as they cannot be readily sold for cash or pledged as collateral to secure funding.

[9] Please note that it is not possible that both i and j are outside sectors, i.e., we do not consider links between outside sectors.

company and gold, that can all be used as collateral to secure liquidity. Reverse repo contracts, denoted as A_{ik}^{RR}, represent exposures whose collateral can be rehypothecated to obtain additional liquidity. In addition, we consider off-balance sheet items L_{ik}^{N} representing undrawn credit facilities offered to bank i by another institution.

The aforementioned assets can be utilised to address funding shortfalls, yet the amount of liquidity that they secure is not always equal to their nominal value. For the collateral assets the amount of liquidity is decreased by the market haircut, while for a reverse repo contract the assets that can be rehypothecated are already a multiple of the nominal value (as the lending bank has already applied a haircut when acquiring the collateral) and the final amount of liquidity is determined by the current market haircut and the collateral received. Finally, we assume henceforth that off-balance sheet items can be fully utilized to secure liquidity.[10] The one type of shock that we consider in our simulation is an increase in the haircuts applied to the asset side items.

On the liability side, wholesale funding from other financial or non-financial institutions is included comprising both secured funding (e.g., repos), denoted by $L_{ik,t}^{S}$, and unsecured funding, denoted by $L_{ik,t}^{U}$. As the experience of the 2007 financial crisis clearly illustrated, this source of funding is more prone to liquidity contagion. Therefore, the second type of shock scenario that we consider features the withdrawal of part of banks' wholesale funding.

The stability of each banks' liquidity position is reflected at each point in time by the LCR measure, which is based upon banks' liquidity-relevant exposures. Specifically, each bank i calculates at time t the LCR ratio[11] as follows:

$$LCR_{i,t} = \frac{\sum_{k=1}^{K^C(i)} \left(1 - h_k^{CB} - h_{i,k,t}\right) A_{ik,t}^{C} + \sum_{k=1}^{K^{RR}(i)} \frac{\left(1 - h_k^{CB} - h_{i,k,t}\right)}{1 - h_k^{CB}} A_{ik,t}^{RR} + \sum_{k=1}^{K^N(i)} L_{ik,t}^{N}}{\sum_{k=1}^{K^U(i)} \lambda_{k,t}^{U} L_{ik,t-1}^{U} + \sum_{k=1}^{K^S(i)} \lambda_{k,t}^{S} L_{ik,t-1}^{S}}$$

The numerator of $LCR_{i,t}$ covers the HQLAs, while the denominator comprises the wholesale funding sources. In particular, the numerator gathers the amount of liquidity that can be secured

[10] This is just to avoid a proliferation of parameters, as the results we obtain below are not dependent on this assumption.

[11] The calculations that we perform using this ratio do not reproduce banks' reported LCR ratio as defined by Basel III. The latter ratio includes the whole banks' balance sheet (using lower weights for the instruments that are not so relevant from a liquidity perspective and that we are not considering in this analysis, such as loans to real economy agents). The use of an LCR ratio that focus on the instruments for which we have granular information allows us to conduct the simulation analysis that follows and captures better the concentrated risk on the most important counterparties.

by collateral assets $A^{C}_{ik,t}$, reverse repo contracts $A^{RR}_{ik,t}$ and undrawn credit facilities (i.e. off-balance items) $L^{N}_{ik,t}$.[12] For each bank i, the set of HQLAs consists of $K^{C}(i)$ individual collateral assets, $K^{RR}(i)$ reverse repo contracts and $K^{N}(i)$ off-balance sheet or new unsecured funding items, with $K^{C}(i), K^{RR}(i), K^{N}(i) \in \mathbb{Z}$. Each of the items in the category of collateral assets or reverse repos is affected by different haircut parameters h (the haircut specification is elaborated in the next section).

The denominator distinguishes between the $K^{U}(i)$ items of unsecured interbank liabilities which are represented by $L^{U}_{ik,t} = \lambda^{U}_{k,t} L^{U}_{ik,t-1}$ and the $K^{S}(i)$ secured funding items, denoted by $L^{S}_{ik,t} = \lambda^{S}_{k,t} L^{S}_{ik,t-1}$, which include repos plus other secured funding items. The parameters $\lambda^{U}_{k,t}$ and $\lambda^{S}_{k,t}$ determine the rate of withdrawal of banks' funding from each counterparty k at time t and therefore are pivotal in the unfolding of the contagion process. Specifically, the values $\lambda^{U}_{k,t} = 1$ and $\lambda^{S}_{k,t} = 1$ correspond to full withdrawal of funding offered by bank k and consequently the maximum possible adverse impact that bank i, receiving funding, experiences.

2.2 Haircuts

An expanding literature has identified that financial instability can be caused by financial institutions' procyclical behaviour[13] regarding margins and haircuts that amplifies an initial shock and lead to the unfolding of a contagion cascade. Brunnermeier and Pedersen (2009) describe a destabilizing feedback effect between traders' funding conditions and market liquidity, that is fuelled by asymmetrical information about the fundamental value of assets. Margin requirements increase price volatility while market illiquidity can further increase margins leading to liquidity spirals. Specifically, contagion takes place as "uninformed" market participants use past volatility to set margins and assume that price volatility fully incorporates fundamental factors. The term "uninformed" refers to the fact that the information set of these market participants includes only the observed prices of securities rather than the intrinsic values.

[12] Undrawn committed liquidity lines are available in our dataset. Gai et al (2011) set this instrument as zero.

[13] Building on the leverage cycle concept developed in Fostel and Geanakoplos (2008) and Geanakoplos (2010), the various sources of procyclical behavior in interbank markets have been reported by Adrian and Shin (2010), Perotti and Suarez (2011), and Tasca and Battiston (2016), among others.

Formally, margins are set so that they cover a position's value-at-risk (VaR) for a level α:

$$\alpha = Pr\left(-\Delta p_{k,t+1} > h_{k,t} | \mathcal{F}_t\right)$$

where $h_{i,k,t}$ is the haircut applied when receiving a security as collateral in return for lending. In other words, the haircut requested by an institution that extends liquidity in return for a security k which is pledged as collateral at time t and conditional on the information set $\mathcal{F}_t$, depends on the probability a of a decrease in the price of the security by an amount $-\Delta p_{k,t+1}$ that would exceed the amount of margin.

The difference of the price from its fundamental value $\upsilon_{k,t}$ is defined as:

$$\Lambda_{k,t} = p_{k,t} - \upsilon_{k,t}$$

where $\upsilon_{k,t}$ is the expected value of the security at its expiry date, i.e., $\upsilon_{k,t} = \mathbb{E}_t[\upsilon_k]$.

In addition, it is assumed that fundamental value changes depend on past volatility in the following way,

$$\Delta \upsilon_{k,t} = \sigma_{k,t} \varepsilon_{k,t}$$

where the shocks ε follow a probability distribution Φ and the dynamics of the volatility are given by,

$$\sigma_{k,t} = b + c\left|\Delta \upsilon_{k,t-1}\right|$$

for $b, c \geq 0$, so that changes in fundamentals increase future volatility.

The assumptions about the content of the information set $\mathcal{F}_t$ determine whether margins will be procyclical or not. Under the full information assumption, $\mathcal{F}_t$ includes all prices, shocks and fundamental values up to time t. Under a bounded rationality assumption, the corresponding information set $\mathcal{F}_t^{BR}$ includes all observed prices of securities which are being exchanged in the interbank market, i.e. $\mathcal{F}_t^{BR} = \{\mathbf{p}_0, \dots, \mathbf{p}_t\}$[14] with $\mathbf{p}_{t'}, t' = 1, \dots, t,$ is a vector of all prices. Therefore, in the latter case the banks observe neither the fundamental value nor the shocks to the system, but only the prices. Faced with this information set the banks assume that

[14] The critical assumption here is that the banks do not observe expected fundamental value, but only the observed price that reflects also market frictions like liquidity shocks.

$$\mathbb{E}_t^{BR}\left[v_{k,t}|\mathcal{F}_t^{BR}\right] = p_{k,t}$$

where $\mathbb{E}^{BR}$ denotes banks' boundedly-rational expectations characterised by the limited information set $\mathcal{F}_t^{BR}$ that includes only observable prices, which also reflect market frictions like liquidity shocks.

Under the full information assumption

$$\alpha = Pr\left(-\Delta p_{k,t+1} > h_{i,k,t}|\mathcal{F}_t\right)$$

$$= 1 - \Phi\left(\frac{h_{i,k,t} - \Lambda_{k,t}}{\sigma_{k,t}}\right)$$

which leads to

$$h_{i,k,t} = \Phi^{-1}(1-\alpha)\left[b + c\left|\Delta v_{k,t-1}\right|\right] + \Lambda_{k,t}$$

The first term, $\Phi^{-1}(1-\alpha)\left[b + c\left|\Delta v_{k,t-1}\right|\right]$, represents the haircut component that protects from volatility, thus the higher the volatility of the fundamental value, $\left|\Delta v_{k,t-1}\right|$, the higher the haircut requested for lending. The term $\Lambda_{k,t}$ corresponds to the haircut component due to the deviation of prices from fundamental values. Consequently, in the absence of informational frictions, haircuts would be stabilised by $\Lambda_{k,t}$ as when the prices remain lower than the fundamentals (i.e., $\Lambda_{k,t} < 0$) the haircuts would be lowered, thus facilitating trading and price correction.

However, when the market participants are not aware of the fundamental price, the haircut-setting formula above becomes

$$h_{i,k,t} = \Phi^{-1}(1-\alpha)\left[b + c\left|\Delta p_{k,t-1}\right|\right]$$

In this case, the dependence of haircuts from the price deviation from fundamentals would change:

$$h_{i,k,t} = \Phi^{-1}(1-\alpha)\left[b + c\left|\Delta v_{k,t-1} + \Delta\Lambda_{k,t-1}\right|\right]$$

So that haircuts increase depending on the shock to fundamental volatility and the change in the deviation of prices from fundamentals. In this case, when the observed price decreases, the haircuts will tend to increase and this could further destabilise the market by inhibiting trading and price correction. Both the deviation of prices from fundamentals and the change in fundamentals feature during periods of uncertainty. Therefore, a link between higher margins and uncertainty can be established, consistent with historical crisis episodes.

Our dataset contains the haircut parameter that would be applied for central bank operations for every asset.[15] This haircut parameter is denoted by $h_{k,CB}$ and is defined as

$$1 - h_k^{CB} = \frac{\text{Collateral value at the Central Bank}}{\text{Nominal value of security}}$$

During periods of market volatility the haircut value could be increased further. This component is more pronounced during a crisis as market information is then scarcer, and the information set $\mathcal{F}_t$ of market participants consists mainly of the observed prices rather than the fundamental values. The total haircut can therefore be decomposed into

$$h_{i,k,t} = h_k^{CB} + \Delta h_{k,t}$$

Gai et al. (2011) assume that the bank-specific component is zero, $\Delta h_{k,t} = 0$, however margin adjustments due to counterparty risk seem to be an important feature of real interbank markets. For example, Dang et al. (2013) show that riskier counterparts would face higher haircuts in a repo transaction.

The $\Delta h_{k,t}$ haircut component, reflects both the counterparty risk as well as the liquidity component

$$\Delta h_{k,t} = \Delta h_{k,t}^{counterparty\ risk} + \Delta h_t^{market-wide}$$

The first term reflects the riskiness of the bank that uses the collateral, i.e., the more risky a bank is perceived, the higher the haircut that will be demanded by the creditor counterparty, whereas the second term depends on the interbank market conditions and the elevated degree of risk aversion that would be heightened during periods of systemic stress and deteriorated market conditions.

In general, the deterioration of the liquidity coverage is linked with increased haircuts: $\Delta h_{k,t}^{counterparty\ risk} = g\left(LCR_{k,t} - LCR_{k,t-1}\right)$ with $\frac{\partial \Delta h_{j,t}^{counterparty\ risk}}{\partial\left(LCR_{j,t} - LCR_{j,t-1}\right)} < 0$. Through the

[15] Credit quality and liquidity are the main criteria determining the central bank haircut. For example, Blindseil et al. (2017, p. 37 and p. 51) states that the haircut framework considers both market and credit risk for liquid assets such as sovereign bonds. The model presented in Li et al. (2012) predict higher haircuts for less liquid assets.

$\Delta h_t^{market-wide}$ term a relationship between haircuts and the interbank market conditions can be posited (see the next Section 2.3 for the specification of $\Delta h_t^{market-wide}$).

2.3 Behavioural rules

We introduce a set of behavioural rules that captures the operation of different contagion channels. The first behavioural response refers to the *direct liquidity effect* consisting of liquidity hoarding in the face of liquidity shortfalls, following Gai et al. (2011, p. 459) and Silva et al. (2017). This is consistent with the theoretical literature (e.g., Diamond and Rajan, 2011) and the empirical studies that confirm this theoretical prediction (e.g., De Haan and Van den End, 2013).[16] This channel is activated when the LCR falls below a certain threshold and then bank i hoards liquidity that so far has been provided to other banks in the interbank network. Concretely, a bank hoards liquidity when the liquidity coverage becomes lower compared to its initial level beyond a specific threshold

$$\frac{LCR_{i,0} - LCR_{i,t}}{LCR_{i,0}} > \rho(\varepsilon_{i,t})$$

where ρ is a function of bank's risk aversion $\varepsilon_{i,t}$ to liquidity risk. [17] Initially, the value of the risk aversion parameter $\varepsilon_{i,0}$ is equal to zero. Higher sensitivity $\frac{\partial \rho}{\partial \varepsilon_{i,t}}$ means that bank i is more responsive to a deterioration of its liquidity position and will hoard liquidity following a relatively smaller degree of LCR deterioration.[18]

Given that $LCR = LCR(\{A_{ik}^{RR}\}, \{A_{ik}^{C}\}, \{L_{ik}^{N}\}, \{L_{ik}^{U}\}, \{L_{ik}^{S}\}, \{h_k^{CB}\}, \Delta h^{market-wide}, \varepsilon_{i,t})$, the direct liquidity channel is triggered by both shocks on banks' balance sheet (either outflows of

[16] Fire sales however are indirectly also considered in our model through the haircut channel, as selling of assets is the primary response of other types of financial institutions that are not modelled here (such as equity funds) to liquidity pressures (Hau and Lai, 2017) and therefore depressed prices of assets could also feature during a crisis episode.
[17] Therefore, institutions will perform no action if the decrease in their *LCR* is below a threshold, similarly to Cont and Shaanning (2017). This is in contrast to 'leverage targeting' models, e.g., as used in Greenwood et al (2015), which prompt symmetric reactions by banks around target ratios, also for arbitrarily small deviations.
[18] We also experimented with an alternative formulation, whereby the level of *LCR* was also considered, i.e., only banks for which the ratio fell below a certain threshold would hoard liquidity. As expected, this formulation made the system more stable, as the condition that would lead to liquidity hoarding was satisfied less frequently. However, it did not change qualitatively our conclusions. One reason for this result, is that in our sample there is no clear relationship between the *LCR* and measures of banks' systemic importance, such as size. To avoid the further proliferation of parameters, we present results using the simpler formulation of the text. The results obtained using the alternative formulation are available upon request.

funding or valuation impact on the asset side) and indirect contagion, through the haircut component $\Delta h_t^{market-wide}$ (market liquidity risk) and the risk aversion parameter $\varepsilon_{i,t}$ (funding risk), which is linked to the hoarding behaviour of the counterparties from which bank i receives funding. Therefore, the various transmission channels feed into each other. The modelling of indirect contagion through the parameters $\Delta h_t^{market-wide}$ and $\varepsilon_{i,t}$ is described in the paragraphs that follow.

