

Heuver, Richard A.; Berndsen, Ron

## Article

# Liquidity coverage ratio in a payment network: Uncovering contagion paths

Latin American Journal of Central Banking (LAJCB)

## Provided in Cooperation with:

Center for Latin American Monetary Studies, Mexico City

*Suggested Citation:* Heuver, Richard A.; Berndsen, Ron (2022) : Liquidity coverage ratio in a payment network: Uncovering contagion paths, Latin American Journal of Central Banking (LAJCB), ISSN 2666-1438, Elsevier, Amsterdam, Vol. 3, Iss. 1, pp. 1-38, <https://doi.org/10.1016/j.latcb.2022.100046>

This Version is available at:

<https://hdl.handle.net/10419/336338>

### Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

### Terms of use:

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*



<https://creativecommons.org/licenses/by-nc-nd/4.0/>

Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

## Latin American Journal of Central Banking

journal homepage: [www.elsevier.com/locate/latchb](http://www.elsevier.com/locate/latchb)Liquidity coverage ratio in a payment network: Uncovering contagion paths<sup>☆</sup>Richard A. Heuver<sup>a,\*</sup>, Ron J. Berndsen<sup>b</sup><sup>a</sup> De Nederlandsche Bank<sup>b</sup> Tilburg University and LCH

## ARTICLE INFO

## Keywords:

Liquidity  
 Basel III  
 Payment systems  
 Graph theory  
 Simulation modeling

## ABSTRACT

The Basel III framework's liquidity coverage ratio (LCR) requirement aims to make banks more resilient against liquidity shocks. LCR indicates the extent to which a bank is able to meet its payment obligations over a 30-day stress period. Notwithstanding the fact that it forms an important addition to information available to regulators, it presents information on the status of a single bank on a monthly reporting basis. In this paper, we generate an LCR-like statistic and simulate liquidity failure for each of the systemically important banks, using historical data from the TARGET2 payment system. Our aim is to uncover paths of contagion. The trigger is a bank with a deteriorating LCR, and we model the knock-on effect as the impact on other banks' LCR. We then generate the cascade of contagion, which in general consists of multiple paths, to determine the extent to which the financial network further deteriorates. In doing so, we provide paths of contagion that give a sense of the systemic risk present in the network. We find that the majority of damage is caused by a small group of large banks. Furthermore, we found groups of banks that are very vulnerable to shocks, regardless of the size or location of the disruption. Our model reveals that a liquidity shortfall at a stressed bank is a more important driver than the addition of liquidity at other banks. A version of our contagion network based on a 14-day period reveals a monthly pattern, which is in line with other literature in which window dressing is addressed. The data used in this paper are available to supervisors, central banks and resolution authorities, making it possible to anticipate the contagion of liquidity coverage failures within their payment network on a daily basis.

## 1. Introduction

The financial crisis that unfolded in 2007 taught that banks had for long neglected measures to withstand financial shocks. To strengthen the banking sector's regulation, supervision, and risk management, the Bank for International Settlements (BIS) launched its Basel III reform measures (BIS, 2010). The liquidity coverage ratio (LCR) requirement of the Basel III framework aims to make banks more resilient against liquidity shocks and indicates the extent to which a bank can meet its payment obligations during a

<sup>☆</sup> The views expressed here do not necessarily represent the views of De Nederlandsche Bank or LCH. Any errors are our own. We would like to thank discussants at the Payments and Settlements Systems Seminar (Bank of Finland, 2017) and the Conference on Big Data Empirics and Policy Analysis (Bank of England, 2017) as well as colleagues in the Supervisory and Resolution divisions of De Nederlandsche Bank, for providing useful comments.

\* Corresponding author.

E-mail addresses: [richard.heuver@dnb.nl](mailto:richard.heuver@dnb.nl) (R.A. Heuver), [r.j.berndsen@uvt.nl](mailto:r.j.berndsen@uvt.nl) (R.J. Berndsen).

<https://doi.org/10.1016/j.latchb.2022.100046>

Received 8 April 2021; Received in revised form 30 November 2021; Accepted 11 January 2022

Available online 2 April 2022

2666-1438/© 2022 The Author(s). Published by Elsevier B.V. on behalf of Center for Latin American Monetary Studies. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>)

30-day stress period. Notwithstanding that the LCR adds to the available information for regulators, it presents information on a single bank's status during a monthly reporting basis.

In this paper, we use payment flows from the TARGET2 payment system<sup>1</sup> to generate an LCR-like statistic and analyze the results of liquidity failure. The addition of this paper lies in the fact that, by utilizing payment data, it becomes possible to enrich the LCR statistic with granularity, timeliness, and the network dimension. To prudential supervisors, it is important to monitor the ability of individual banks to meet LCR outflows in times of stress. By adding the network dimension, we seek to anticipate the causes and the consequences of banks' liquidity coverage failure within the financial system. To resolution authorities, the question remains what the consequences are in case of one bank's failing liquidity coverage. Whenever a bank becomes illiquid and a bank run occurs, it is crucial for financial stability to anticipate which other banks are likely to become affected.

The remainder of this paper is as follows: in [Section 2](#), we present a literature review; [Section 3](#) contains our methodology; [Section 4](#) contains results; and [Section 5](#) contains conclusions and recommendations.

## 2. Literature review

### 2.1. Liquidity coverage ratio

A major part of the liquidity requirements is the LCR, which aims to make banks more resilient against short-term liquidity shocks (BIS, 2013). The implementation is well monitored by the BIS (BIS, 2016) and the European Banking Authority (EBA, 2016). As two of the first researchers to anticipate the implementation of LCR, [Bech and Keister \(2012\)](#) concluded that the introduction of the LCR requirement will alter the demand for high liquid assets and the behaviour in money markets. [Bonner and Eijffinger \(2015\)](#) analyzed the Dutch case by using data on a liquidity requirement implemented in 2003 that was similar to LCR and compared this to an added data source on interbank market trades. They found evidence that the implementation of the liquidity requirement influenced interest rates and maturity volumes within the interbank market. [Duijm and Wierts \(2016\)](#) compared the Dutch LCR to banks' monthly bank balance sheets and found that banks adjusted their funding mixes when the Dutch LCR fell below its long-run equilibrium. Furthermore, they found that additional monitoring should be implemented at the institutional level and the aggregated level.

### 2.2. The systemic aspect

From 2008 to 2010, the FED provided a USD 1.2 trillion FED emergency loan program for global financial institutions. By combining this with data on equity investment relations, [Battiston et al. \(2012\)](#) and [Battiston et al. \(2015\)](#) developed a measure to indicate to what extent a participant's default can cause damage to the other participants using a network model. They conclude that the too-big-to-fail concept implicitly contains the question of whether a bank is too-connected-to-fail. Furthermore, financial shocks do not solely propagate through the interbank market channel, but through a diversity of markets and trading book channels, as [Silva et al. \(2017\)](#) and [Silva et al. \(2020\)](#) found. [Gai et al. \(2011\)](#) examined the network of large interbank exposures between the UK banks and performed a large set of experiments in which different shocks propagated through the network. They found that concentration and complexity of the financial network formed key amplifiers of fragility and identified mitigating policy measures. [Poledna et al. \(2015\)](#) used the availability of a data set containing four individual contract sources in Mexico to build a unique multi-layer network model and quantified systemic risk on a nation-wide level. Amongst other findings, they saw a nonlinear effect, where the sum of systemic risk of the individual layers underestimated the total risk. Contagion can also spread across nations, as is described by [Eijffinger et al. \(2015\)](#), who found that the increased spread on government bonds of one bailed-out country, can possibly lead to increased spreads in untroubled but possibly risky countries. They concluded that countries within the European economic and monetary union were strongly interconnected. Furthermore, more robust mechanisms are needed for the current Stability and Growth Pact and the no bail-out clause included in the Maastricht Treaty.