Theoretical work has shown that funding shocks can negatively affect market liquidity (Brunnermeier and Pedersen 2009; Gromb and Vayanos 2010; Dudley 2016), so financial institutions that would normally engage in market-making, e.g., brokers and dealers, cannot easily obtain the required funding to perform their intermediation role. As a result, market liquidity is impaired, leading to further disruptions on the funding liquidity of individual entities.[19] The potential impact of funding disturbances to market liquidity provides the motivation to incorporate this mechanism into our model, specifically through the haircuts applied to the financial instruments.[20]

Specifically, the more banks are affected by funding liquidity shocks and withdraw their provision of liquidity from the market, the ensuing lack of depth of the market would impair price discovery of the fundamental value of financial securities. Therefore, it is plausible to assume that, during a distress period, the information set $\mathcal{F}_t$ of market participants is restricted to the observed prices. Under these conditions, the haircuts will tend to be pro-cyclical and a positive relation can be assumed between the extent to which banks hoard liquidity and the increase in the overall level of haircuts. Brunnermeier and Pedersen (2009) call this phenomenon *margin spirals*. Heider et al (2015) also find that a higher level and dispersion of risk within the interbank market, decrease lenders' willingness to lend and lead to the rationing of interbank lending. This link between the haircut component $\Delta h_t^{market-wide}$ and the number of banks in the market that are hoarding liquidity is included in our model through

$$\Delta h_t^{market-wide} = f(\bar{n}_t)$$

[19] According to a survey conducted by the European Systemic Risk Board (ESRB 2016) among the thirteen largest market makers in Europe, the scarcity of repo financing has a negative impact on market liquidity.
[20] Market liquidity is also reflected in the trading volume and the amount of market-makers' inventories, however our model emphasises the role of haircuts rather than that of volumes, given also our focus on the short-run.

where $\bar{n}_t$ is the number of banks hoarding liquidity at t.[21] The specification we use for f is that $f(\bar{n}_t) = min(1, \delta\bar{n}_t)$, where δ is the premium on haircut that is charged in the market for every additional bank which faces liquidity shortages, e.g. $\delta = 0.02$ means a 2% increase in haircuts after each additional bank in the network hoards liquidity. We call this mechanism as the *pro-cyclical haircut effect* that captures the way that worsening funding liquidity feeds into tighter market liquidity conditions. The pro-cyclical haircuts mechanism represents an indirect contagion mechanism as it is not caused by the direct contractual links between banks.[22]

Additionally, changes in the risk aversion parameter $\varepsilon_{i,t}$ lead to an indirect informational contagion channel operating through liquidity funding risk. This *risk aversion effect* posits that whenever a bank's liquidity position, as reflected in the LCR, deteriorates to the extent that the bank hoards liquidity, the counterparties receiving funding from that bank are becoming more risk averse with respect to the assessment of their liquidity position. The reason is that after observing that their counterparty has engaged in liquidity hoarding, they will tend to become more risk averse. This assumption draws on the endogenous risk aversion literature that finds that agents facing negative shocks tend to become more risk-averse as they update their 'fragile' beliefs in the light of events and news signals (Malmendier and Nagel, 2011; Giuliano and Spilimbergo, 2014; Benzoni et al., 2015; Guisio et al., 2018). The effect is modelled through the term θ that

$$\varepsilon_{i,t} = \varepsilon_{i,t-1} + \theta$$

By setting $\rho(\varepsilon_{i,t}) = \rho_0 - \varepsilon_{i,t}$, the parameter θ represents the decrease in the LCR threshold that will lead the bank to liquidity hoarding. For example, if $\rho_0 = 0.25$ (i.e. an LCR threshold of 25%) then a value of $\theta = 0.05$ means that after the first time that a counterparty of the bank hoards liquidity, the bank will set its liquidity threshold to 20% $(= 100 \times (0.25 - 0.05)\%)$ instead of 25%, which was the threshold that would trigger liquidity hoarding at $t = 0$.

The use of the initial ratio $LCR_{i,0}$ as the benchmark against which changes in liquidity position are assessed for each bank is based on the assumption that initially all banks have a liquidity position which does not put them in the position to hoard liquidity. Although there will be differences in the extent to which various financial institutions satisfy the liquidity regulatory

[21] Our formulation has certain analogies with how Arinaminpathy et al. (2012) model swings of confidence.
[22] This can also be interpreted as an informational contagion channel, as news about banks facing liquidity issues will prompt more prudent haircut policies. A model with informational contagion channel is provided by Ahnert and Georg (2018).

requirements, a plausible assumption is that none of the banks in our sample faces such a liquidity crisis in the initial state.[23]

Finally, we also posit a behavioural rule that captures direct contagion in a forward-looking manner. A bank i with an LCR that falls below the liquidity threshold will withdraw liquidity from its counterparts when this funding expires, following the *direct liquidity effect* described above. It is assumed that this information is publicly available and consequently the banks that will be affected will react to the ensuing refinancing risk. Concretely, each bank sums the amounts of expected funding that will not be rolled over in the future and when the part of funding that will not be refinanced exceeds a specified threshold, the forward-looking liquidity position of bank i can be assessed as vulnerable and the bank will hoard liquidity. This *refinancing risk effect* can be interpreted as a forward-looking version of the direct liquidity effect, operating when the current liquidity position becomes precarious due to the prevailing market conditions.

Specifically, banks adopt a forward-looking perspective on their funding balance-sheet components and calculate their respective expected loss of funding (*ELF*)

$$ELF_{i,t} = \sum_{k=1}^{K(i)} \mathbf{I}(ik,t) \times L_{ik,0}$$

where $\mathbf{I}(ik,t)$ is an indicator function, which is equal to 1 if the counterparty k will not renew its funding to the bank i due to a deterioration of its liquidity coverage position, $K(i) = K^S(i) + K^U(i)$ and $L_{ik,0} = L_{ik,0}^U + L_{ik,0}^S$. The corresponding condition that could trigger liquidity hoarding is as follows,

$$ELF_{i,t} > \varphi \sum_{k=1}^{K(i)} L_{ik,0}$$

[23] This is consistent with the regulatory monitoring exercises that were conducted during the period 2014-15 and illustrate that the large majority of banks in Europe satisfy the respective liquidity regulatory requirements. For example, EBA (2016) reports that in a sample of 297 European banks, using data exactly in middle of the period 2014-15 that we consider here (June 2015), 91% of the banks exhibit LCR ratios above the required during that period (70%) and this applies for all large banks in the sample. Therefore, it is reasonable to assume that all euro area banking institutions in our sample, start from a sustainable liquidity position and thus we consider perturbations from that initial position as the distress scenarios examined in our study. Furthermore, we would like to focus on the topological properties of the network and how these affect the contagion transmission process. Considering an additional layer of heterogeneity, i.e., with respect to differential initial liquidity conditions, would unnecessarily complicate the analysis.

The parameter ϕ represents the percentage of banks' funding for which if refinancing risk becomes elevated the bank will decide to secure its liquidity position by hoarding lending from its borrowers. Therefore, this behavioural rule implements the transmission of forward-looking direct contagion through the existing links between banks. The realisation of market liquidity risk drives this effect as banks hedge their liquidity risk by reacting to an observed tightening of liquidity conditions for other banks, even if their current liquidity position has not been yet affected at that moment.[24]

Table 1 summarises the mechanisms that are taken into consideration in the model, distinguishing between direct and indirect contagion.[25]

Table 1: Channels of contagion and the respective formulations.

Channels of contagion	**Direct contagion**	**Indirect contagion**
Impact of funding liquidity risk	$\frac{LCR_{i,0} - LCR_{i,t}}{LCR_{i,0}} > \rho$ *(**Direct liquidity effect** due to impact of lower funding liquidity)*	$\varepsilon_{i,t} = \varepsilon_{i,t-1} + \theta$ *(**Risk aversion effect** leading to indirect contagion due to funding liquidity risk)*
Impact of market liquidity risk	$ELF_{i,t} > \varphi \sum_{k=1}^{N^{tot}} L_{ik,0}$ *(**Refinancing risk effect** due to lower market liquidity materialising through refinancing risk)*	$\Delta h_t^{market-wide} = f(\bar{n}_t)$ *(**Pro-cyclical haircut effect** leading to indirect contagion through higher haircuts)*

[24] We experimented also with an alternative formulation, according to which the change in haircuts is a function of the total expected loss of funding, rather than the number of banks, i.e., $\Delta h_t^{market-wide} = f\left(\sum_{k=1}^{K} ELF_{kt}\right)$. In particular, we specified this channel through the equation $\Delta h_t^{market-wide} = min\left(1, \delta_2 \times log(\sum_{k=1}^{K} ELF_{kt})\right)$. The interpretation would be that liquidity problems in large institutions would have stronger impact in market perceptions of risk than they would if they occurred in smaller institutions, and therefore would lead to relatively higher increases in haircuts. To compare this specification with the one we use in the text, we set $\delta_2 = \delta / (\sum_{i,j=1}^{K} V_{ij} / 2K)$, where the denominator is the total amount of interbank liquidity in the network divided by the number of banks, so that δ and δ_2 lead to comparable effects in the sense that the maximum impact of the two specifications (i.e. if all banks in the network would hoard the interbank liquidity they provide) would be the same. We find that the specification based on the liquidity amount leads to higher indirect effect compared to our baseline specification, reflecting the highly skewed distribution of banks' size.

[25] Our model aims to capture the dynamics evolving during crisis rather than tranquil times and therefore highlights mechanisms such as liquidity hoarding, fire sales leading to higher haircuts and the updating of risk perceptions as the banks' primary responses to a worsening liquidity situation. Seeking of alternative liquidity providers within the interbank network, modelled through a counterparty search component, is employed e.g. in Georg (2013).

3. Data

The contagion model is built upon the network of bilateral exposures between the SIs operating in the euro area. Given the granularity level of the dataset, the reconstructed network also covers assets and liabilities involved in the balance-sheet of SIs from outside economic entities that are not directly included in the interbank market, i.e., smaller banks, other financial institutions, non-financial corporations, households etc. Information on these outside links allows us to identify the sectors which are the most important sources of risk for the interbank network or which may be affected most severely from a dry-up of bank liquidity.

3.1 Data

We utilize a dataset collected based on the harmonised supervisory reporting requirements applicable to the banks of the EU countries participating to the Single Supervisory Mechanism (SSM) that centralises supervision of SIs. The data we use are available for the reference dates 2014Q4, 2015Q1, 2015Q2, 2015Q3 and the number of the banks is equal to 125, 122, 123, 123, respectively.[26]

These reference dates belong to a relatively calm phase within the decade 2010-2020.[27] Therefore, the corresponding network represents a suitable starting point to analyse stress scenarios. If we had used a network constructed with data from a period during which the interbank network had been strongly perturbed by external shocks our results would potentially be highly specific to the type of shocks prevailing at the given point in time.[28]

The dataset has been collected for supervisory purposes and consequently a large amount of adjustments and manual work was required to construct the network of interbank exposures and concentrated outside assets and liabilities. The lack of standardisation and common

[26] The small change in the number of banks across dates is due to changes in the list of SIs which are caused, e.g., by changes in the banks' size.
[27] For example, as quantified by the CISS index of financial stress, compiled by the ECB. See https://sdw.ecb.europa.eu/quickview.do?SERIES_KEY=290.CISS.D.U2.Z0Z.4F.EC.SS_CIN.IDX.
[28] Still, it would be of interest to analyse changes of the network in the time dimension, including the more recent period. We leave this expansion of the analysis for future work. In addition to the conceptual issue highlighted above, constructing consistent time series of the interbank network would require multiple amounts of manual work which is necessary to reconstruct each snapshot. Furthermore, changes in the reporting templates have been introduced in subsequent points in time, which would impair comparability across time.

formatting as regards the counterparties represented the most serious challenge. Specifically, the reporting of the sector and the name of each counterparty was done in the templates that we used through non-standardised text entries, sometimes leading to the non-consistent reporting of the same counterpart across the banks in the sample. Furthermore, LEIs which are needed to identify uniquely entities were missing in some cases and had to be filled using additional sources, mainly LEI repositories. Finally, the reporting of counterparties was not done on a consistent basis as regards the different levels of consolidation, therefore we utilised the data on group structures and LEIs in order to create a consistent dataset. Given these features of the dataset, we had to hard-code a number of manual checks and develop code the enables the mapping of counterparties.

3.2 Description of the network of bilateral exposures

The exposures included in the dataset comprise around 8% of banks' total assets and more than 100% of banks' equity (see Table 2).[29] Taking into account that the largest percentage of banks' assets represent loans to or deposits from the non-financial sector and households, items that are not directly relevant for the phenomenon of contagion examined in our model, the exposures we consider represent a significant part of the exposures that are relevant when studying the contagion potential through the interbank market.

Table 2: Concentrated exposures in the SI interbank market

	(€ billion)				
	Concentrated funding between SIs	Total concentrating funding	Total assets	Percentage of concentrated funding over equity	Percentage of concentrated funding over total assets
2014Q4	262.8	1,707.9	22,133.3	128.7%	7.7%
2015Q1	247.2	1,732.3	23,446.2	124.7%	7.3%
2015Q2	211.4	1,876.9	22,688.6	137.9%	8.2%
2015Q3	255.4	1,865.8	22,716.2	137.1%	8.2%

[29] Craig and Ma (2018) examine the German interbank market and note that the total volume of interbank loans was around 8% of total assets in 2007.

The sectoral decomposition of the concentrated funding exposures is presented in Table 3 and Table 4. We have classified the outside counterparties, which refer to entities that are not included in the SIs list, into nine categories: central banks of EU countries, central banks of non-EU countries, central clearing counterparties (CCPs), non-SI credit institutions (CIs, henceforth this term refers to credit institutions that are not SIs), governments, households, non-financial corporations (NFCs), international funding institutions (IFIs) such as the European Investment Bank, the International Monetary Fund and the European Stability Mechanism, and other financial institutions (OFIs) which refer to non-bank financial intermediaries (such as insurance firms or investment funds).

Some of the sectors are, by nature, concentrated as the corresponding entities are country-wide (e.g., sovereigns) or euro area-wide (e.g., the ECB), therefore it is expected that funding from these sectors originates from a small set of counterparties or a single counterparty. Specifically, this applies to the funding received from central banks, general governments, IFIs and to a large extent from CCPs. However, it is important to observe that sectors like the OFIs or CIs, which correspond to a potentially large set of entities, also represent a large percentage of the concentrated funding exposures. This means that also in these sectors there are entities which are large compared to the SIs considered here, so that their exposures exceed the above-mentioned reporting threshold of 1% of total banks' liabilities and therefore included in our dataset.

Table 3: Concentrated funding from other sectors (a) – Central banks, CCPs, other credit institutions and general governments

	(€ billion)				
	Central banks (EU)	Central banks (non-EU)	CCPs	Other credit institutions	General governments
2014Q4	374.8	38.3	241.6	199.9	283.9
2015Q1	356.0	33.4	274.9	218.0	277.5
2015Q2	483.3	42.1	272.2	249.4	277.5
2015Q3	448.5	32.4	263.5	232.4	297.1

Table 4: Concentrated funding from other sectors (b) – Households, international funding institutions, non-financial corporations, other financial corporations and other.

	(€ billion)				
	Households	International funding institutions	Non-financial corporations	Other financial corporations	Other
2014Q4	0.1	50.7	41.3	213.9	0.1
2015Q1	0.1	47.5	40.9	235.7	0.1
2015Q2	0.1	56.1	39.8	289.5	0.1
2015Q3	2.4	49.9	39.8	243.9	0.0

A visual depiction of the structure of the interbank network is presented in Figure 2 (the graph refers to 2015Q3 reference date; see the Section A of the supplementary material for the constructed snapshots for the remaining reference dates). The most prevailing empirical feature of the network structure is the presence of heterogeneity across two dimensions: i) node heterogeneity, corresponding to the different sizes of SIs, and ii) edge heterogeneity, referring to the diversity of amounts in the bilateral obligations linking the SIs. The heterogeneous nature of the interbank market is a well-established empirical property in the banking literature nowadays[30] and highlights the importance of using actual data to calibrate and construct financial networks. Omitting this pivotal feature in either empirical or theoretical models of the interbank market can lead to misperceptions regarding the origins of systemic risk and underestimate the degree of contagion in the financial network (see Mistrulli, 2011).

[30] Various aspects of heterogeneity in interbank markets have been reported by Markose et al. (2012) for the US banks involved in the CDS market, Alves et al. (2013) for large banks in EU, Bargigli et al. (2014) for financial institutions in Japan, in ’t Veld and van Lelyveld (2014) for the Netherlands, Cimini et al. (2015) and Barucca, and Lillo (2016) for the Italian e-MID market, Levy-Carciente et al. (2015) for Venezuela, Silva et al. (2017) for Brazil, Langfield et al. (2014) and Bardoscia et al. (2019) for the UK, and Chen et al. (2020) for the Chinese banking network, among others.

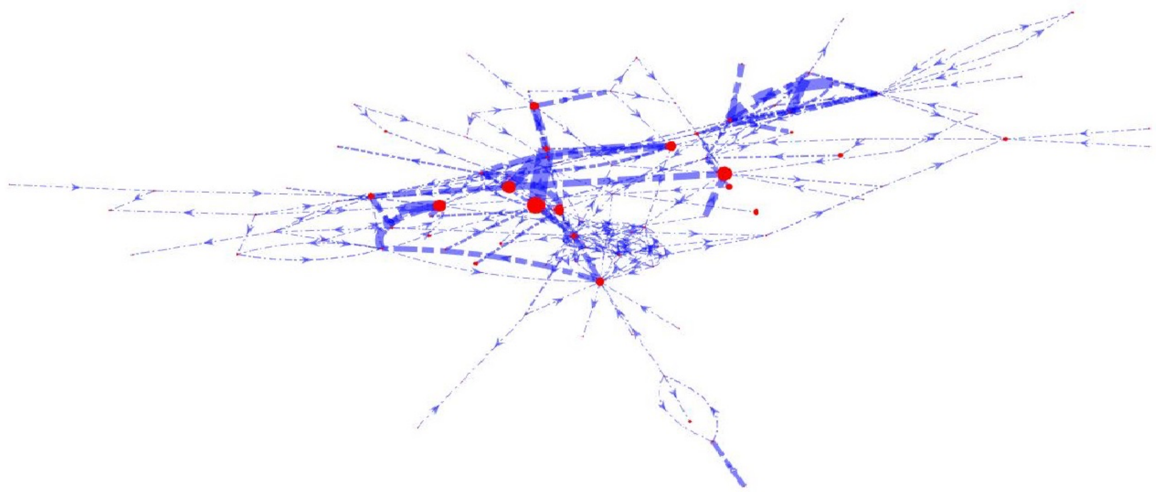


Figure 2: Constructed interbank network (reference date 2015Q2). The sizes of the nodes and the links are proportional to the respective amounts.

The structure of the network as presented above is consistent with the argument of Craig and Ma (2018) that the formation of interbank networks is not primarily an arrangement to smooth idiosyncratic liquidity needs but rather aims to reduce inefficiencies due to duplicated monitoring, and that is why intermediary banks act as hubs and consequently exhibit much higher connectivity than the rest.

The observed highly-skewed distribution of banks' and exposures' sizes hints at the significance of using real data when analysing contagion potential and amplification. The reconstructed networks from partial information (using methods like RAS, and minimum or maximum entropy) simply assume exogenously given values for those distributions and thus could induce biases and affect decisively the policy conclusions.

4. Results

In this section, we perform simulations on the constructed network of the real concentrated exposures between the SIs in the euro area, using the behavioural model of interbank contagion specified in Section 2. Our aim is to identify the sectors that pose the greatest systemic risk to the interbank network and study the relative contributions of direct and indirect transmission channels. We consider sectoral shocks of different intensities in order to investigate the existence of 'tipping points' in the network's behaviour and characterize the convexity of the network's responses to each shock (Taleb et al. 2012).

4.1 Impact of sectoral shocks

We define two general categories of shocks, pertaining to the liability or the asset side of the SIs' liquidity-relevant balance sheet positions, respectively. The shocks on the liability side are triggered by the non-renewal of funding from a subset of counterparties, i.e. represent funding liquidity shocks, and lead to contagion effects due to the dry-up of liquidity throughout the network. Whereas the shocks on the asset side affect the haircuts applicable to the financial instruments that banks hold to address unexpected liquidity outflows. The latter category corresponds to market shocks that could be attributed e.g., to elevated sovereign risk in the case that the sector receiving the shock is the general government sector. Specifically, an asset-side shock originating from sector s of intensity $m \in (0,1]$ lead to re-assessed asset values $\hat{A}_{ik}^{C}$ and $\hat{A}_{ik}^{RR}$ according to,

$$\mathbf{1}_s(\hat{A}_{ik}^{C} + \hat{A}_{ik}^{RR}) = \mathbf{1}_s \times m \times (A_{ik}^{C} + A_{ik}^{RR})$$

where $\mathbf{1}_s$ is the indicator function for the asset exposures of bank i towards sector s. Therefore, such shocks trigger banks' response, as they lead to a deterioration of their initial LCR position. Similarly, in the presence of funding shocks, a new $\widehat{ELF}_{i,t,s}$, reflecting the expected loss of funding from sector $\boldsymbol{s}$, is related to the prior $ELF_{i,t,s}$ as follows,

$$\mathbf{1}_s\left(\widehat{ELF}_{i,t,s}\right) = \mathbf{1}_s \times m \times \left(ELF_{i,t,s}\right)$$

Therefore, this category of shocks affects expectations about the renewal of the funding provided to the SIs from these sectors and trigger banks' response due to the deterioration of their *ELF*. For example, a shock originating from the credit institutions outside the network, would imply an expected $m \times 100\%$ withdrawal of their funding towards the banks in the interbank network.[31]

[31] Our approach to the definition of stress scenarios with a percentage loss across asset classes is similar to that used in the stress test literature, see, e.g., Cont and Schaanning (2017).

Although the two aforementioned types of shocks are applied to the two opposite sides of the balance sheet, they give rise to similar phenomena of contagion, as banks' behaviour, and the corresponding contagion channels that are triggered, operate symmetrically, irrespectively of the balance sheet side where developments may have led to a deterioration of the LCR. Therefore, our simulations utilise these two types of shocks to extend the sample of scenarios under consideration. The simulations based on the shocks originating each time from one of the outside sectors allow gauging the potential impact of sector-specific shocks to the SIs. The magnitude of shocks considered ranges from 5% to 45%, i.e., $m \in (0.05, 0.45]$. Each time one specific outside sector, e.g., CIs, withdraws m fraction of the liquidity it provides from all the banks in the interbank network.

The impact of the shock is measured based on the number of banks that hoard liquidity after the contagion phenomenon has spread through the network. As an alternative way to measure the shock impact, we also calculate the liquidity hoarded, as a percentage of total liquidity. The results thus obtained did not show significant differences (see supplementary material).

The baseline calibration used in the simulations below is shown in Table 5.[32]

Table 5: Calibration parameters and definitions.

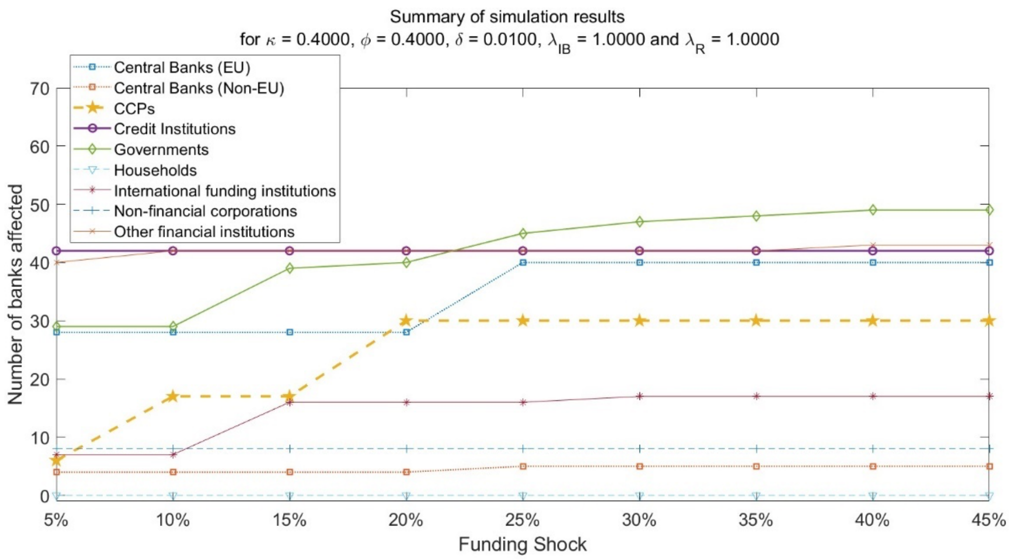
Parameter	Value	Contagion channel	Interpretation
k	0.4	*Direct liquidity effect*	A function of bank's risk aversion ε_i due to funding risk.
φ	0.4	*Refinancing risk effect*	Sensitivity to a loss of funding due to market risk.
δ	0.01	*Pro-cyclical haircut effect*	Premium on haircut due to market risk.
θ	0.01	*Risk aversion effect*	Degree of risk-aversion due to funding risk.

In Figure 3, the impact of sectoral shocks on the funding side is shown, for each of the four snapshots of the network. It is clear that shocks to the official sector (i.e., EU central banks and governments) lead to the highest impact scenarios. These results should be interpreted as pointing to the importance of official sector funding in banks' balance sheets. The high ranking of the government sector on the liability side reflects the activities of the treasury and the transaction-banking services provided by the commercial banks to their national governments.

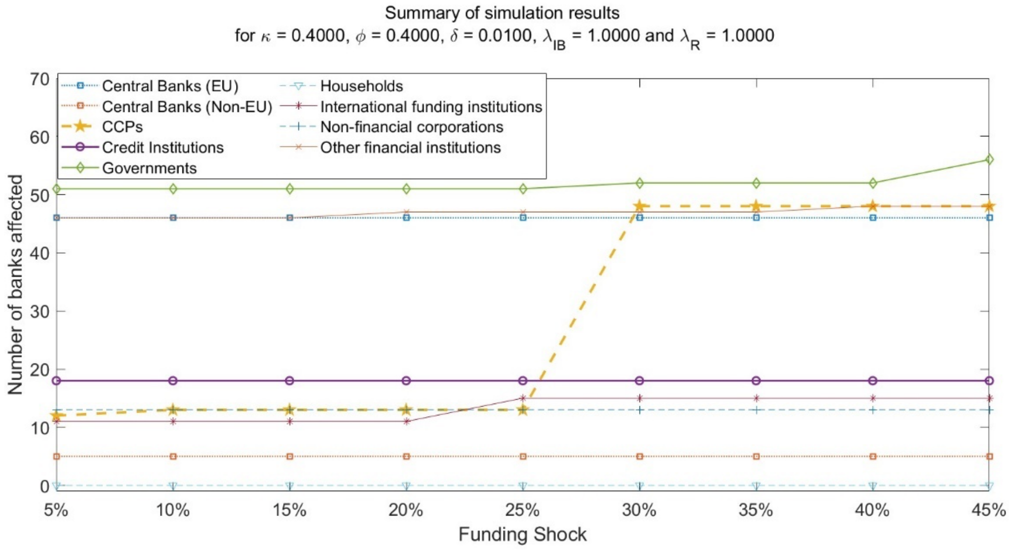
[32] The broad results presented below are not sensitive to this calibration, which affects however the size of the impact.

The outcome of the simulations provide evidence on the importance of the OFI and CCP sectors, which can be considered as significant drivers of contagion risk. These results have important implications for macro-prudential policy and the assessment of financial stability risks. The high ranking of the OFI sector with respect to the overall impact that a shock in this sector may cause shows that there is important contagion potential from the non-banking part of the financial sector, including shadow banking entities, insurance companies and pension funds. These results point to the crucial role of interconnectedness within the different segments of the financial system and highlight the spillover potential originating from non-bank financial institutions in the case that the latter face liquidity shocks and remove their deposits or repo funding to the SIs. This result is consistent with the literature emphasizing the systemic importance of the shadow-banking activities (Adrian and Shin, 2009; Gennaioli et al., 2013; Levy-Carciente et al., 2015). Additionally, the effect of contagion induced by the sector of CIs shows that the smaller banks are also important funding counterparties to the SIs.

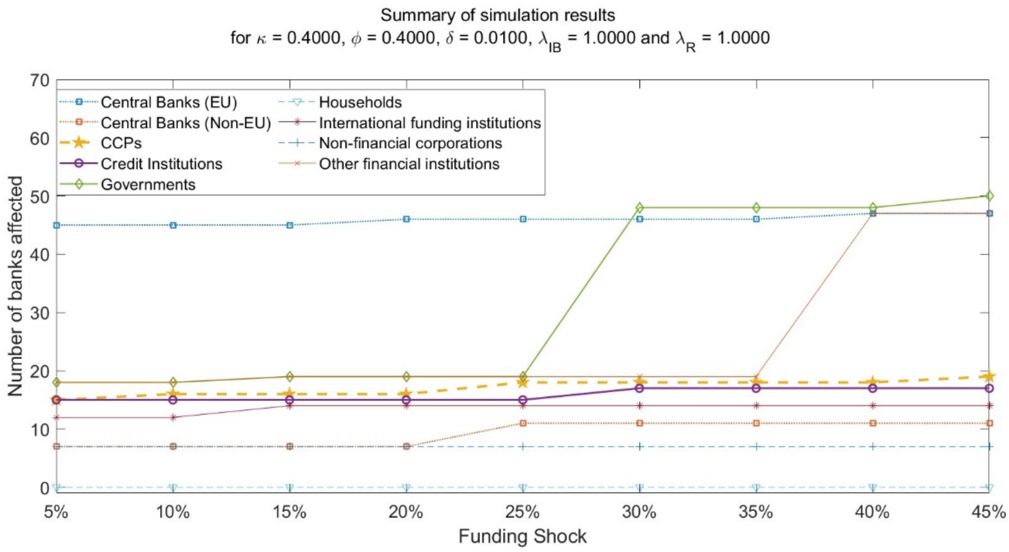
(a) 2014Q4



(b) 2015Q1



(c) 2015Q2



(d) 2015Q3

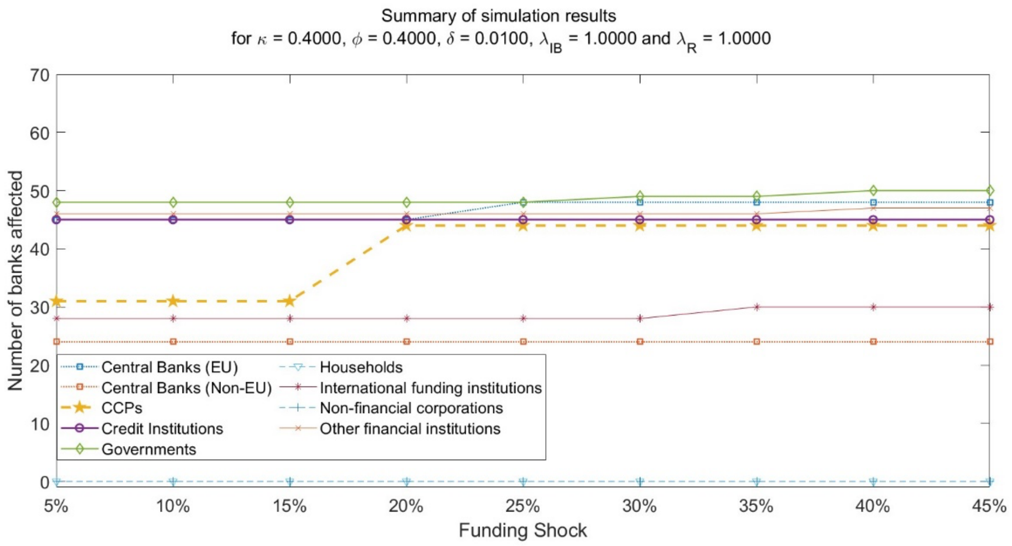


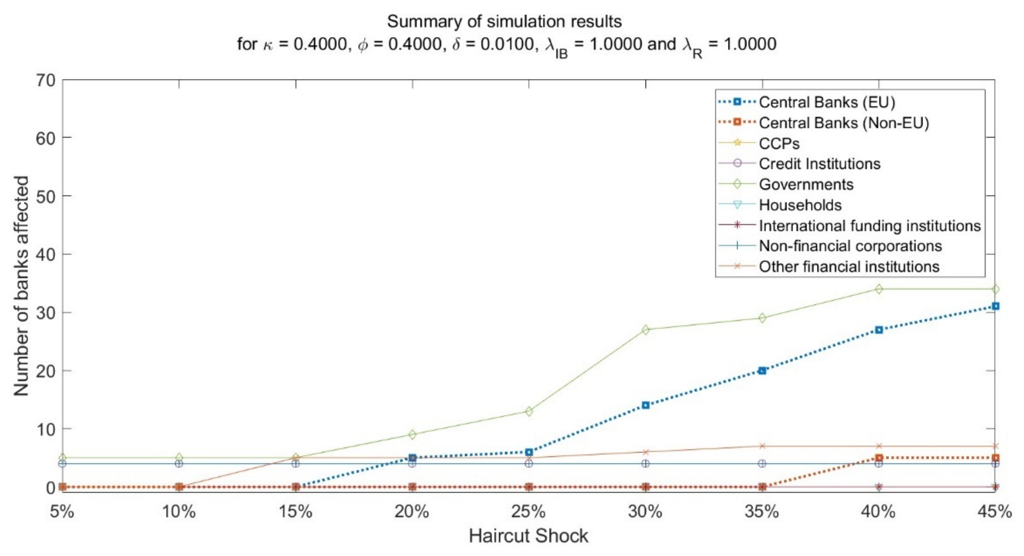
Figure 3: Sectoral contagion due to shocks on the funding side, for different snapshots in time**.** The intensity of the shock (representing the percentage of funding withdrawal from the sector that is being hit by an external shock) changes along the x-axis. The y-axis depicts the number of banks that hoard liquidity in each scenario.