### 2.3. Adding information from financial market infrastructures

Financial market infrastructures (FMIs) are often called the financial backbone of our modern society. FMIs' main purpose is to facilitate the clearing, settlement, and recording of monetary and other financial transactions (BIS, 2012).

The most important FMIs are the large value payment systems (LVPSs), which central banks originally were developed to administer monetary policy operations, followed by the possibility to process high value interbank payments. Examples of these systems are Fedwire in the United States, CHAPS in the United Kingdom, BOJ-NET in Japan, and TARGET2 (Trans-European Automated Real-time Gross Settlement Express Transfer System, second generation) in the Euro area. [Table 1](#) shows that these systems transfer huge payment amounts, often the value of a country's GDP within one week.

LVPSs currently process payments immediately and irrevocably, thus ensuring the participants that funds have been transferred successfully. This so-called real-time gross settlement gives the receiving participants immediate control over the incoming funds. To generate payments, the sender is required to hold liquidity either in the form of account balance or by using a credit line backed by collateral.

Early research mainly focused on the design of the payment system regarding the use of liquidity. In recent decades it became clear that liquidity located within the payment systems cannot be seen apart from other locations of liquidity or the shortage thereof, thus

<sup>1</sup> A description of TARGET2 and its network characteristics can be found in [Galbiati and Stanciu-Viziteu \(2015\)](#).

**Table 1**  
Daily turnover of the main LVPSs in the world.

Country	System	2013	2014	2015	2016	2017
<i>In USD billions</i>						
Japan	BOJ-NET	1146	1131	1072	1214	1229
United Kingdom	Kingdom	430	439	410	400	424
United States	Fedwire	2797	3469	3273	3008	2902
European Union	TARGET2	2914	2594	2213	2108	2148
<i>As % of GDP</i>						
Japan	BOJ-NET	22.2	23.3	24.4	24.5	25.2
United Kingdom	CHAPS	15.6	14.5	14.2	15.0	16.1
United States	Fedwire	16.4	19.4	17.8	15.8	14.6
European Union	TARGET2	22.1	19.2	18.9	17.6	17.0

Source: BIS (2019).

research now focuses on the behavior of banks and makes use of multiple data sources to obtain a broader view of banks' liquidity. Berndsen et al. (2016) combined different Columbian financial networks and concluded that the study of the full network enabled a much broader view on contagion and financial infrastructures' systemic risk.

For a bank's liquidity manager, the focus of liquidity management is mainly to "last through the day" and at the end of the day, to meet the monetary policy minimum reserve requirement. Although research on liquidity within LVPSs has often focused on the intraday time span, payment data can be presented as (daily) balances<sup>2</sup> and it is possible to prolong the focus of research to the maintenance period or even longer.

When a bank starts to encounter problems that affect the liquidity availability, it is expected that the first signs of an unfolding bank run become visible in the LVPS. Therefore, we can conclude that, although not all information on the underlying nature of payment flows is present, this payment data available to central banks is well suited for simulations of liquidity failure in the financial network.

#### 2.4. The LCR statistic

The LCR statistics are generated at monthly intervals based on individual banks' balance sheet items and expectations of inflow and outflow of funds. Moreover, although this brings a wealth of information on the liquidity position of individual banks, supervisors and other authorities would benefit from the addition of the following dimensions.

First, the current reporting period concerns a month. What happens in between these monthly snapshots remains hidden to the supervisors. Banks are aware of reporting requirements and are able, to a certain level, to steer their balance sheets. Window dressing is used by institutions that want to appear more attractive near reporting periods and has been studied by several researchers. Furfine (1999) found a significant increase in the price in the federal funds market at year-end, which is due partly to window dressing. Heijmans et al. (2013) found that Dutch money market rates contained a monthly calendar effect, which indicated window dressing. Lynch et al. (2014) used a large database on institutional trades and discovered a turn-of-the-year effect caused by selling small, poorly performing stocks at year end and/or buying the same stocks in early January. Bucalossi and Scalia (2016) found that the low frequency (end-of-quarter) of Basel III Leverage Ratio reporting, as mandated by EU rules, facilitated window dressing. They concluded that banks adjusted quickly to the new leverage framework, well in advance of the 2018 deadline, by improving their Leverage Ratio at quarter end. Munyan (2017) investigated the U.S. repurchase market and found quarterly window dressing that spilled over into broader market liquidity.

Second, the information lags one month because the reporting deadline is currently set at 30 days after the reporting month ends. The liquidity position of banks can be easily and quickly disrupted, and bank runs can arise within days. Timeliness of information is crucial for supervisors, and it would be ideal to have the information immediately after or even before the end of the month.

Third, to prudential supervisors, it is important to monitor the ability of banks to meet LCR outflows in times of stress. To resolution authorities however, the question remains: What are the consequences in case of one bank's failing liquidity coverage? Whenever a bank becomes illiquid and a bank run awakens, it is crucial for financial stability to anticipate which other banks are likely to become affected.

### 3. Methodology

#### 3.1. Data used

We use historical payment data from the most important European payment system, TARGET2, which on average processes 350,000 transactions per day between 2200 participants (which for the remainder of this paper have been condensed into 1236 institutions). The data set spans June 2008 to December 2016, comprising 2295 days and 786 million transactions. Though timely available (next day), these large and granular data sets are designed to store historical transactions and are not suited for analysis. To maintain good performance, this data is transferred into a data warehouse.

<sup>2</sup> See Heijmans and Heuver (2010), in which a set of indicators was developed to monitor the daily liquidity positions of banks.

### 3.2. Simulating stress cascades

We want to simulate liquidity failure for each day in the data set, using the payment flows of the 30 day period ahead. We define a set of the 100 largest institutions in the payments network, denoted by  $\mathbb{L}100$ . To generate this list, we first take the list of systemically important financial institutions (SIFIs), as defined and published by the Financial Stability Board (FSB, 2016), denoted by  $\mathbb{S}$ . Afterward, we add the list of critical participants as defined by the ECB<sup>3</sup>, which we denote by  $\mathbb{C}$ , and remove duplications. As there are some overlaps between the two, the list then contains 66 institutions, which we complete by selecting the largest institutions within TARGET2, based, in turn, on the total value of outgoing payments or on the weighted Eigenvector centrality.<sup>4</sup>

For each of the banks in  $\mathbb{L}100$ , we separately simulate the failure of its liquidity management and follow what happens in the payment network. Liquidity failure of one stressed bank will lead to decreased outflow of payments to the connected receiving banks. We assume that all other banks manage their liquidity well and investigate how much the decreased incoming payments from the initially stressed bank affect their LCRs; we denote LCR by  $L$ . Whenever one or more of the affected banks'  $L$  deteriorates below the level of 1 (or, equivalently, 100%), we investigate to what effects this leads in the following rounds.

The simulation's starting point forms the liquidity buffer,  $B$ , for all banks in case of proper liquidity coverage, which means that the banks are able to fulfill all payment obligations within a 30-day stress period. Furthermore,  $L$  is the ratio of the liquidity buffer  $B$  divided by the 30 day stressed net outflow,  $O_n$ ;

$$L = \frac{B}{O_n}, \text{ where} \quad (1)$$

$L$  = liquidity coverage ratio,  $B$  = liquidity buffer, and  $O_n$  = outflow, netted during a 30-day period.

The netted outflow  $O_n$  is the difference between total outflow  $O$  and total inflow  $I$ . One important restriction in the BIS definition of  $L$  is that the total inflow  $I$  is capped to 0.75 of the total outflow  $O$  (i.e.,  $O_n = O - I_c$ ). Therefore, the capped inflow  $I_c$  therefore has the following definition:

$$I_c = \min(I, 0.75O), \text{ where} \quad (2)$$

$I_c$  = inflow, capped,  $I$  = inflow during a 30-day period ( $I \geq 0$ ), and  $O$  = outflow during a 30-day period ( $O \geq 0$ ).

For the Basel III calculation of net outflow  $O_n$ , a balance sheet approach is used. For each item on the balance sheet, corresponding runoff rates are applicable (e.g., stable retail deposits 3%, less stable deposits 10%, ..., see BIS 2013 in Annex 4, for a stylized example of the LCR). In the absence of these data, we calculate the net outflow  $O_n$  by using the actual settled payment outflow,  $O$ , minus the inflow,  $I$ , of the 30-day period ahead using the aforementioned cap of 0.75. When  $L = 1$ , a bank can fulfil all of its payment obligations for a maximum 30-day stress period. When  $L$  is greater than 1, a bank will be able to withstand even larger shocks. For every bank in the analysis the initial  $L$  is set to  $1 + \alpha$ , where  $\alpha$  denotes the additional amount of liquidity above  $L = 1$ . We take 0.1 as a starting value of parameter  $\alpha$ .

In case we want to calculate which liquidity buffer  $B$  is needed for an  $L$  at this level, we rewrite Eqs. (1) and (2) to

$$\begin{aligned} B &= LO_n, \text{ or} \\ B &= (1 + \alpha)O_n \\ B &= (1 + \alpha)(O - I_c) \\ B &= (1 + \alpha)(O - \min(I, 0.75O)). \end{aligned} \quad (3)$$

After calculating the liquidity buffer for all banks, we start separate simulations of stress for each of the banks in the  $\mathbb{L}100$  set of largest institutions, decreasing this bank's  $L$  to a level less than 1. All other banks start with the calculated liquidity buffer. To lower the level of the stressed bank's  $L$ , we introduce a parameter for shortage,  $\sigma$ , and take 0.2 as the starting level. During each simulation, the stressed bank starts with a level of

$$B = (1 - \sigma)(O - \min(I, 0.75O)). \quad (4)$$

This shortage of liquidity will lead to decreasing outflow (i.e. decreasing inflows for the receiving banks) and therefore, to a possible stress cascade. In case these decreased inflows lead to an  $L$  less than 1 for the receiving banks, we continue the exercise to a new round in which each of the stressed banks becomes the source of a new stress cascade. Again, if the resulting decreased outflows lead to a decrease of the receiving banks'  $L$  less than 1, the exercise is continued to the next round. We introduce parameter  $\rho$ , which indicates up to which round we investigate whether the stress is dampened or continues to affect other banks, and take arbitrary  $\rho = 6$  as a starting point.<sup>5</sup>

The decrease of the stressed bank's outgoing payments is set at  $1 - L$ . For example, a current value of  $L = 0.7$  will lead to a 30% decrease of outgoing payments. We assume that the decrease of outgoing payments is evenly distributed across all payment types

<sup>3</sup> This list contains all participants that are considered critical on the basis of the value of their outgoing payments and the size of non-settlements in a simulation of failure. For further information, see the TARGET2 User Guide (ECB, 2016), Section 3.5.2, and the report on stress-testing of liquidity risk in TARGET2 (ECB, 2017).

<sup>4</sup> We choose this statistic because it is widely accepted as a good measure for the strength of nodes in a weighted network.

<sup>5</sup> As we were not certain of the nature of the simulations, we made sure that the simulations would end by introducing  $\rho$ . An other approach would have been to check for convergence and end the simulation runs when a threshold parameter for the added amount of damage was reached.

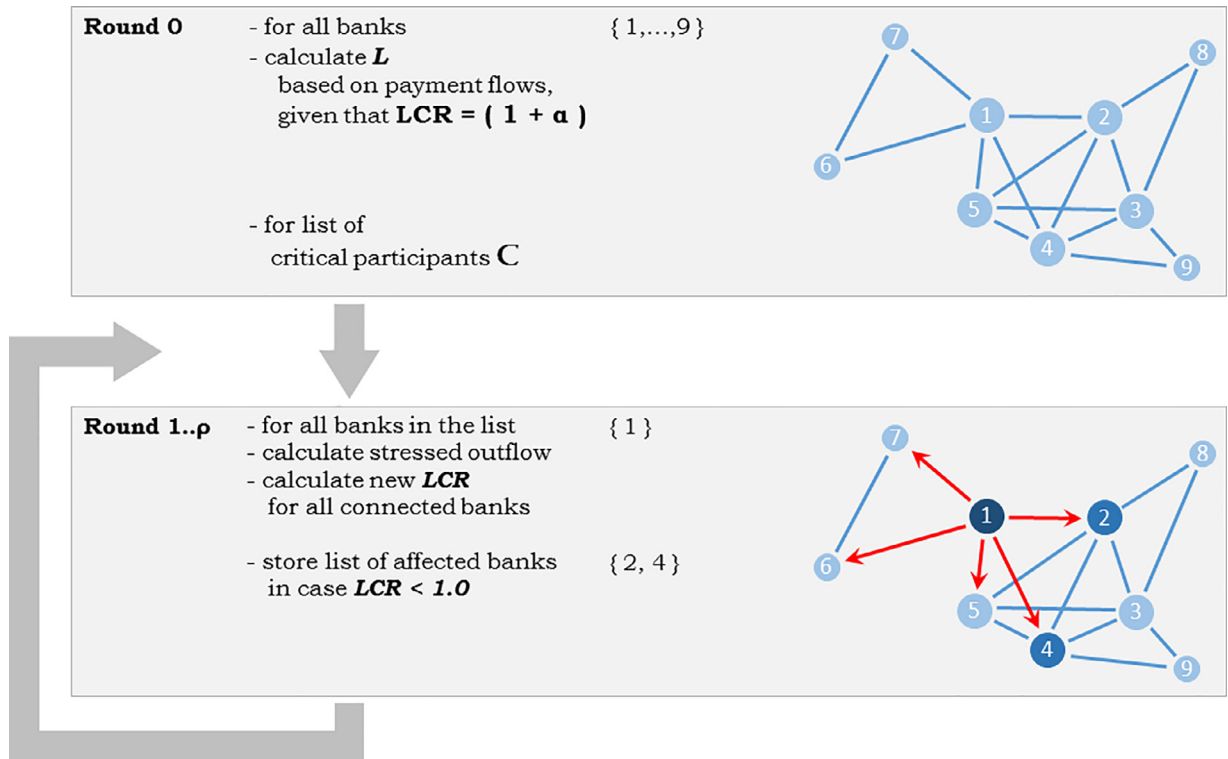


Fig. 1. Network visualization of the formation of a stress cascade.

and counterparties.<sup>6</sup> We realize that it would be more realistic to differentiate between different payment types, as well as different counterparties types, but we do not want to make our model too complicated.<sup>7</sup>

The simulation of  $L$  deterioration through the network rounds is visualized in Fig. 1 and contains the following scenario:

- Round 0 is used for the calculation of the liquidity buffer in case  $L = (1 + \alpha)$  for all banks.
- From the initial list of stressed banks, one bank is picked (in this case bank 1). The payment outflows from this bank to all receiving banks (2, 3, 5, 6, and 7) are decreased, and the new  $L$  of the receiving banks is calculated and stored. The  $L$  of banks 2 and 3 fall below 1, and these numbers are stored in the list of affected banks.
- For these two banks, the effects are calculated in the next round. This is repeated until round  $\rho$  is reached.