There are differences across sectors in the extent to which the overall impact caused by a sectoral shock depends on the intensity of the original shock. In some cases, the impact reaches a plateau even for small values of the shock intensity. This is observed for sectors to which exposure is high and widely spread within the network, e.g., the sectors of government, central banks, and CIs. In other cases, there is a threshold shock intensity point above which the impact increases substantially, e.g., as in the case of CCPs, to which only a few banks are exposed to and therefore, shock intensity should exceed a threshold so that it is transmitted to the banks which are not exposed to the initial shock. Finally, there are also cases of a steep but continuous impact increase with the intensity of the shock when there is widespread exposure to a sector but to different degrees across banks and therefore we observe the monotonic increase of the overall impact with the size of the shock.

Another finding is that the maximum shock impact does not differ significantly among the snapshots examined. Specifically, the maximum impact is around 50 banks for all reference dates, which suggests that these are the banks which are the most vulnerable. In addition, the relative ranking of the sectors as regards their potential to lead to systemic events if withdrawing funding remains relatively stable across reference dates.

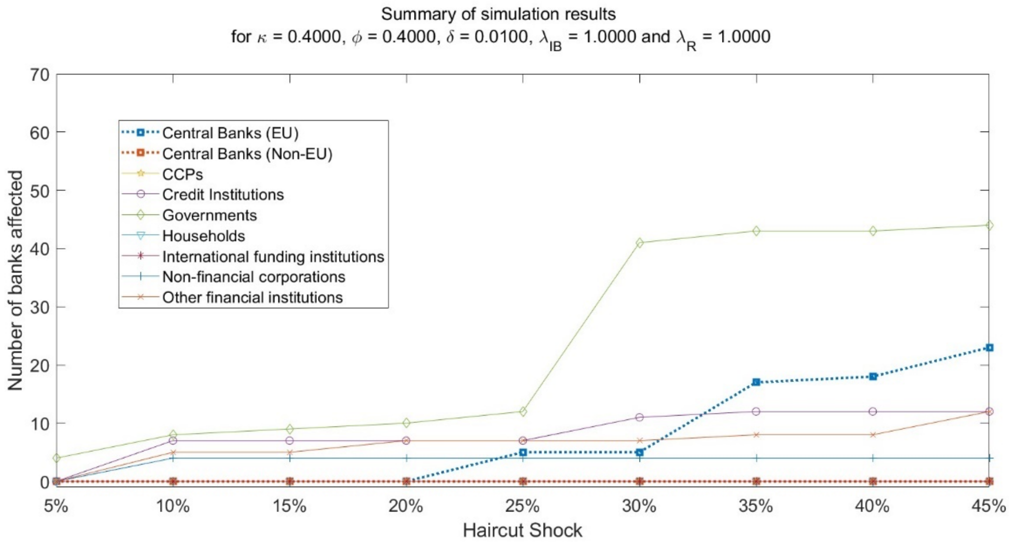
In Figure 4, the impact of sectoral shocks on the asset side is shown, again for each of the four snapshots of the network. The interbank network is shown to be vulnerable to shocks on the valuation of assets issued by governments, EU central banks, credit institutions and OFIs. The potential for financial contagion posed by shocks to sovereign exposures hints at the possibility of triggering the sovereign-bank nexus. Consequently, shocks to the credibility of the governments could lead to systemic events in the financial system.[33] In addition, as regards the EU central banks, our results provide evidence on the extent to which the SIs deposit significant amounts to the European System of Central Banks in order to meet potential liquidity shocks or as an intermediate step before lending out received funding. In addition, the interbank network of the SIs is linked to the smaller banks (i.e., the set of 'credit institutions') also on the asset side, therefore there is potential for contagion from the latter to the former. Finally, the SIs are also exposed to the OFIs' assets to a degree that could potentially lead to a contamination from the non-banking financial sector to the SI interbank network in a scenario whereby the OFIs' assets feature elevated risk.

(a) 2014Q4

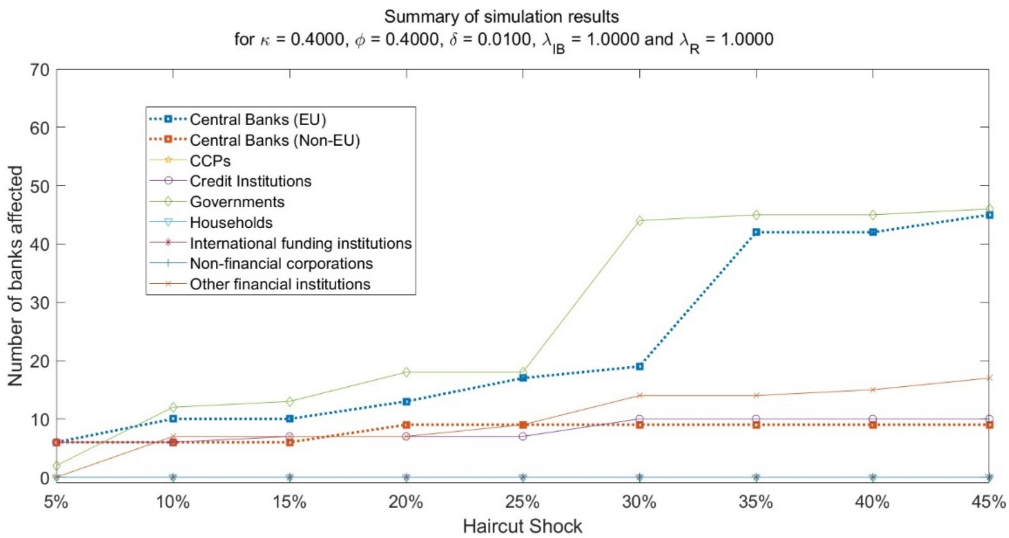


[33] A more detailed examination of the "diabolic loop" between sovereigns and banks (Brunnermeier et al. 2016) is beyond the scope of this paper, because this loop is intermediated by additional layers beyond banks' asset holdings and in addition it is affected by policy responses, such as the possibility of funding to sovereigns by international institutions (such as the IMF) and the banking supervision regime (Farnè and Vouldis 2021). In addition, here we posit the rather strong scenario of a simultaneous materialisation of risk across all sovereign bond holdings, which provides an upper limit of the corresponding risk. A more specialised stress test would consider the different possibilities of risk materialising across countries and the corresponding correlations.

(b) 2015Q1



(c) 2015Q2



(d) 2015Q3

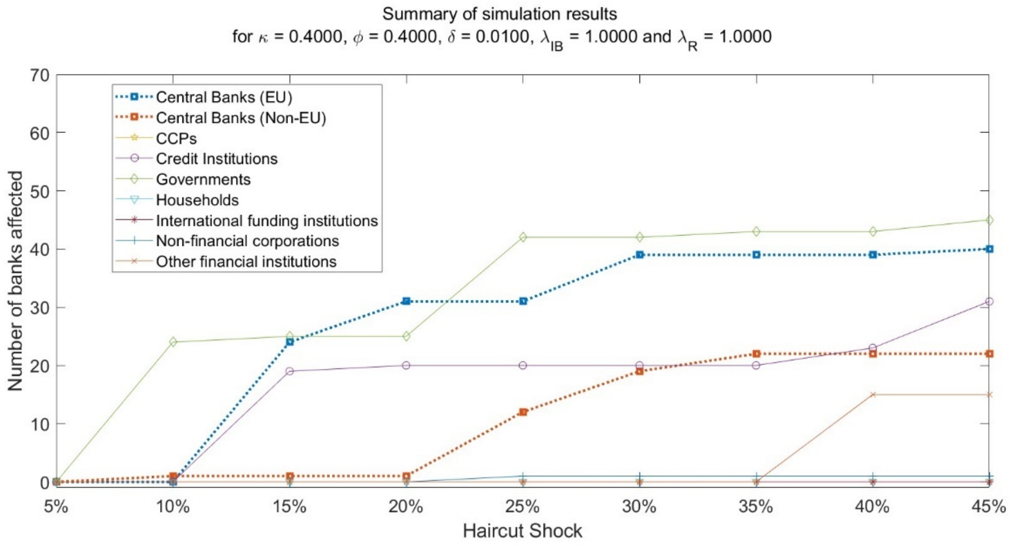


Figure 4: Sectoral contagion due to valuation shocks on the asset side, for different snapshots in time. The intensity of the shock (representing the haircut increase in the assets of the sector that is being hit by an external shock) changes along the x-axis. The y-axis depicts the number of banks that hoard liquidity in each scenario.

4.2 Quantifying the relative contributions of direct and indirect contagion

To dig deeper into the relative importance of the transmission channels operating during the simulated contagion scenarios, we compare the magnitude of the effects driven by the direct and indirect mechanisms. Specifically, let us denote by I_{t^*} the total impact of a scenario in terms of the number of banks that are led to hoard liquidity. The impact is conditional on the simulation parameters (specifically, $k, \varphi, \delta, \theta$, which have been defined in Section 2) and scenario parameters, namely $\boldsymbol{s}$ (originally impacted sector), m (shock size) and $b \in \{Assets, Liabilities\}$ which specifies the balance sheet side affected in the scenario i.e. whether it refers to haircut shocks on the asset side or a funding shock on the liability side. The four transmission mechanisms described in Section 2 affect the N-dimensional vectors $\boldsymbol{LCR}_t$, $\boldsymbol{ELF}_t$ (direct mechanisms) and $\boldsymbol{\varepsilon}_t$, $\boldsymbol{\Delta h}_t$ (indirect mechanisms). If we denote by t^* the last point in time of each scenario (i.e., when the maximum number of banks have been impacted by the various transmission mechanisms), the total impact equals

$$I_{t^*}(\boldsymbol{LCR}_{t^*}, \boldsymbol{ELF}_{t^*}, \boldsymbol{\varepsilon}_{t^*}, \boldsymbol{\Delta h}_{t^*} \mid k, \varphi, \delta, \theta, b, m, \boldsymbol{s})$$

To decompose the total impact into the contribution of the direct and indirect mechanisms, we also compute the impact when only direct mechanisms are operating:

$$I_{t^*}^{DIRECT}(\boldsymbol{LCR}_{t^*}, \boldsymbol{ELF}_{t^*}, \boldsymbol{\varepsilon}_0, \boldsymbol{\Delta h} = \mathbf{0} \mid k, \varphi, \delta, \theta, b, m, \boldsymbol{s})$$

The contribution of indirect mechanisms is thus computed as a difference:

$$\begin{aligned} I_{t^*}^{INDIRECT} = {} & I_{t^*}(\boldsymbol{LCR}_{t^*}, \boldsymbol{ELF}_{t^*}, \boldsymbol{\varepsilon}_{t^*}, \boldsymbol{\Delta h}_{t^*} \mid k, \varphi, \delta, \theta, b, m, \boldsymbol{s}) \\ & - I_{t^*}^{DIRECT}(\boldsymbol{LCR}_{t^*}, \boldsymbol{ELF}_{t^*}, \boldsymbol{\varepsilon}_0, \boldsymbol{\Delta h} = \mathbf{0} \mid k, \varphi, \delta, \theta, b, m, \boldsymbol{s}) \end{aligned}$$

Therefore, our decomposition approach derives the contribution of indirect channels as the additional impact that occurs when both indirect and direct channels are active compared to the case where the indirect channels are not active. This decomposition method is called henceforth "scenario comparison" approach and is based on the implementation of the simulation as described in Appendix A.

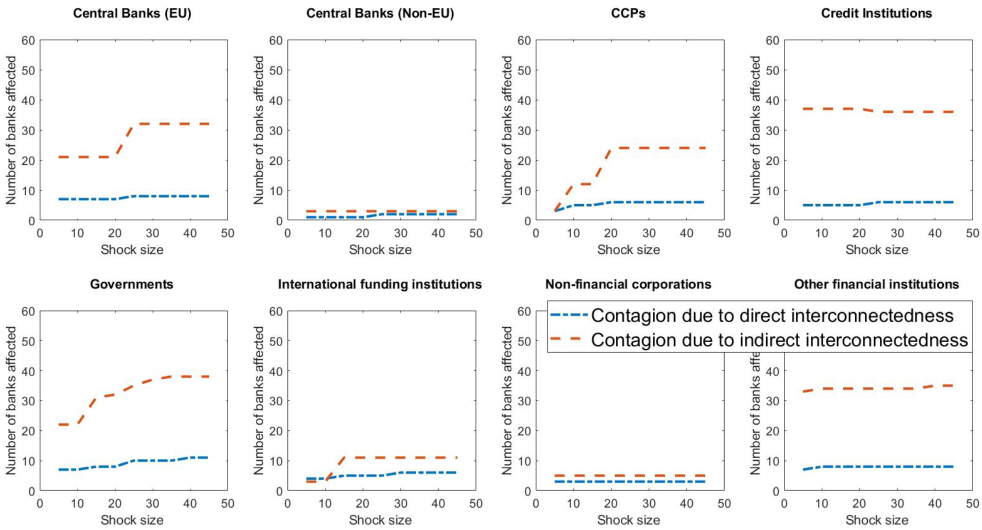
It must be noted that $I_{t^*}^{INDIRECT}$ is larger than the impact that would result if only the two indirect mechanisms of our model (i.e., the risk aversion and the pro-cyclical haircut effects) were to be applied. There are two reasons, first is that stress amplification results from the interaction of direct and indirect mechanisms, which would tend to boost $I_{t^*}^{INDIRECT}$. On the other hand, some banks would have been affected either by the direct or the indirect impact. The above decomposition method would attribute the shock to these banks on the direct mechanism.

To check the robustness of our results, we have also implemented an alternative decomposition method, presented in Appendix B, whereby the decomposition takes place within the same simulation, i.e., without the need to compare alternative scenarios ("within-scenario" allocation of direct and indirect effects). In the econometric study that follows we find that the relationship between direct and indirect contagion is qualitatively similar when this decomposition method is used.