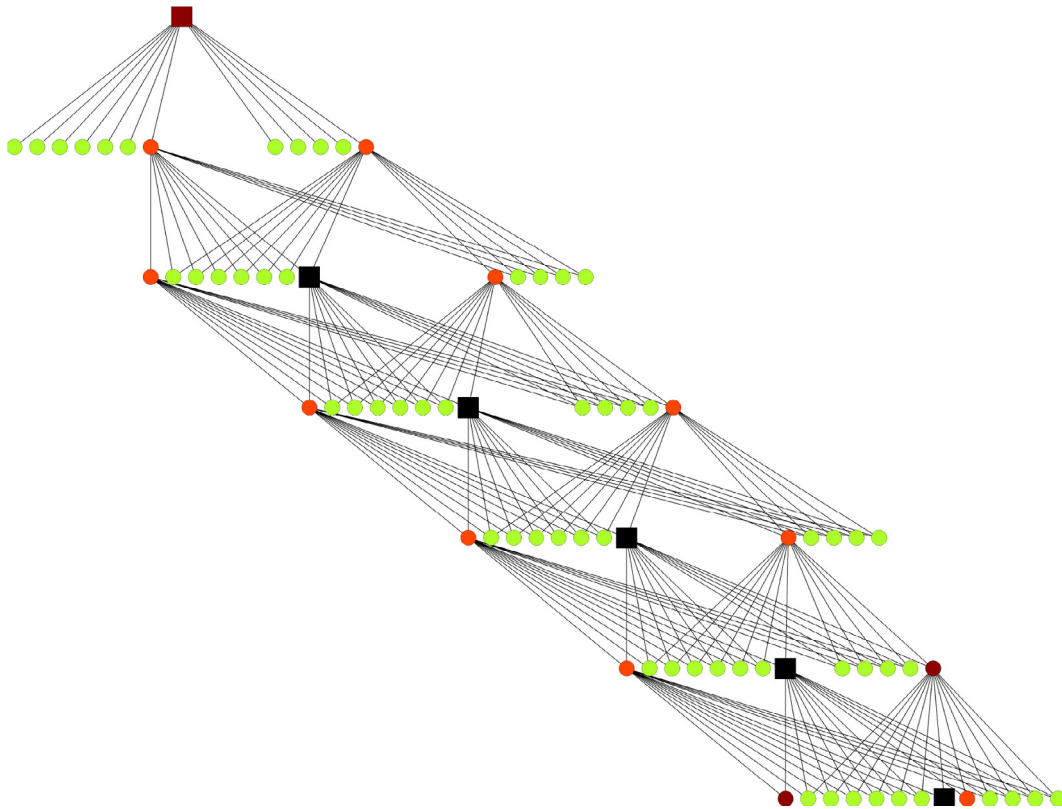
When the simulation of the stressed bank is finalized, all values of the network are restored to the initial situation, and the next bank stress simulation is started.

Viewing the simulation of stress cascades from a network perspective, we begin with a weighted and directed network graph  $G$ , consisting of a set of vertices (or nodes)  $V$  and a set of edges  $E$ ,  $G = (V, E)$ . In our case, there are no loops, meaning for all edges there is the constraint that they cannot originate and end in the same bank,  $E_{ij} | i \neq j$ . Each bank  $i$  (or vertex) from the list of initially stressed banks will possibly pass through the stress to its outgoing connected neighbours, denoted by  $V(i)$ . The cascade takes place in a subgraph  $G'$  of  $G$ ,  $G' \subseteq G$ , of which the vertices and edges are a subset of the full graph,  $V' \subseteq V$  and  $E' \subseteq E$ . Each of the connected banks that becomes affected in case  $L < 1$  will, in turn, start a stress cascade in the following round, within a newly selected subgraph  $G'$  of the complete graph  $G$ . When all cascades have been calculated from the start until round  $\rho$ , the result is a set of connected subgraphs,  $\{G'_1, \dots, G'_n\}$ . Each bank, including the initially stressed bank, is possibly part of one or several subgraphs, with the exception that the initially stressed bank cannot be present in the first round.

Fig. 2 contains a representation of the stress cascade caused by one bank. The stressed bank is visualized by a square, starting at the top. All other banks are represented by circles. The arrows indicate the outgoing payment flows to all neighboring banks. The darkening of colors reflects the banks'  $L$  deterioration. Banks that become stressed by the decrease of the incoming payment flows (in case  $L < 1$ ) have been colored dark blue and, in turn, start a new cascade in the following round.

<sup>6</sup> This is in line with Battiston et al. (2012) and Eisenberg and Noe (2001).

<sup>7</sup> Most likely, some participants will react more strongly due to risk aversion. Furthermore, participants most likely show similarities in portfolios and activities and will react simultaneously, which will lead to stronger effects in the subsequent rounds.



**Fig. 2.** Example of a stress cascade caused by one bank. Notes: Each level in the graph represents a round in the cascade (starting at the top with level 0, and ending at the bottom with round 6). The stressed bank is represented by a square. Darkening of nodes reflects the deterioration of  $L$  at four levels (1.1 - 1, 1 - 0.7, 0.7 - 0.35, and 0.35 - 0). Used parameters:  $\alpha = 0.1$ ,  $\sigma = 0.2$ , and  $\rho = 6$ .

### 3.3. Storage and analysis of simulation outcome

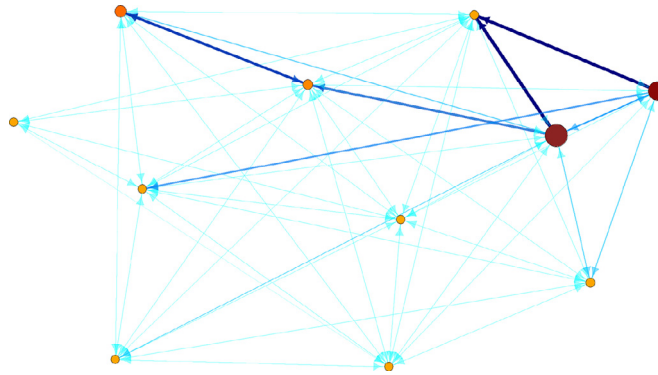
During each round, the  $L$  of the affected banks is recalculated for each of the outgoing payment flows. Each calculation of  $L$  results in a record containing the following:

- day of simulation,
- round (0 for the calculation of initial liquidity buffers, 1- $\rho$  for the cascades thereafter),
- initial stressed bank,
- currently stressed bank (in rounds 2- $\rho$ ),
- affected bank (which will be added to the list of stressed banks in case  $L < 1$ ),
- current inflow,
- current outflow,
- current  $L$ .

In doing so, we can analyze the outcome of a cascade from different perspectives. Furthermore, by performing series of simulations on the same payment networks, we can compare different values of liquidity shortage,  $\sigma$ , of the stressed banks and the liquidity addition,  $\alpha$ , of the other banks.

The original payments network forms the input for initial buffer calculation and stress cascades in which each of the institutions became stressed. As the resulting non-settlements contain the same network dimension, the resulting data sets can be viewed as networks of damage. Fig. 3 is an example of such a deterioration network, in which the nodes represent the institutions and the edges (or links) the amount of damage. The size and darkening of colors of nodes reflect the institutions' outgoing strength, indicating the power to cause damage.<sup>8</sup> The size and darkening of colors of the edges reflect the value of damage caused and visualize paths of destruction.

<sup>8</sup> Kleinberg's hub centrality measure has been applied, which highly ranks nodes having outgoing links to most central nodes.



**Fig. 3.** Example of a network of LCR deterioration. *Note:* The figure shows the damage caused, as well as suffered, within a subset of the banking network. The node color and size (banks) corresponds to the amount of damage caused (i.e., outgoing direction)<sup>8</sup> and visualizes paths of destruction.

### 3.4. Damage calculation

When a bank becomes stressed, its outgoing payments will decrease. We define the damage as the value weighted non-settlement of payments. This can be calculated at the bank and network (global) levels.

### 3.5. Taking a subset of the network

There are 1236 institutions present during the full period spanning June 2008 through December 2016. As calculation of stress cascades would take too long, we decided to take a subset of the whole network by selecting the  $\mathbb{L}100$  institutions. As contagion of stress could possibly be transferred via smaller institutions not part of the sample, we conducted separate tests using network subsets of 200 and 150 institutions. As this was not the case, we decided that, for the remainder of this paper, the stress cascades included the  $\mathbb{L}100$  subset of the network.

## 4. Results

### 4.1. Liquidity buffer

The liquidity buffer is calculated for each institution at the beginning of each stress cascade and is based on the payment flows of the 30 day period ahead. Fig. 4 contains the total of the outgoing payment flows of all institutions and the calculated liquidity buffers at four levels of additional liquidity  $\alpha$ .

In the graph, there is an apparent linear relationship between the total value of payments and the calculated buffers. This indeed follows from

$$L = \frac{B}{O_n} \quad (\text{see 1}), \text{ which can be rewritten to}$$

$$L = \frac{B}{(O - 0.75O)} \quad | \quad I < 0.75O$$

$$B = L \cdot 0.25 O$$

$$B = (1 + \alpha) \cdot 0.25 O \quad | \quad I < 0.75O.$$

The only case of nonlinearity happens when a bank's inflow is less than  $0.75O$ , which would lead to a higher liquidity buffer. This is apparently negligible.

### 4.2. High frequency networks

As the data from the LVPS is timely and granular, it is possible to generate stress cascades on a daily basis that contain transactions of the subsequent 30-day period. This enables exploration of more granular versions of LCR damage networks. Fig. 5 gives an example of daily generated LCR damage. The amount of damage differs significantly. Furthermore, the concentration amount of damage caused by the institutions is calculated using the Herfindahl-Hirschman index, ( $HHI$ ), which is the sum of the squares of the institutions' proportions of damage:

$$HHI = \sum_{i=1}^n p_i^2, \text{ where} \tag{5}$$

$p$  = proportion of damage caused.

The  $HHI$  is indicated by darkening of the colors; darker colors represent a higher centrality (i.e. a smaller share of the institutions accounts for a larger proportion of the damage value).

For the remainder of this paper we have selected a representative LCR period in 2016.

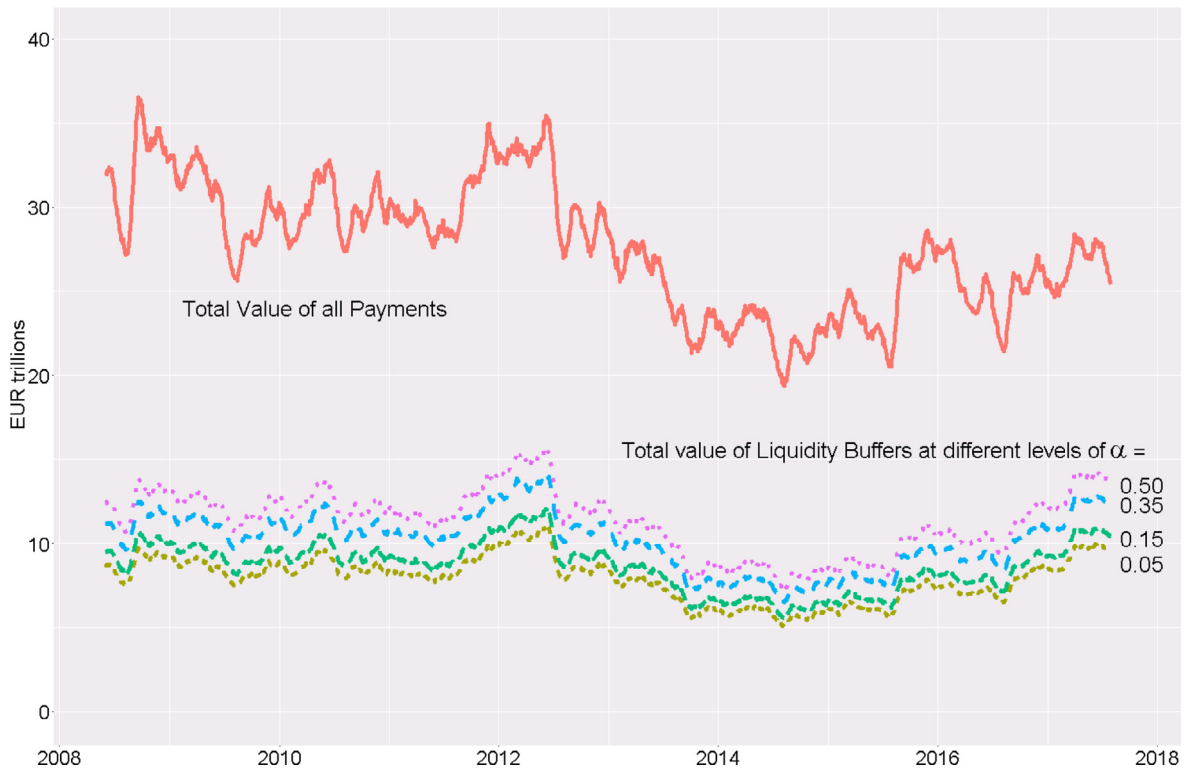


Fig. 4. Value of outgoing payment flows and calculated liquidity buffers at different levels of  $\alpha$ .

#### 4.3. Damage per round

At the start of each cascade, the stressed bank's outflow to the connected banks will be decreased. These affected banks will become stressed themselves when their  $L$  becomes less than 1, in which case, during the following rounds, their outflows become decreased as well. Fig. 6 gives an example of the effects of stress through six rounds. In this example, it is clear that the largest part of the damage already occurs during the first rounds because, most likely, the parameters were set at a relatively high liquidity shortage and minimal liquidity addition ( $\sigma = 0.50$ , and  $\alpha = 0.05$ ).

#### 4.4. The institutional aspect

The damage of non-settlement brings two sides of interest. On the one hand, it is interesting to find out which institutions cause the most damage when their liquidity management fails. On the other hand, it is interesting to know which institutions are most vulnerable to damage caused by others, despite their proper liquidity management. Both sides occur in the network of damage and can be viewed when selecting either the outgoing links or the incoming links. Although it can be expected that the largest institutions will account for the majority of damage caused, from network theory it is known that the position within the network is important; the more central, the more harm can be caused. At the same time, it can be expected that the largest institutions will not easily be harmed by stress at smaller institutions, but again, centrality cannot be ignored. Fig. 7 shows the amount of damage per institution from the causing and suffering sides. The left-hand side shows the damage caused, and the right-hand side shows the damage suffered. The institutions are ordered according to the size of damage caused, which results in a power law distribution.<sup>9</sup> The red dot shows the difference between the causing and suffering sides and, indeed, shows that the largest three institutions cause far more damage than they suffer.

To explore the network topology of the damage further, Fig. 8 presents the network adjacency matrices. Each row in an adjacency matrix represents the damage caused by one institution, and each column represents the damage suffered by one institution. In the left figure, the color of each cell represents the weight of the damage caused by one institution and suffered by another institution. In the right graph, the coloring is used to represent communities<sup>10</sup> found in the network.

<sup>9</sup> The first indication of this was found in a log-log plot that shows a linear distribution. As the original payment network follows a power law distribution, it is to be expected that the resulting damage network also does. However, further research will be necessary to prove this.

<sup>10</sup> Communities in a network are groups of nodes (institutions) having more connections within the groups than between groups.