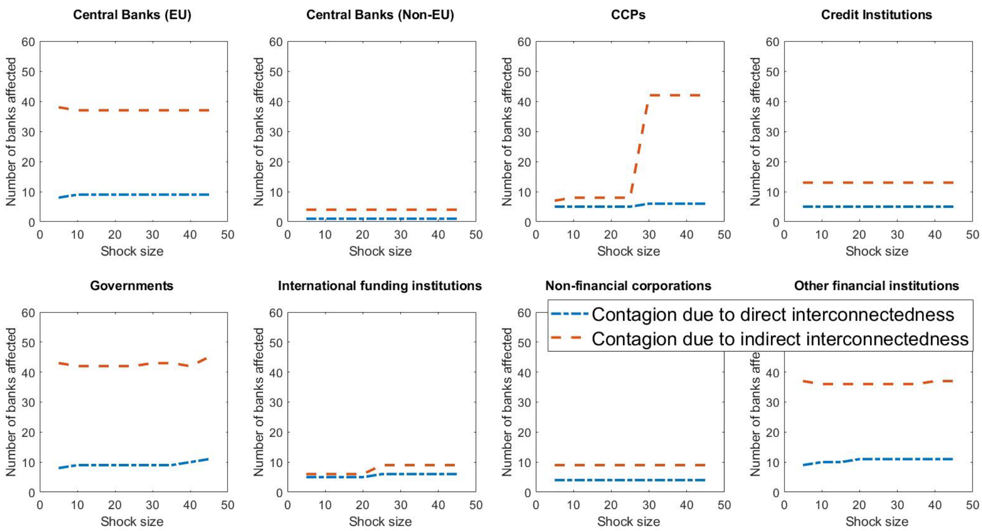
The "scenario comparison" approach avoids the ambiguities that would ensue if we attributed the impact to each individual bank to direct or indirect channels within the same scenario. The problem with the "within-scenario" approach is that in some cases a bank would hoard liquidity due to the impact of both a direct and indirect channel, i.e., the effect of either would suffice, so the allocation of a cause is ambiguous. In addition, when both channels are active, it could happen that a bank is, e.g., affected by an indirect channel but this occurs only because the direct channel has been active and has affected the banks that subsequently transmitted stress to the former bank.

The decomposition of the overall contagion impact between the direct and indirect channels for the various shocks on the funding size, based on the “scenario comparison” approach, is shown in Figure 5.

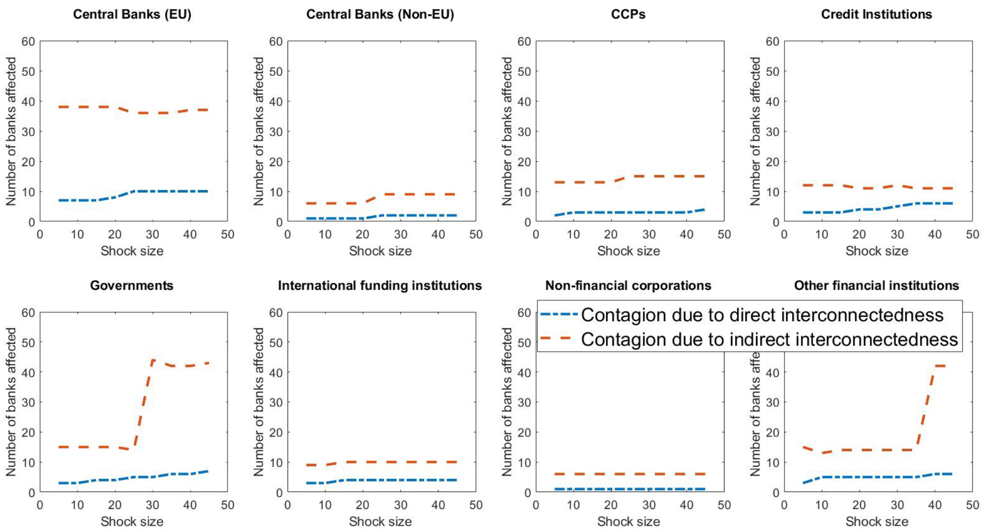
(a) 2014Q4



(b) 2015Q1



(c) 2015Q2



(d) 2015Q3

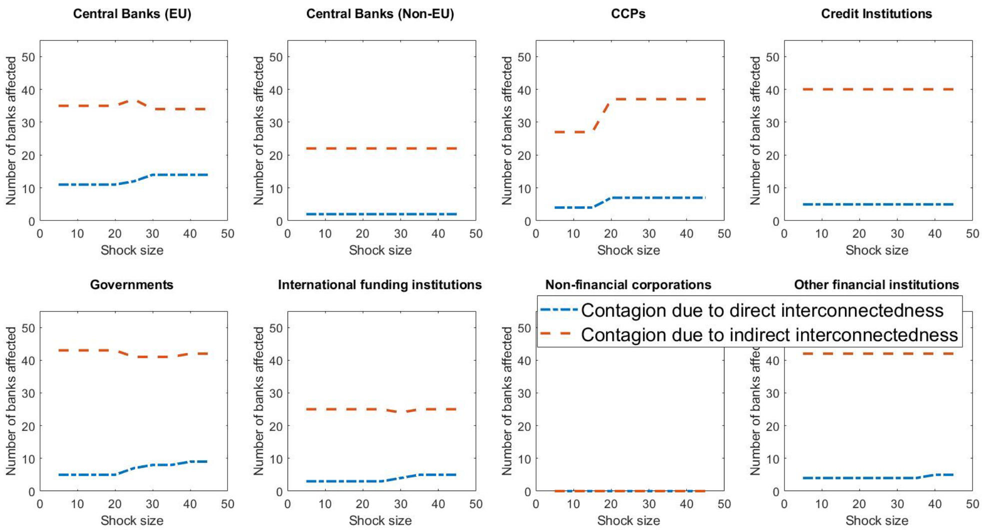


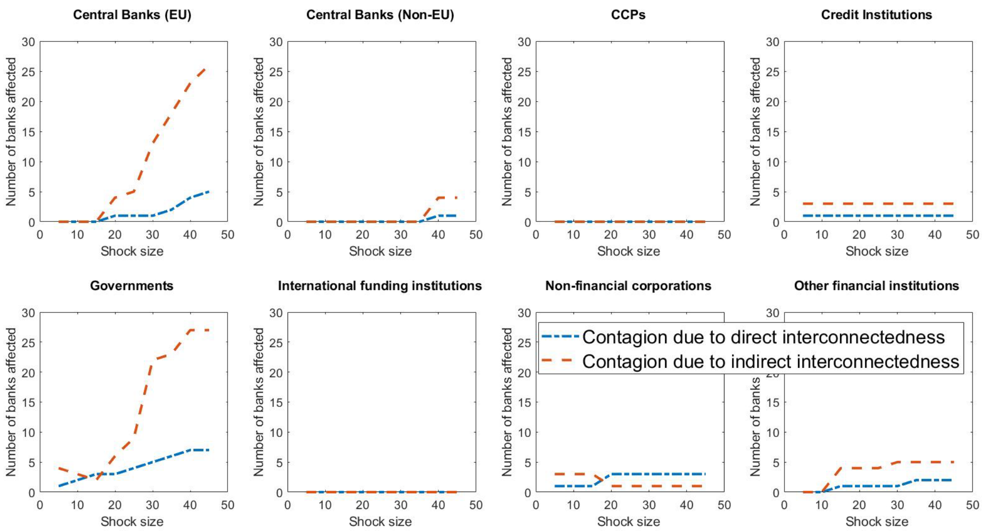
Figure 5: Decomposition between direct and indirect channels of sectoral contagion due to shocks on the funding side. Each subfigure refers to one reference date and each graph contains scenarios featuring shocks to a specific sector for variable intensity degrees. The intensity of the shock changes along the x-axis and takes values from 5% to 45%. The y-axis depicts the number of banks that had to hoard liquidity. The household sector is not shown as the impact is zero for all intensity degrees.

A first important observation is that the overall effect of indirect contagion is higher than that of direct contagion for most cases, sometimes acting as a substantial amplifier of the contagion phenomenon (e.g., in the scenario of shocks to government funding at the reference date 2014Q4).

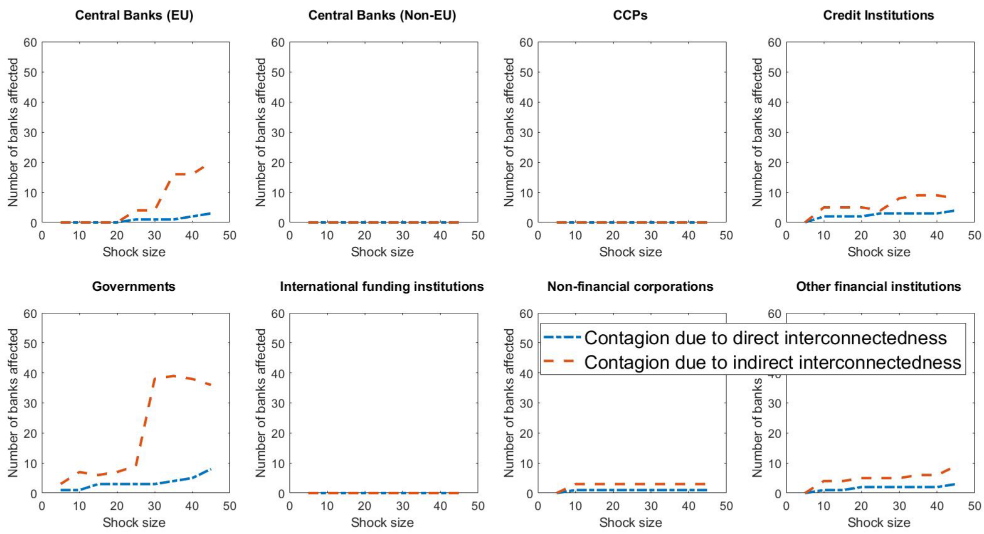
There is also a difference between the dependence of direct and indirect contagion to the shock size. In general, we observe large upward jumps in the size of indirect effects for a unit increase in the shock size, in contrast to the size of direct effects which change in a smoother way to shock size changes. We observe cases where an increase in the shock size leads to the simultaneous increase of direct and indirect effects (i.e., shock intensification amplifies both effects) and also cases where an increase in the direct effect due to a shock size increase is accompanied by a decrease of the indirect effect (i.e., shock intensification leads to the substitution of the indirect effect by the direct effect). The latter case can be observed, e.g., in the scenarios of 2015Q3 in which funding from central banks (EU), CCPs and international funding institutions is being stressed.

The decomposition of the transmission between the direct and the indirect component in the case of asset side shocks is presented in Figure 6. Similar observations to those made for Figure 5 can be made for the case of asset side shocks.

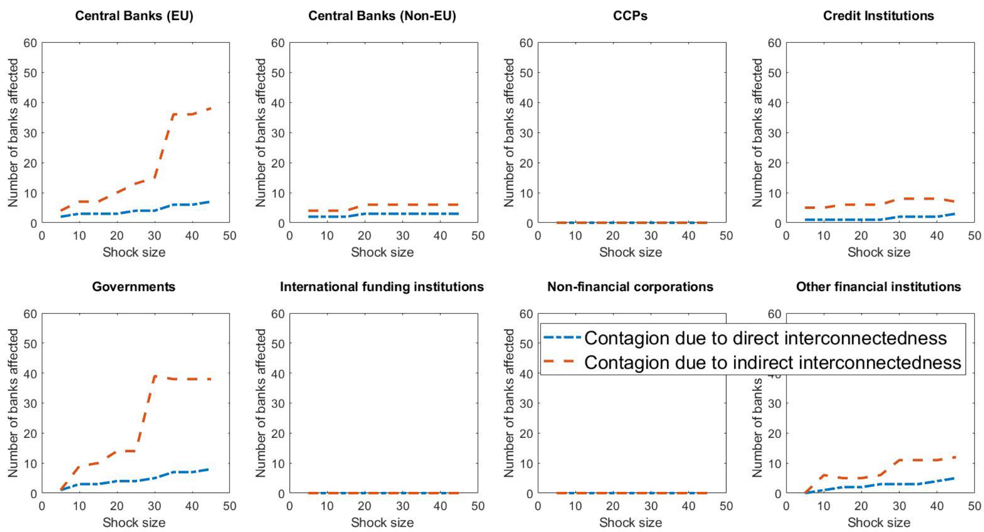
(a) 2014Q4



(b) 2015Q1



(c) 2015Q2



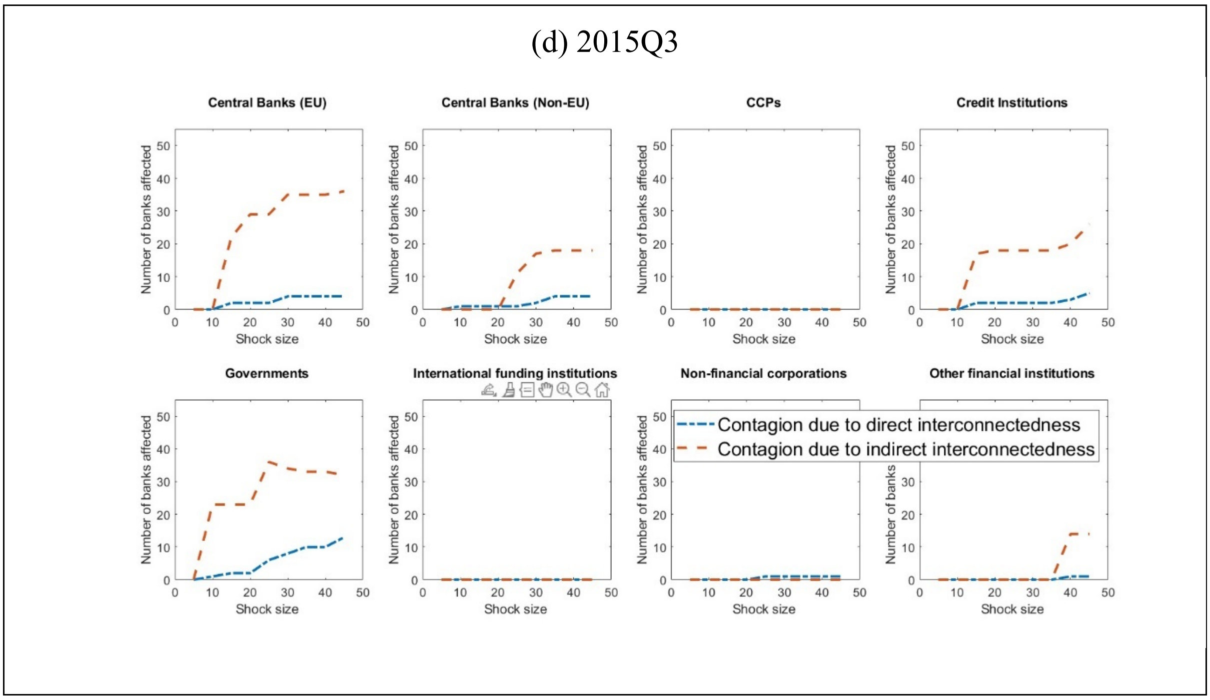


Figure 6: Decomposition of sectoral contagion due to shocks on the asset side between direct and indirect channels. Each subfigure refers to one reference date and each graph contains scenarios featuring shocks to a specific sector for variable intensity degrees. The intensity of the shock changes along the x-axis and takes values from 5% to 45%. The y-axis depicts the number of banks that had to hoard liquidity. The household sector is not shown as the impact is zero for all intensity degrees.

To investigate in a quantitative way the relationship between direct and indirect effects we conduct an econometric analysis. We estimate a specification in which the impact due to indirect channels is expressed as a function of the shock size and the impact of the direct channels. The rationale for conditioning on the shock size is that the relative contributions of the two types of transmission could differ across scenarios of different intensity, e.g., because higher intensity will be strongly associated with the activation of indirect effects that do not depend on the network's topology.

The model has the following general form,

$$I_i^{INDIRECT} = \beta_0 + \beta_1 I_i^{DIRECT} + \beta_2\, m_i + \beta_3 I_i^{DIRECT} \times m_i + \varepsilon_i$$

where $I_i^{INDIRECT}$, I_i^{DIRECT} denote the impact due to indirect and direct factors and m_i the magnitude of the initial shock. We also include an interaction term between the direct impact and the shock magnitude to capture the potentially varying relationship of direct and indirect impact, depending on the shock size. The index i runs through all scenarios. In other words, the index points to the elements of the set featuring all scenarios, i.e., the Cartesian product of the set of reference dates (4 values), shock intensities (9 values), type of shocks (2 values, i.e., liability or asset side shocks), sectors shocked (10 values). Consequently, the maximum number of scenarios equals $4 \times 9 \times 2 \times 10 = 720$, however after excluding the scenarios with zero overall impact, this number shrinks to 440. We estimate the model separately for the two methods used to decompose the overall impact into direct and indirect effects.