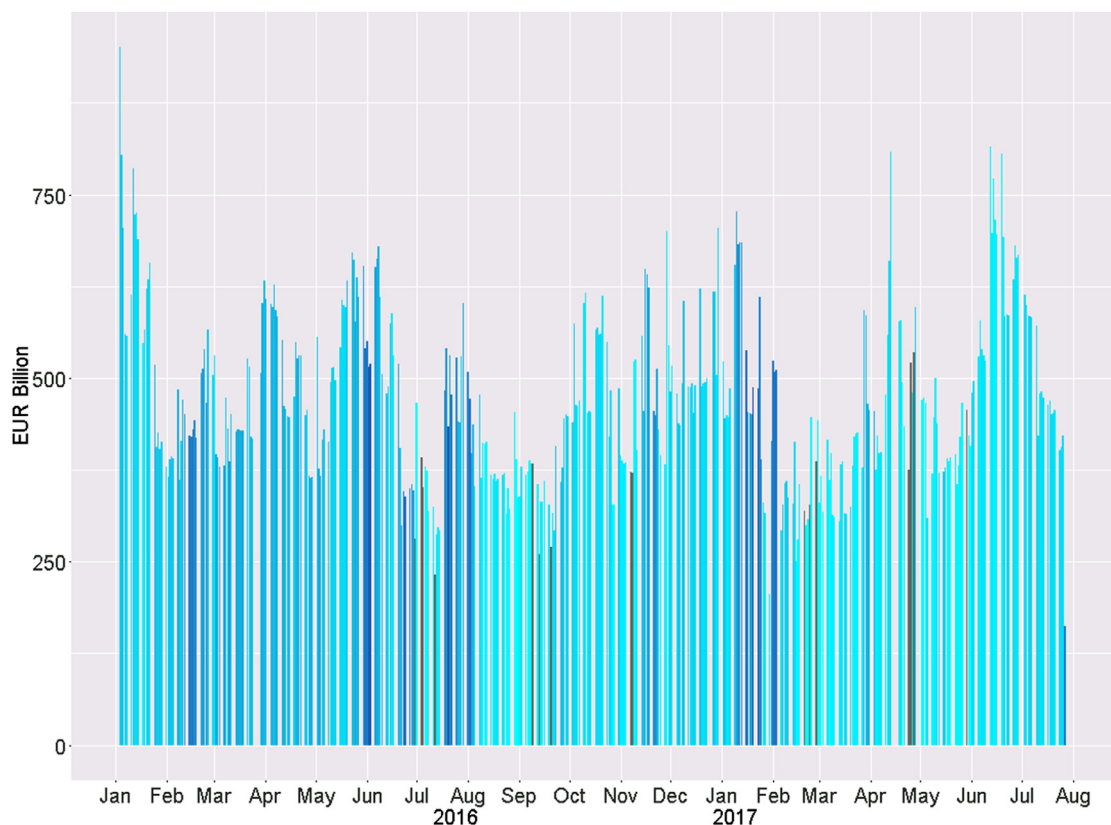


Fig. 5. Example of high frequency LCR damage networks. Note: The figure shows the amount of deterioration at daily frequency. The darkening of the color reflects the increase of centrality of the deterioration network, using the Herfindahl-Hirschman index.

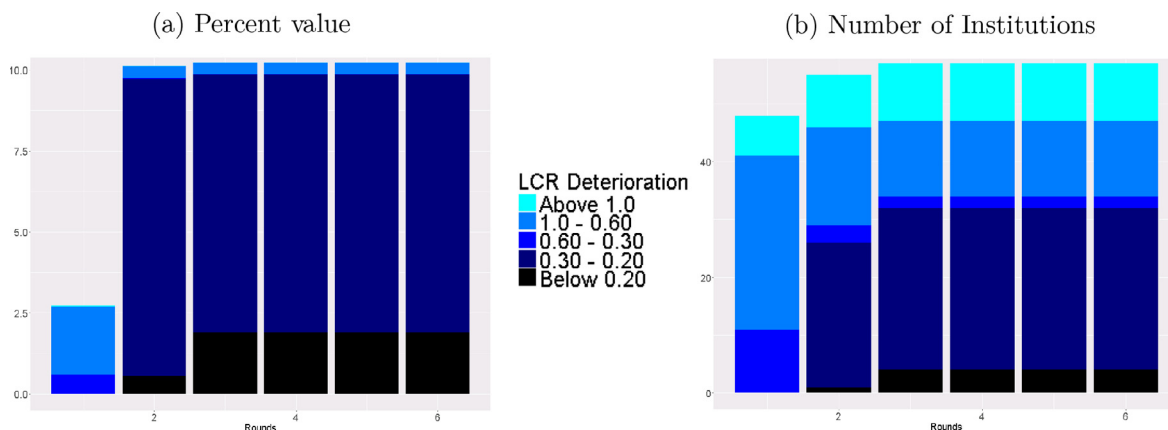
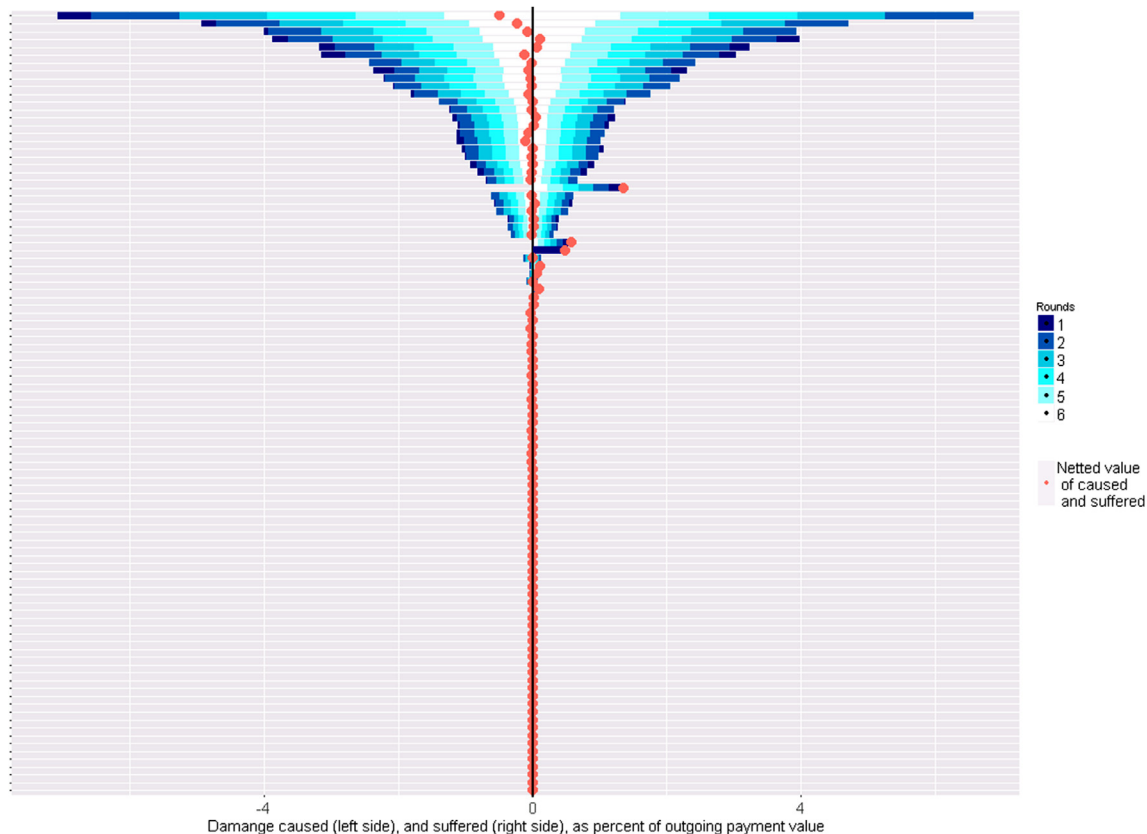


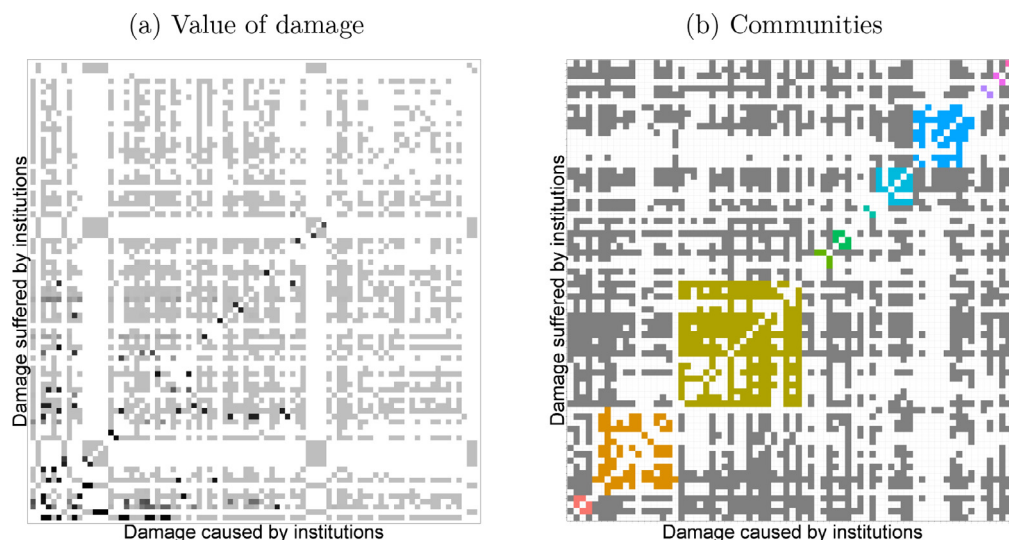
Fig. 6. Damage per round. Note: Parameters:  $\alpha = 0.05$ ,  $\sigma = 0.50$ , and  $\rho = 6$ .

#### 4.5. The relation between liquidity shortage and liquidity addition

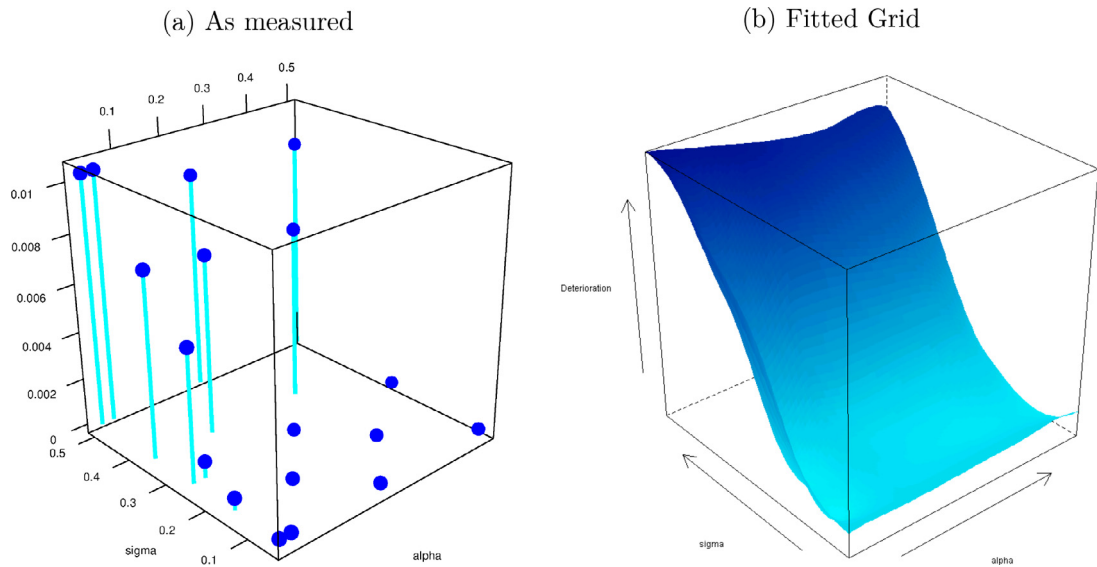
To analyse the relation between liquidity shortage,  $\sigma$ , and liquidity addition,  $\alpha$ , series of stress cascades have been conducted containing parameter values (0.05, 0.15, 0.25, 0.35, and 0.50). This results in 25 damage networks for which the total damage is visualized in Fig. 9. Both figures show the total damage (Y-axis) for each value of liquidity shortage (sigma, left hand axis) and liquidity addition (alpha, right hand axis). The left hand figure shows the individual value as measured, and the right hand figure shows an applied surface grid. As expected, we observe that the highest damage occurs at values of  $\sigma = 0.50$  and  $\alpha = 0.05$  (left corner) and that the smallest damage occurs at opposite values (i.e.  $\sigma = 0.05$  and  $\alpha = 0.50$ ). When viewing the paths between these two points, it



**Fig. 7.** Damage caused and suffered by the banks. *Note:* For each bank, one line is reserved (e.g., the y-axis represents all banks). The red dots represent the difference between damage caused and suffered. If the dot is placed on the left, it means that a bank causes more damage to others than it suffers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



**Fig. 8.** Adjacency matrices of damage caused and suffered by the banks. *Note:* The figures show the networks of damage caused and suffered. Each institution is visualized by one row and one column. Each cell represents one connection. In the left graph, the institutions are ordered by their value of damage caused (columns) and suffered (rows). This results in ordering the strongest banks toward the lower left corner. Dark colors represent high values of connections. In the right graph, the institutions are ordered and colored according to their presence in communities, which is found by an optimization algorithm (Brandes et al., 2008). The maximal modularity score is 0.52, which indicates a highly grouped structure.



**Fig. 9.** Relation between liquidity shortage and liquidity addition. *Note:* The figures show the amount of deterioration ( $Y$ -axis) caused by the liquidity shortage  $\sigma = \text{sigma}$  on the left axis or prevented by the liquidity addition  $\alpha = \text{alpha}$  on the right axis. The left figure shows the measured combinations of  $\sigma$  and  $\alpha$  and the right figure shows an applied surface grid.

becomes clear that the most important changes in damage occur when  $\sigma$  is decreased (and not when  $\alpha$  is increased). Therefore, we conclude that, in our model, it is more important to prevent liquidity shortfall than to add more liquidity.

#### 4.6. Monthly cyclicity

As the high frequency networks are based on the total of the transaction values of 30-day periods, any monthly patterns will not be present. In order to explore monthly cyclicity the period length of simulations was brought down to 14 days. Damage networks were then generated for the period January 2016 to July 2017, resulting in a time series of 405 daily networks. The partial autocorrelation function of this time series revealed significant auto correlation in lags 10, 11, and 12. This corresponds with the monthly cycle, as, due to working days, the 14-day periods contain 10 observations, and month periods contain 20–22 observations. Therefore, we conclude that the damage networks contain significant monthly cycles, which corresponds with literature described in [Section 2.4](#).

## 5. Conclusions

Using payment flows from the major European payment system TARGET2, we generate daily approximations of the LCR and focus on what happens to the other institutions when we stress each bank. In each simulation, the stressed bank starts with an LCR that has decreased to less than 1 (using a shortage parameter), and all other banks start with an LCR greater than 1 (having a surplus parameter). In doing so, we generate and store networks of LCR deterioration, which enables analysis from different perspectives. We find that the majority of damage is caused by a small group of large banks. Furthermore, we find groups of banks that are very vulnerable to shocks, regardless of the size or location of the disruption. The two drivers of damage in our model are the addition of liquidity and the shortfall of a bank's LCR. Our model shows that the most important driver is the shortfall of LCR of the stressed bank. Once a bank becomes stressed, cascades can and will occur quickly. A short version of the contagion network based on a 14-day period reveals monthly cyclicity, which is in line with literature on window dressing. To bring our model closer to reality, it could be further extended. Whenever banks are faced with a deteriorating LCR, measures will be taken to correct for this. Furthermore, banks closely monitor bilateral limits and act upon changes. Experiments have shown that the addition of a parameter for bank alertness leads to faster extinction of damage. Last, the model contains no distinction according to payment types. It can be expected that, during stress, outgoing payments will be prioritized according to the type. This model can be further developed by using current LCR statistics, by incorporating different run-off channels (e.g., depositor runs, short term loans, and participant types), and by introducing diverse reactions from participants that are faced with liquidity shocks. We conclude that the presented method enables supervisors and resolution authorities to add a network dimension to LCR that can be helpful when anticipating the causes and the consequences of banks' liquidity coverage failures. Due to the timeliness and granularity, this can be done on a daily basis.