	"Scenario comparison" allocation approach		*"Within scenario" allocation approach*	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Dependent variable	$I_i^{INDIRECT}$	$I_i^{INDIRECT}$	$I_i^{INDIRECT}$	$I_i^{INDIRECT}$
Constant	2.998*	0.924	-0.868	-5.165***
	(0.825)	(1.847)	(0.825)	(1.875)
I_i^{DIRECT}	3.597***	3.953***	1.582***	2.044***
	(0.155)	(0.381)	(0.076)	(0.188)
m_i		0.082		0.160**
		(0.066)		(0.065)
$I_i^{DIRECT} \times m_i$		-0.013		-0.016***
		(0.012)		(0.006)
Observations\	440	440	440	440
Adj. R^2	0.548	0.547	0.497	0.503
Log. likelihood	-1618.30	-1617.51	-1577.12	-1573.47
AIC	3242.60	3245.03	3160.25	3156.93

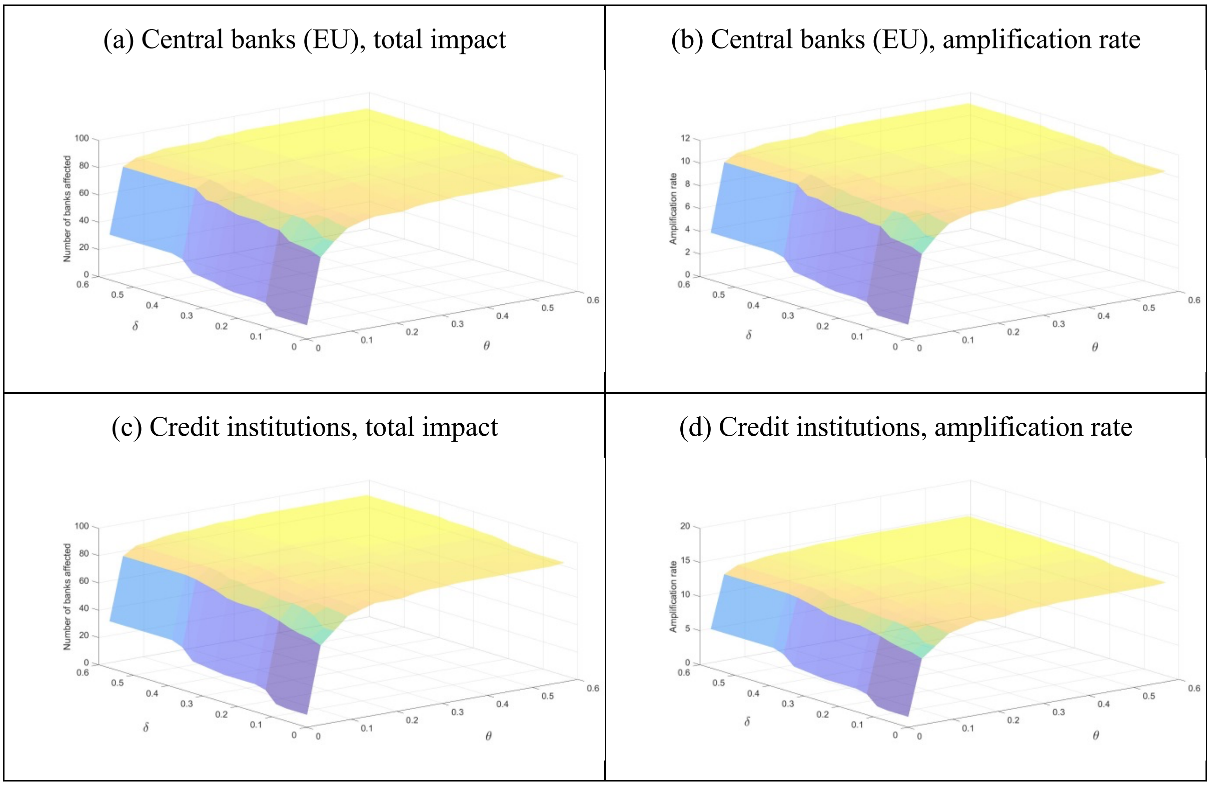
Table 6: Regression results on the sample of all scenarios with non-zero overall impact, using two alternative specifications (with or without interaction term between intensity and direct impact) and two alternative ways to allocate the impact between direct and indirect effect ("scenario comparison" and "within-scenario" allocation approaches, as presented in Appendices A and B, respectively). $\boldsymbol{I_i^{DIRECT}}$ and $\boldsymbol{I_i^{INDIRECT}}$ represent the number of banks who were hoarded liquidity due to direct and indirect channels of transmission, respectively. The variable $\boldsymbol{m_i}$ represents the shock intensity and takes values between 5 and 45 (reflecting percentage points of haircuts or funding withdrawal, depending on the scenario).

The estimations (see Table 6) show that a unit increase in the direct impact leads to a more than one-to-one increase of the indirect impact (Models 1 and 3), irrespective of the exact allocation algorithm used ("scenario comparison" or "within-scenario"). When we include an interaction term between the direct impact and the shock intensity, we find that conditional on increasing values of shock intensity, the unit increase in the direct impact leads to a lower increase of the indirect impact (Models 2 and 4). In other words, the mutual amplification of the two types of transmission channels is stronger for smaller triggering shocks.

When the "within-scenario" allocation method is used and the shock intensity is large the relation between transmission channels may turn negative so that an increase in the direct impact may be associated with a decrease of the indirect impact, i.e., the two channels become substitutes rather than complements. This can be seen when we consider values of m_i around the upper limit in our scenarios (e.g., around 45) and the estimated coefficients for the direct impact and the interaction term between the direct impact and the shock intensity.

4.3 Global and local indirect contagion

Given the systemic importance of the indirect channels of contagion, we investigate how sensitive our results are to the calibration of the parameters determining the strength of the indirect contagion. Specifically, we focus on the calibration of the parameters θ and δ which determine the strength of the channels of risk aversion and pro-cyclical haircuts, respectively (see Figure 7).



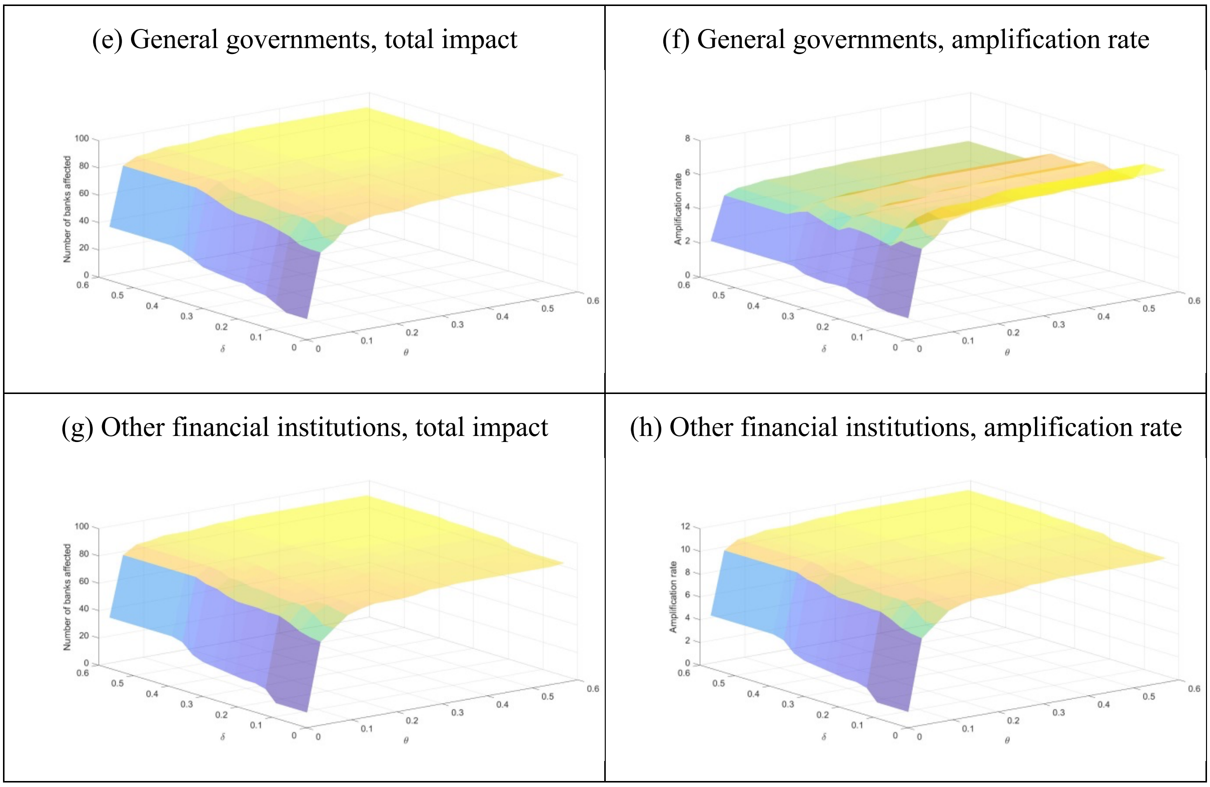


Figure 7: Sensitivity analysis for the indirect contagion mechanisms. The z-axis in the left column shows the impact in terms of affected banks while the z-axis in the right column shows the amplification rate, for the same sector. These results have been obtained for the network with reference date 2014Q4, defining shocks on the funding side, with parameters $\boldsymbol{k} = \mathbf{0.4}$ and $\boldsymbol{\varphi} = \mathbf{0.4}$ and with shocks equal to 45%.

Figure 7 shows that the extent of contagion is much more sensitive to the θ parameter compared to the δ parameter. The intuition for this is the following. The sensitivity of risk aversion to neighbouring banks hoarding liquidity has a local effect (as it affects a set of banks linked to the bank facing liquidity stress) compared to the global impact of the haircut sensitivity δ (that affects all banks in the network), and as a result the impact of the δ parameter is already high even for relatively low values. In contrast, the impact of the θ parameter is low when this parameter is in the low values range, however its impact exhibits an inflection point around 0.1 and then reaches a plateau. Interestingly, in all cases, a plateau is reached whereby all banks of the interbank network are affected. This plateau of maximum impact is reached quickly when the parameter δ increases and more slowly when θ increases. The fact that this plateau is ultimately reached also for the θ parameter means that the interbank network is dense enough so that even indirect contagion which exhibits a local effect, by construction, may lead ultimately to a systemic event.

5. Conclusions

We formulate a model of financial contagion that includes both direct and indirect transmission channels and apply it to a unique supervisory dataset comprising the largest exposures of the systemically important banks in the euro area. Specifically, we have extended the simulation approach of Gai et al. (2011) to incorporate also indirect mechanisms, due to time-varying risk aversion and pro-cyclical haircuts. The model is applied consequently to the network of bilateral exposures constructed from the supervisory dataset submitted by the SIs in the euro area and we examine different scenarios whereby risk originates in one of the outside sectors and impacts either the liability or the asset side of the SIs.

We find clear evidence of the strong interconnectedness characterising the various segments of the financial system, reflected in the links between systemically important credit institutions on the hand and on the other hand non-bank financial entities (such as shadow banking entities, insurers and pension funds) and smaller credit institutions. In addition, the risk posed by the sovereign-bank links through banks' asset holdings is also reflected in our results as sovereigns represent a counterparty with concentrated and large amounts both on the asset and the liability side of banks' balance sheets. Furthermore, CCPs is another source of concentrated funding for large banks, which could represent a destabilising factor if hit by a shock.

Our decomposition of the total impact resulting from the different contagion scenarios points to differences between the impact of the direct and indirect transmission channels. In general, indirect contagion exhibits steeper increases with the shock intensity, featuring a relatively large additional impact for a relatively small increase in the shock intensity, for example in the case of shocks to the government sector. In addition, indirect contagion exhibits inflection points in some scenarios. Our econometric analysis has shown that, on average, a unit increase in the impact of direct channels is associated by a multiple increase in the impact of indirect channels, especially for shocks of lower intensity. Therefore, consideration of indirect effects is especially significant to identify the extent to which relatively small shocks can lead to a systemic event. Furthermore, the upper bound of impact due to indirect contagion is significantly higher compared to that of direct contagion and can potentially pertain to the whole network. Overall, indirect contagion has the potential to substantially dominate the contagion phenomenon, especially during most severe shocks.

Our results can be extended in a number of directions. The model of financial contagion presented in this paper could be also used to examine the systemic importance of individual banks and potentially link systemic risk contribution with either their size (e.g., measured by total assets or interbank assets) or topological metrics. In addition, indirect channels could be explicitly analysed with respect to price changes caused by fire sales, which are implicit in the formulation presented here. Moreover, extending the analysis in the time dimension would be especially interesting from a stress-testing perspective, to investigate how sources of risk have evolved across time. Finally, the analysis presented is based on the set of concentrated exposures while it would be interesting to examine whether the consideration of more diversified portfolios of exposures would affect the conclusions reached.

Appendix A. Simulation algorithm

Our baseline results have been obtained using scenario comparisons to decompose the total impact into the fraction caused by direct and indirect channels, respectively ("scenario comparison" approach). Specifically, we compare the results when both channels are activated to the results obtained when only direct mechanisms operate. The pseudo-code of the former simulation is shown below:

Algorithm 1: Confounding channels ("scenario comparison" approach)
1. Initialisations: $t = 0, \Delta\bar{n}_t = 0, \boldsymbol{ELF_t} = \boldsymbol{0}$ 2. **While** $\Delta\bar{n}_t = 0$ /* *While no further bank is hoarding liquidity* 3. $t = t + 1$ /* Iteration index increased 4. $\boldsymbol{ELF_t} = \boldsymbol{ELF_{t-1}}$ /* *Funding-at-risk is initialised to the value of the previous iteration* 5. **For** $I = 1, \dots, N$ /* *A loop running through all banks and examining which will hoard liquidity.* 6. Calculate $LCR_{k,t}$ for bank i 7. **If** $\frac{LCR_{i,0} - LCR_{i,t}}{LCR_{i,0}} > \rho(k)$ **OR** $ELF_{i,t} > \varphi \sum_{k=1}^{K(i)} L_{ik,0}$ /* *Liquidity risk increases* 8. Bank i is hoarding liquidity. The number of banks hoarding is increased: $\bar{n}_t = \bar{n}_t + 1$ 9. The set of banks B_i that borrow from bank i calculate increased refinancing risk for subsequent iterations: $ELF_{k,t+1} = ELF_{k,t} + L_{ki}, \forall k \in B_i$. 10. In addition, this set of banks become more risk-averse: $\varepsilon_{k,t+1} = \varepsilon_{k,t} + \theta, \forall k \in B_i$. 11. **end-if**

12. **end-for**
13. Update haircuts: $\Delta h_{t+1}^{market-wide} = f(\bar{n}_t)$
14. **Go to step 2**

In order to decompose the total impact into the direct and indirect effects, we also run the above algorithm deactivating steps 10 and 13 and then subtract the total impact calculated from the two simulations, as described in Section 4.2.

Appendix B. Attribution of direct and indirect effects ("within-scenario allocation")

Our chosen method of decomposing contagion into the direct and indirect effects is driven by the impossibility of attributing the cause of a bank facing liquidity risk to a specific mechanism when all channels are operating (as in Algorithm 1 above). The reason is that when a bank calculates its current LCR, it uses the current value of a number of parameters, related to the effect of both direct and indirect past channels. Therefore, comparing the results when both direct and indirect channels are active with those obtained when indirect are switched off seems to be a clean way to obtain the decomposition and solve this causality attribution problem. On the other hand, this method is not unequivocal as it could allocate to indirect effects cases of affected banks that could occur also if *at that point in time* the indirect effects were not operating.