## Declaration of Competing Interest

Herewith, we declare no competing interests for the publication of this paper.

## References

- Battiston, S., Caldarelli, G., May, R.M., Roukny, T., Stiglitz, J.E., 2015. The price of complexity in financial networks. *Sci. Rep.* [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2594028](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2594028)
- Battiston, S., Puliga, M., Kaushik, R., Tasca, P., Caldarelli, G., 2012. DebtRank: too central to fail? Financial networks, the FED and systemic risk. *Sci. Rep.* doi:10.1038/srep00541. <http://www.nature.com/srep/2012/120802/srep00541/full/srep00541.html>
- Bech, M.L., Keister, T., 2012. On the liquidity coverage ratio and monetary policy implementation. *BIS Q. Rev.* [http://www.bis.org/publ/qtrpdf/r\\_qt1212g.pdf](http://www.bis.org/publ/qtrpdf/r_qt1212g.pdf)
- Berndsen, R.J., León, C., Renneboog, L., 2016. Financial stability in networks of financial institutions and market infrastructures. *J. Financ. Stab.* doi:10.1016/j.jfs.2016.12.007. <http://www.sciencedirect.com/science/article/pii/S1572308916302340>
- BIS, 2010. Compilation of documents that form the global regulatory framework for capital and liquidity. Bank for International Settlements. <https://www.bis.org/bcb/basel3/compilation.htm>
- BIS, 2012. Quarterly review.
- BIS, 2013. Basel III: the liquidity coverage ratio and liquidity risk monitoring tools. Bank for International Settlements. <https://www.bis.org/publ/bcb238.pdf>
- BIS, 2016. Basel III monitoring report september 2016. Bank for International Settlements. <http://www.bis.org/bcb/basel3/monitoring/201609.pdf>
- BIS, 2019. BIS statistics explorer - payments and financial market infrastructures. Bank for International Settlements. <https://stats.bis.org/statx/toc/CPML.html>
- Bonner, C., Eijffinger, S.C.W., 2015. The impact of liquidity regulation on bank intermediation. *Rev. Financ.* <http://rof.oxfordjournals.org/content/early/2015/11/23/rof.rfv058.short>
- Brandes, U., Dellling, D., Gaertler, M., Gorke, R., Hofer, M., Nikoloski, Z., Wagner, D., 2008. On modularity clustering. *Knowl. Data Eng. IEEE Trans.* 20, 172–188. doi:10.1109/TKDE.2007.190689. [https://www.researchgate.net/publication/3297832\\_On\\_Modularity\\_Clustering](https://www.researchgate.net/publication/3297832_On_Modularity_Clustering)
- Bucalossi, A., Scalia, A., 2016. Leverage ratio, central bank operations and repo market. Banca d'Italia Occasional Papers doi:10.2139/ssrn.2863903. [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2863903](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2863903)
- Duijm, P., Wierds, P., 2016. The effects of liquidity regulation on bank assets and liabilities. *Int. J. Cent. Bank.* 12 (2), 385–411. <http://www.ijcb.org/journal/ijcb16q2a9.pdf>
- EBA, 2016. Basel III monitoring exercise. European Banking Authority. <https://www.eba.europa.eu/documents/10180/1360107/CRDIV-CRR+Basel+III+Monitoring+Exercise+Report+-+1309.pdf>
- ECB, 2016. TARGET2 User Information Guide v 10.0. ECB Website. [https://www.ecb.europa.eu/paym/t2/professional/nov\\_2016/html/index.en.html](https://www.ecb.europa.eu/paym/t2/professional/nov_2016/html/index.en.html)
- ECB, 2017. Stress-Testing of Liquidity Risk in TARGET2. ECB Website. <http://www.ecb.europa.eu/pub/pdf/scpops/ecbop183.en.pdf>
- Eijffinger, S. W. C., Kobieliarz, M. L., Uras, R. B., 2015. Sovereign debt, bail-outs and contagion in a monetary union [https://pure.uvt.nl/portal/en/publications/sovereign-debt-bailouts-and-contagion-in-a-monetary-union\(3a1338db-3d69-448b-92c0-85d57f44a988\).html](https://pure.uvt.nl/portal/en/publications/sovereign-debt-bailouts-and-contagion-in-a-monetary-union(3a1338db-3d69-448b-92c0-85d57f44a988).html)
- Eisenberg, L., Noe, T., 2001. Systemic risk in financial systems. *Manage. Sci.* 47, 236–249. doi:10.1287/mnsc.47.2.236.9835. [https://www.researchgate.net/publication/226641913\\_Systemic\\_Risk\\_in\\_Financial\\_Systems](https://www.researchgate.net/publication/226641913_Systemic_Risk_in_Financial_Systems)
- FSB, 2016. 2016 List of Global Systemically Important Banks (g-SIBs). FSB Website. <http://www.fsb.org/wp-content/uploads/2016-list-of-global-systemically-important-banks-G-SIBs.pdf>
- Furfine, C., 1999. The Price of Risk at year-End: Evidence from Interbank Lending. *BIS* doi:10.2139/ssrn.181668. <https://ssrn.com/abstract=181668>
- Gai, P., Haldane, A., Kapadia, S., 2011. Complexity, concentration and contagion. *J. Monet. Econ.* 58 (5), 453–470. doi:10.1016/j.jmoneco.2011.05.005. Carnegie-Rochester Conference on public policy: Normalizing Central Bank Practice in Light of the credit Turmoi, 1213 November 2010
- Galbiati, M., Stanciu-Viziteu, L., 2015. Communities and driver nodes in the TARGET2 payment system, 3. *Risk.net*, pp. 31–61. <https://www.risk.net/journal-of-financial-market-infrastructures/2413553/communities-and-driver-nodes-in-the-target2-payment-system>
- Heijmans, R., Heuver, R., 2010. Is this bank ill? The diagnosis of doctor TARGET2. In: Proceedings from the Bank of Finland Payment and Settlement System Seminars 2009–2011. Bank of Finland, pp. 77–118. chapter 04
- Heijmans, R., Heuver, R., Hernández-Hernández, L., 2013. Determinants of the Rate of the Dutch Unsecured Overnight Money Market. DNB Working Paper 374. <http://www.dnb.nl/publicatie/publicaties-dnb/dnb-working-papers-reeks/dnb-working-papers/working-papers-2013/dnb287016.jsp>
- Lynch, A., Puckett, A., Yan, X.S., 2014. Institutions and the turn-of-the-year effect: evidence from actual institutional trades. *J. Bank. Finance* doi:10.1016/j.jbankfin.2014.06.028. <http://www.sciencedirect.com/science/article/pii/S0378426614002441>
- Munyan, B.K., 2017. Regulatory Arbitrage in Repo Markets. Office of Financial Research Working Paper No. 15–22. <https://ssrn.com/abstract=2685592>
- Poledna, S., Molina-Borboa, J.L., Martínez-Jaramillo, S., Van der Leij, M., Thurner, S., 2015. The multi-layer network nature of systemic risk and its implications for the costs of financial crises. *arXiv*. <http://arxiv.org/pdf/1505.04276v1.pdf>
- Silva, T., Silva, M.A.d., Tabak, B.M., 2017. Systemic risk in financial systems: a feedback approach. *J. Econ. Behav. Organ.* 144, 97–120. <https://www.semanticscholar.org/paper/Systemic-Risk-in-Financial-Systems%3A-a-feedback-Silva-Silva/Od5051cf80193d3d9815c449018d3383888ce1d6>
- Silva, T.C., Guerra, S.M., da Silva, M.A., Tabak, B.M., 2020. Micro-level transmission of monetary policy shocks: the trading book channel. *J. Econ. Behav. Organ.* 179, 279–298. doi:10.1016/j.jebo.2020.09.013. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7509538/>