Therefore, we investigated the effect of alternative methods to attribute the cause of banks' hoarding of liquidity to direct and indirect channels. The main alternative is to separate the main loop running through all banks in Algorithm 1 (i.e. steps 5-11) into two loops, whereby direct effects would be activated in the first one, and indirect effects would be active in the second. Henceforth this algorithm is referred to as "within-scenario allocation". In this version, banks affected in the former loop would contribute to the measured impact attributed to the direct effects and those affected in the second loop to the measured impact of indirect effects. Specifically, the algorithm is as follows:

Algorithm 2: Sequential application of direct and indirect channels ("within-scenario allocation")

1. Initialisations: $t = 0$, $\Delta\bar{n}_t = 0, \boldsymbol{ELF_t} = \boldsymbol{0}$
2. **While** $\Delta\bar{n}_t = 0$ /* *While no further bank is hoarding liquidity*
3. $t = t + 1$ /* Iteration index increased
4. $\boldsymbol{ELF_t} = \boldsymbol{ELF_{t-1}}$ /* *Funding-at-risk is initialised to the value of the previous iteration*
5. **For** $I = 1, \ldots, N$ /* *Loop to calculate direct effects*
6. Calculate $LCR_{k,t}$ for bank *i*
7. **If** $\frac{LCR_{i,0} - LCR_{i,t}}{LCR_{i,0}} > \rho(k)$ **OR** $ELF_{i,t} > \varphi \sum_{k=1}^{K(i)} \; L_{ik,0}$ /* *Liquidity risk increases*
8. Bank *i* is hoarding liquidity. The number of banks hoarding is increased: $\bar{n}_t = \bar{n}_t + 1$
9. The set of banks B_i that borrow from bank *i* calculate increased refinancing risk for subsequent iterations: $ELF_{k,t+1} = ELF_{k,t} + L_{ki}, \forall k \in B_i$.
10. **end-if**
11. **end-for**

12. Update haircuts: $\Delta h_{t+1}^{market-wide} = f(\bar{n}_t)$
13. **For** $I = 1, \ldots, K$ /* *Loop to calculate indirect effects*
14. Calculate $LCR_{k,t}$ for bank *i*
15. **If** $\frac{LCR_{i,0} - LCR_{i,t}}{LCR_{i,0}} > \rho(k)$ **OR** $ELF_{i,t} > \varphi \sum_{k=1}^{K(i)} \; L_{ik,0}$ /* *Liquidity risk increases*
16. Bank *i* is hoarding liquidity. The number of banks hoarding is increased: $\bar{n}_t = \bar{n}_t + 1$
17. The set of banks B_i that borrow from bank *i* calculate increased refinancing risk for subsequent iterations: $ELF_{k,t+1} = ELF_{k,t} + L_{ki}, \forall k \in B_i$.
18. In addition, this set of banks become more risk-averse: $\varepsilon_{k,t+1} = \varepsilon_{k,t} + \theta, \forall k \in B_i$.
19. **end-if**
20. **end-for**
21. **Go to step 2**

Compared to Algorithm 1, this method of attributing causes of contagion prioritises the attribution of effects to the direct channels. This is because the direct channels are first applied, through the first loop of the algorithm, and only those banks which were not affected in that step may subsequently contribute to the indirect impact.[34]

However, the above effect does not render arbitrary the general patterns observed regarding the relationship between direct and indirect effects. First, it is important to note that the overall impact produced by Algorithms 1 and 2 is identical and the difference lies only in the fraction

[34] If we apply the loop with the indirect effects before the loop with the direct effects the opposite is the case and the ascribed indirect effect is higher.

attributed to direct and indirect effects, respectively. Second, the latter difference reflects primarily a fixed scaling effect rather than a change in the change of either direct and indirect impact associated with a change of the shock intensity. In other words, Algorithm 2 has a positive fixed effect on the fraction attributed to direct effects and, consequently, a negative one on the fraction attributed to indirect effects. See also the results of the econometric analysis presented in section 4.2.

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Supplementary material

A. Supervisory data

The dataset originates from a set of templates labelled "additional monitoring tools" that aim to provide measures of credit institutions' liquidity risk. Specifically, we merge the information contained in the template C.67 (labelled as "Concentration of funding by counterparty")[35] that reports the ten (10) most important funding counterparties for which funding exceeds 1% of total liabilities in each bank in the sample and template C.71 (labelled as "Concentration of counterbalancing capacity") that contains the main assets that can be used to address liquidity shortfalls (hence the term "counterbalancing capacity") at both the counterparty and exposure level.

The construction of the interbank network is based on the principle of the *ultimate risk basis* methodology.[36] The idea of this approach is that exposures should be traced back to the ultimate counterparty both at the lender and the borrower legs of an exposure. The alternative approach is that of the *immediate borrower basis* whereby the immediate borrower or lender are considered in the analysis.[37] To apply the ultimate risk basis approach, we have substituted each reported counterparty with its ultimate risk bearer using data on group structure that are reported to the ECB in the framework of the supervisory reporting requirements. The adjustment to obtain the ultimate risk basis is required only for the counterparties and not for the reporting banks, as the supervisory data are reported already at the highest level of consolidation within the euro area.

B. Constructed networks and their descriptive statistics

A visual depiction of the structure of the interbank network for various reference dates is shown in Figure S-8.

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[35] The templates used here can be found in https://www.eba.europa.eu/regulation-and-policy/liquidity-risk/draft-implementing-technical-standards-on-additional-liquidity-monitoring-metrics, under the links "Annex IV" and "Annex VI".

[36] The ultimate risk basis methodology is applied, for example, in the International Consolidated Banking Statistics published by the BIS.

[37] However, our results remain qualitatively similar when the network constructed with the immediate borrower basis is used. Espinosa-Vega and Solé (2011) compares results obtained by a network simulation analysis using both ultimate risk basis data and the alternative immediate borrower basis data from the BIS.

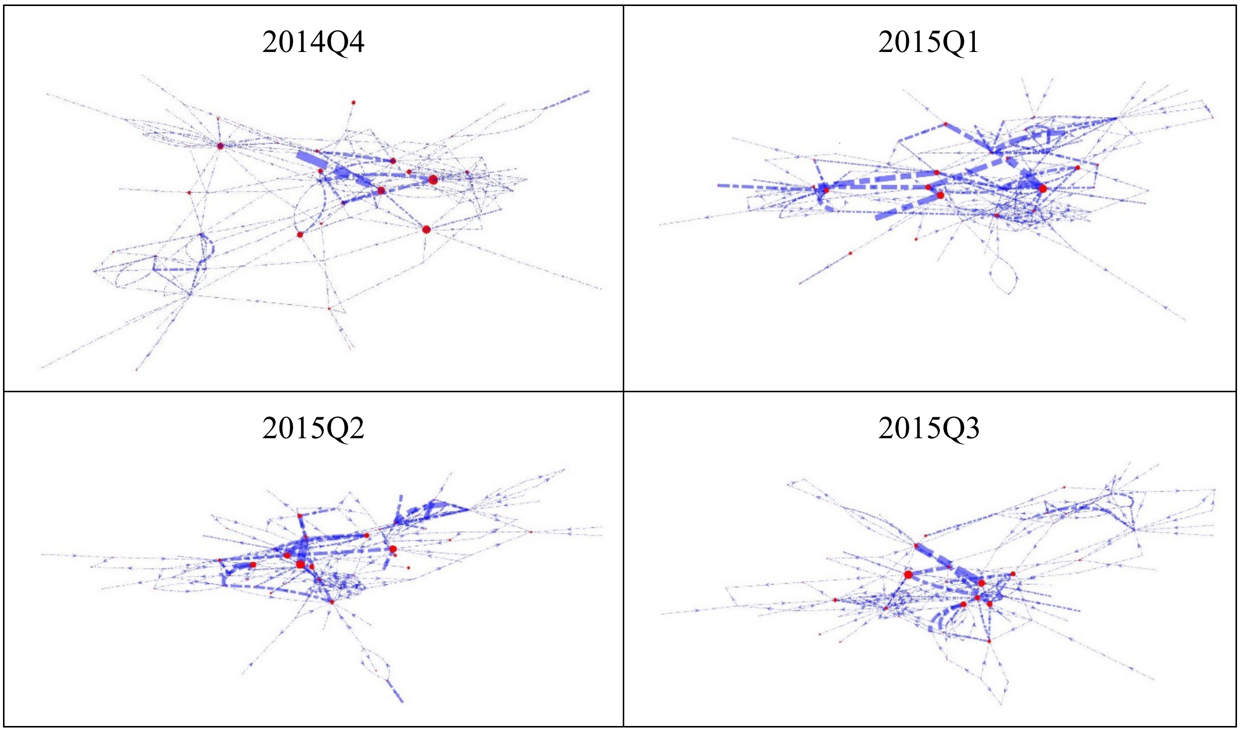


Figure S-8: Constructed interbank networks from 2014Q4 until 2015Q3.

The prevailing empirical features of i) node heterogeneity, corresponding to the different sizes of SIs, and ii) edge heterogeneity, referring to the diversity of amounts in the bilateral obligations linking the Sis, are present in all snapshots.

We quantify the degree of heterogeneity present in the dataset using a number of network metrics. First, while the median and mean node degrees in the interbank network range between 2 and 3 (e.g. for 2014Q4 network the mean node degree equals 3.79 while the median degree is equal to 3.0, meaning that on average each bank is connected to approximately three other banks in the network), there are a few banks with zero node degree (suggesting that they are only connected to outside sectors) and a few other banks with much higher node degree e.g. around 20 (see Figure S-9). The latter set of banks is obviously systemically important as these can be considered as central players in the interbank network. Also, this result points to the existence of a core-periphery structure in the euro area interbank network.

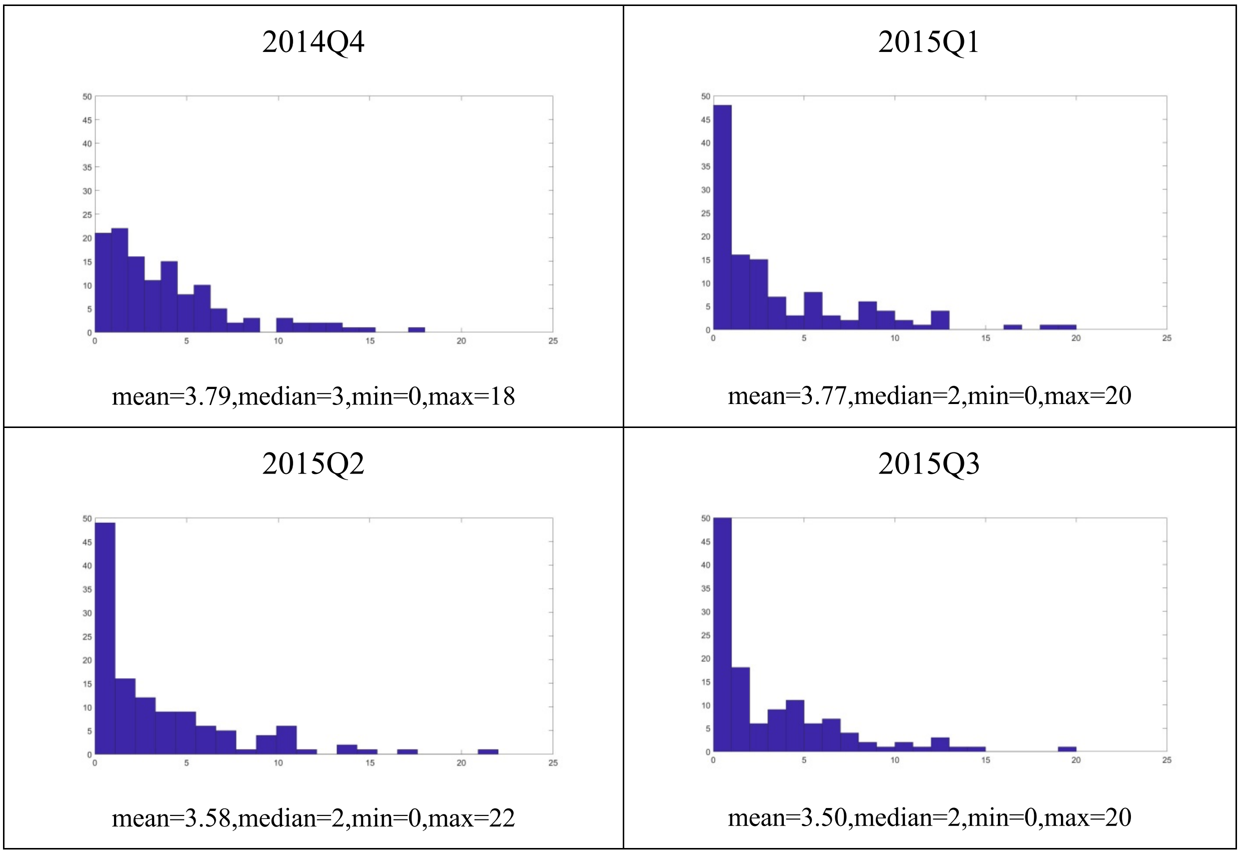
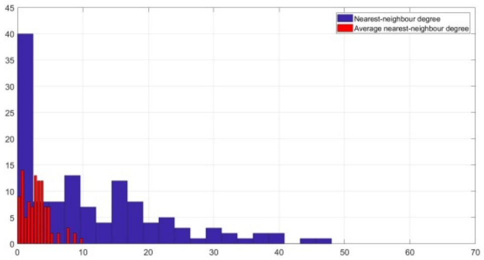


Figure S-9: Distribution of node degrees in the interbank network across time.

Similar conclusion can be drawn from other topological measures such as the nearest-neighbour degree and the average nearest neighbour degree, which are critical to understand the potential for second-order effects (see Figure S-10). Specifically, a bank that is financially sound may not be able to refinance its expiring liabilities as its creditors may also extend credit to another bank that has defaulted on its debt and thus face liquidity shortfalls. The potential of this risk is captured by the nearest neighbour degree. In our reconstructed networks the median/mean of the average nearest neighbour degree is around 3 with maximum values around 10. Importantly, although the absolute nearest neighbour degree attains a mean value in the interval of 11 to 14, there are banks with even higher nearest-neighbour degree (i.e., from 50 to 83, for the 2015Q1 network) implying that a shock on these banks has the potential to affect through second order effects almost the whole interbank network, thus pointing to a very large degree of heterogeneity across banks.

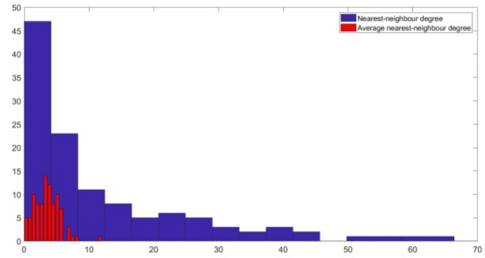
2014Q4



Absolute: mean=11.18,median=9,min=0,max=48

Average: mean=3.04,median=3.00,min=0,max=10

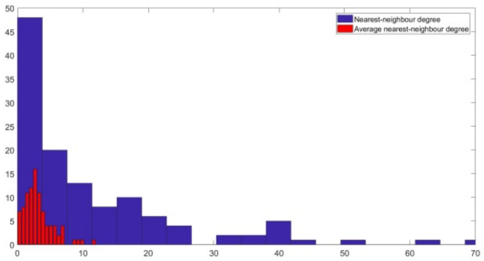
2015Q1



Absolute: mean=13.44,median=7,min=0,max=83

Average: mean=3.53,median=3.50,min=0,max=12

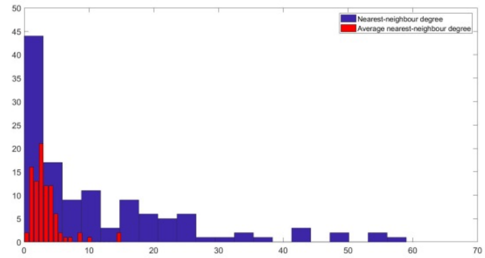
2015Q2



Absolute: mean=11.40,median=7,min=0,max=76

Average: mean=3.22,median=2.84,min=0,max=12

2015Q3



Absolute: mean=11.07,median=6,min=0,max=59

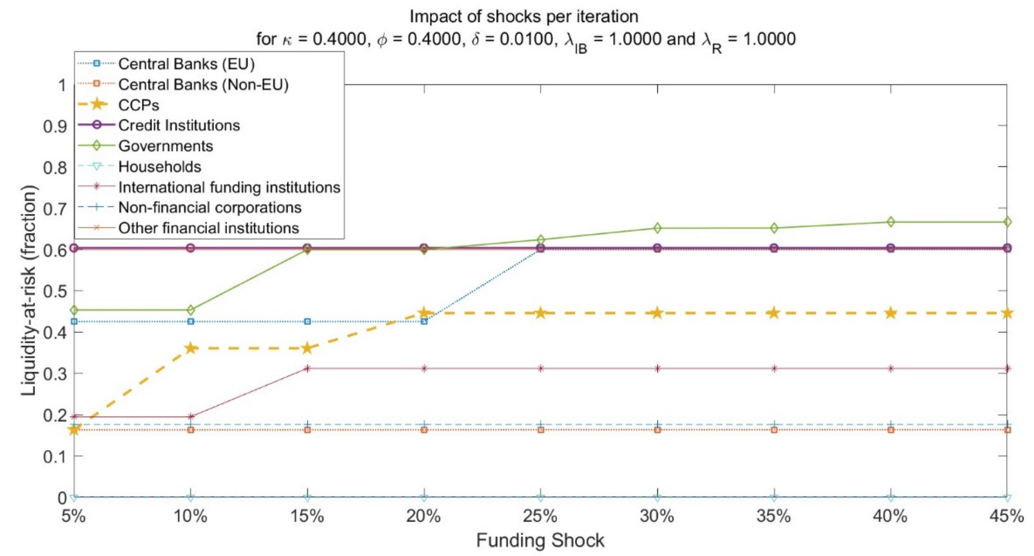
Average: mean=3.34,median=3,min=0,max=15

Figure S-10: Distribution of nearest-neighbour degrees (blue) and average nearest-neighbour degrees (red) in the interbank network across time.

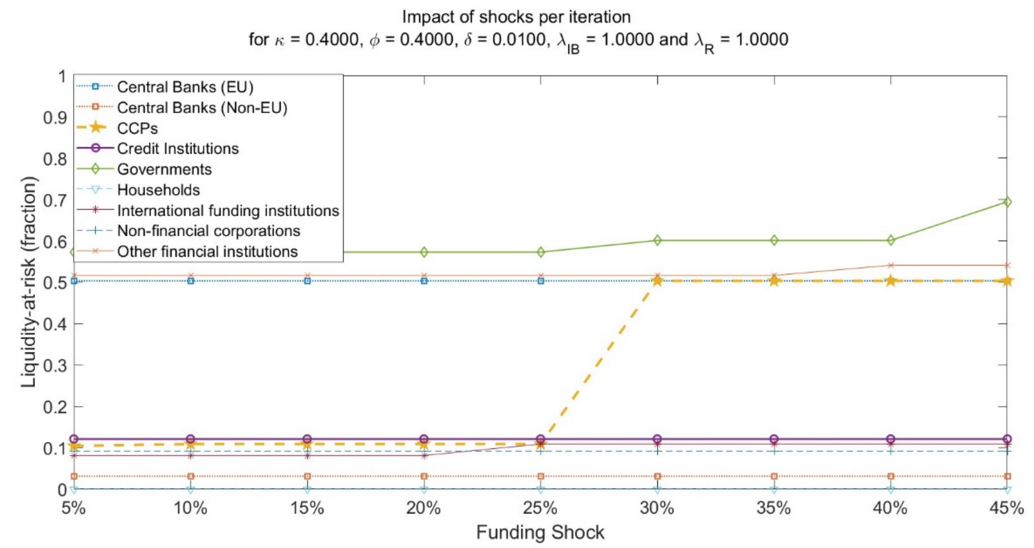
C. Measuring impact through liquidity-at-risk

For all the scenario examined in Section 4.1, we have also calculated the results based on the total amount of liquidity hoarded (as a percentage of the total), rather than the number of banks hoarding liquidity. As can be seen (Figures S-11 and S-12), the ranking of the various sectors with respect to the systemic risk that they represent is not affected, reflecting the fact that there are no systematic differences in the composition of banks' exposures or liabilities depending on their size.

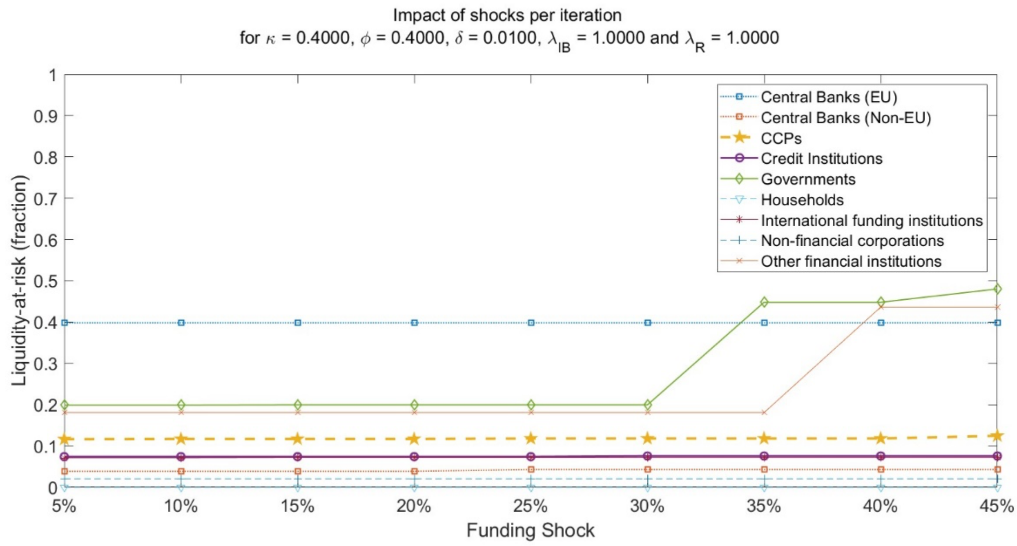
(a) 2014Q4



(b) 2015Q1



(c) 2015Q2



(d) 2015Q3

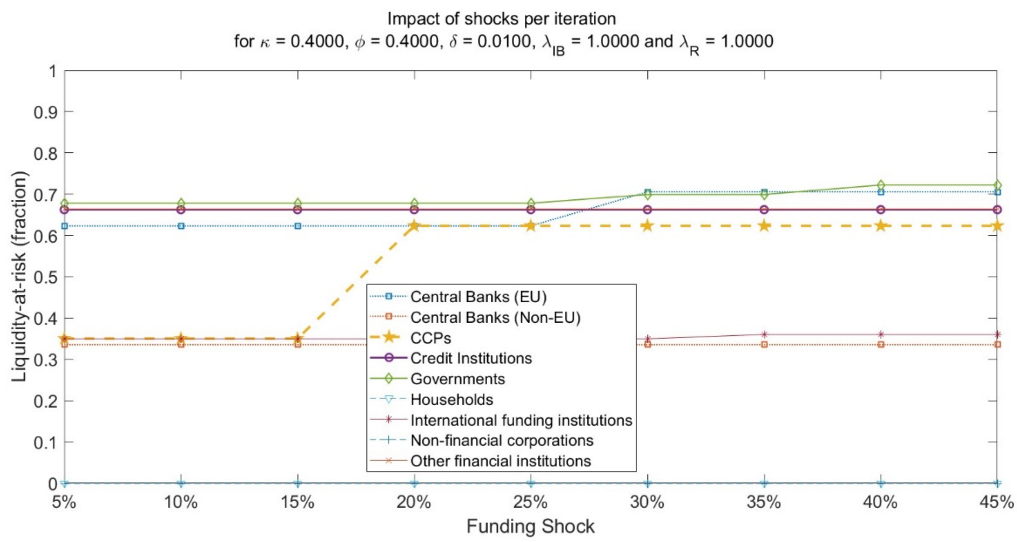
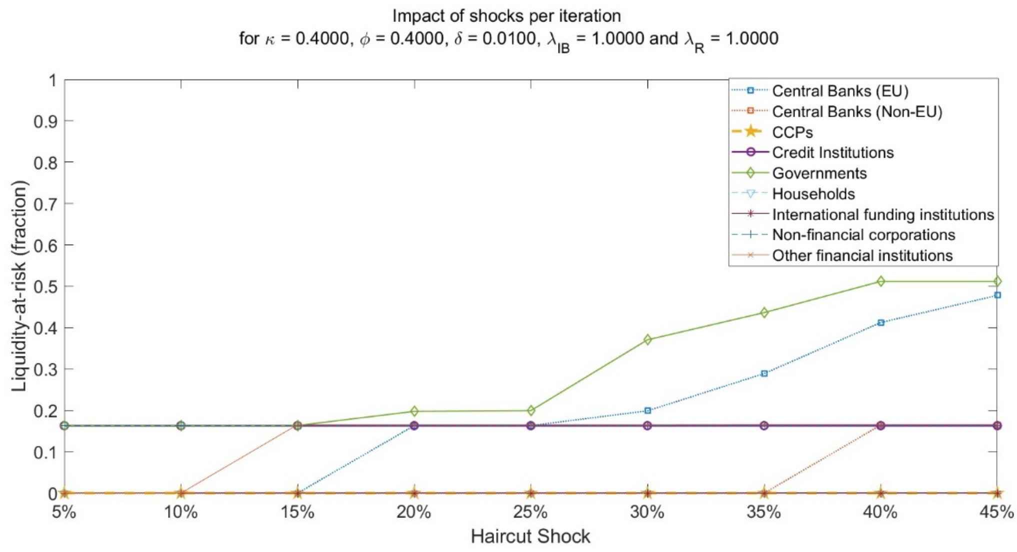
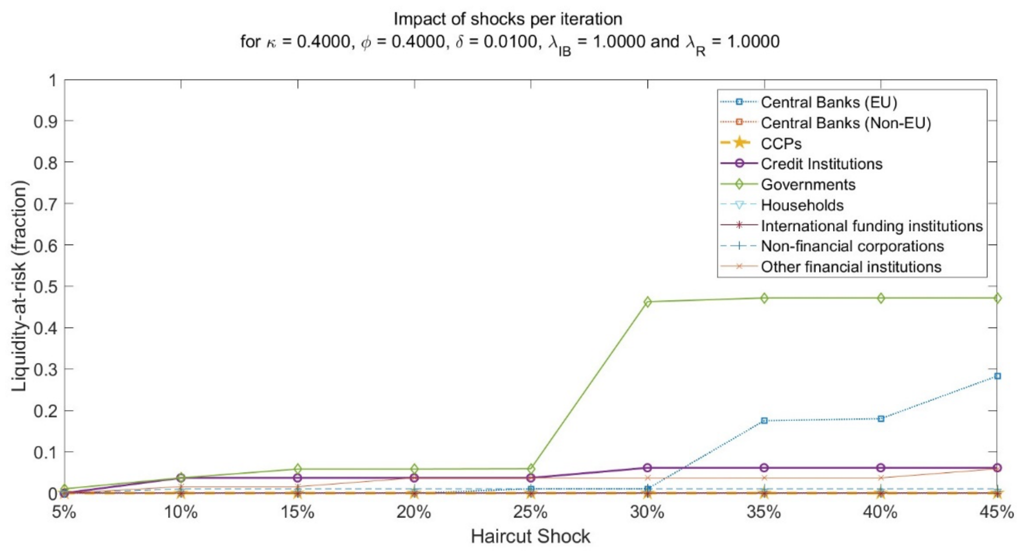


Figure S-11: Sectoral contagion due to shocks on the funding side, for different snapshots in time. The intensity of the shock (representing the percentage of funding withdrawal from the sector that is being hit by an external shock) changes in the x-axis. The y-axis depicts the liquidity hoarded in each scenario, as percentage of the total available liquidity.

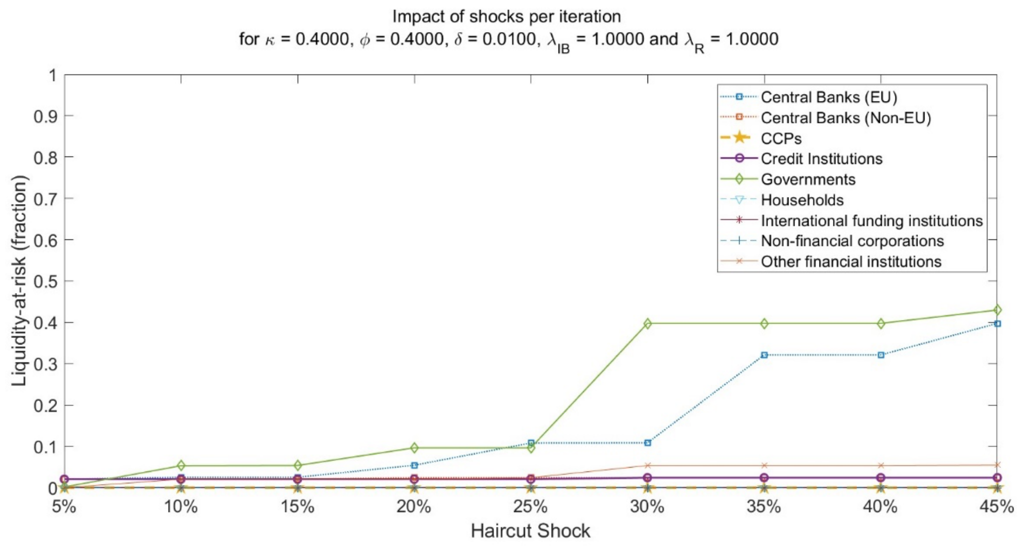
(a) 2014Q4



(b) 2015Q1



(c) 2015Q2



(d) 2015Q3

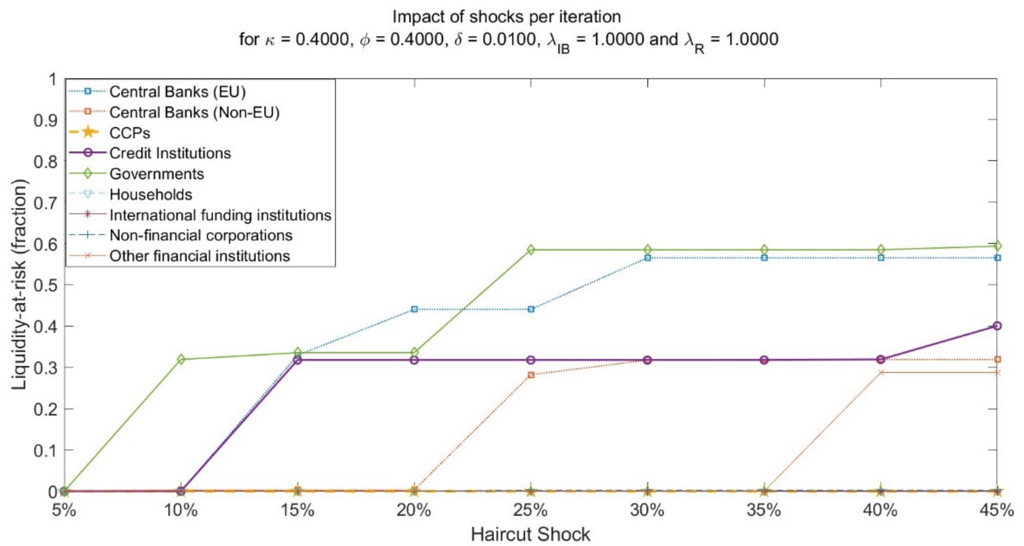


Figure S-12: Sectoral contagion due to shocks on the asset side, for different snapshots in time. The intensity of the shock (representing the haircut increase in the assets of the sector that is being hit by an external shock) changes in the x-axis. The y-axis depicts the liquidity hoarded in each scenario, as percentage of the total available liquidity.

Acknowledgements

The authors are grateful to Francesco Donat, Doyne Farmer, Michael Fedesin, Ghamami Samim, Michael Kumhof, Catherine Kyrtsou, Anastasios Malliaris, Peter Raupach and participants at the 6th conference of the Society for Economic Measurement (Goethe University, 17 August 2019, Frankfurt) and in seminars at the European Central Bank and Christ's College at the University of Cambridge for insightful comments and discussions. The responsibility for the views expressed and for any remaining errors lies with the authors.
This research was conducted while the first author was affiliated with the European Central Bank.
The views expressed are those of the authors and do not necessarily reflect those of the European Central Bank.

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PDF ISBN 978-92-899-6260-5 ISSN 1725-2806 doi:10.2866/079297 QB-AR-23-120-EN-N