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Liquidity Coverage Ratio in a Payments Network: Uncovering Contagion Paths[*]

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Abstract

The Liquidity Coverage Ratio (LCR) requirement of the Basel III framework is aimed at making banks more resilient against liquidity shocks and 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 the available information for 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 on a daily basis and simulate liquidity failure of each of the systemically important banks, using historical payments data from TARGET2. The aim of the paper is to uncover paths of contagion. The trigger is a bank with a deteriorating LCR and the knock-on effect is modelled as the impact on the LCR of other banks. We generate then the cascade of contagion, which in general consists of multiple paths, trying to answer the question to what extent the financial network further deteriorates. In doing so we provide paths of contagion which give a sense of potential systemic risk present in the network.

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. Our model reveals that the shortfall of liquidity at the stressed bank is a more important driver than the addition of liquidity at the other banks. A version of the 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, therefore making it possible to anticipate contagion of failing liquidity coverage within their payment network on a daily basis.

Keywords: Liquidity Coverage, Basel III, payment systems, graph theory, simulation modeling

JEL Codes: E58, G21, E42, C63

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1 Introduction

The financial crisis that unfolded in 2007 has taught us that banks had for long neglected measures to withstand financial shocks. In order to strengthen the regulation, supervision and risk management of the banking sector, the Bank for International Settlements (BIS) launched its Basel III reform measures (BIS, 2010).

1.1 Liquidity coverage ratio

A major part of the liquidity requirements is the liquidity coverage ratio (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) as well as the European Banking Authority (EBA, 2016).

One of the first researchers to anticipate the implementation of LCR were Bech & Keister (2012) who concluded that the introduction of the LCR requirement will alter the demand for high liquid assets and the behaviour in money markets.

Bonner & Eijffinger (2015) analyze the Dutch case by using data on a liquidity requirement rather similar to LCR that has been implemented since 2003 and compare this to an added data source on interbank market trades. They find evidence that the implementation of the liquidity requirement influences interest rates as well as maturity volumes within the interbank market. Duijm & Wierts (2016) compare the Dutch LCR to banks' monthly bank balance sheets and find that banks adjust their funding mix when the Dutch LCR falls below its long-run equilibrium. They further more find that additional monitoring should be implemented, both at institutional level as well as at aggregated level.

1.2 The systemic aspect

During the years 2008 to 2010 the FED provided a USD 1.2 trillion FED emergency loans program for global financial institutions. By combining this with data on equity investment relations among them, Battiston et al. (2012) and Battiston et al. (2015), developed a measure to indicate to what extent the default of a participant can cause damage to the other participants in a network using a network model. As well as is mentioned in other papers, in this paper it is concluded that the too-big-to-fail concept should at the least be accompanied

by the question whether a bank is too-connected-to-fail.

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 quantify systemic risk on a nation-wide level. Amongst other findings they see a non-linear effect where the sum of systemic risk of the individual layers underestimates the total risk.

Contagion can also spread across nations, as is described by Eijffinger et al. (2015), who find that the increased spread on government bonds of one country that was bailed-out, can possibly lead to increased spreads in untroubled but possibly risky countries. They conclude that countries within the European economic and monetary union are strongly interconnected, and that more robust mechanisms are needed for the current Stability and Growth Pact and the no bail-out clause included in the Maastricht Treaty.

1.3 Adding information from financial market infrastructures

Financial market infrastructures (FMIs) are often called the financial backbone of our modern society. Their 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 originally were developed by central banks to administer monetary policy operations, soon after followed by the possibility to process high value interbank payments. Examples of these systems are Fedwire in the United States, CHAPS in the United Kindom, BOJ-NET in Japan, and TARGET (Trans-European Automated Real-time Gross Settlement Express Transfer System) 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.

Table 1 about here.

Large value payment systems nowadays process payments immediately and irrevocably, therefore 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. In order 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.

Research in the early days mainly focused on the design of the payment system regarding the use of liquidity. As during the more 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, nowadays research is also focused on the behavior of banks and makes use of multiple data sources to obtain of broader view on banks' liquidity. Berndsen et al. (2016) combine different Columbian financial networks and conclude that the study of the full network enables a much broader view on contagion as well as on 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 meet the monetary policy minimum reserve requirement. While research on liquidity within LVPSs was therefore often focused on the intraday time span, however, as payments data can be presented as (daily) balance sheets[1] it is also possible to prolong the focus of research to the maintenance period or even longer.

When a bank starts to encounter problems that effect the availability of liquidity, it is expected that the first signs of an unfolding bank run become visible in the LVPS. Therefore we can conclude that, though 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.

1.4 The LCR statistic

The LCR statistics are generated at monthly interval based on individual banks' balance sheet items and expectations of inflow and outflow of funds. And 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 calender month. What happens in between these monthly snapshots remains hidden to the supervisors. Banks are aware of reporting requirements and are - up to a certain level - able to steer their balance sheets. Window dressing is used by institution that want to appear more attractive near reporting periods and has been studied by several researchers. Furfine (1999) found a significant increase in

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[1]See Heijmans & Heuver (2010), in which a set of indicators is developed to monitor the daily liquidity position of banks.

the price in the federal funds market at year-end that for a part is due to window dressing. Heijmans et al. (2013) find that Dutch money market rates contain a monthly calender effect, which indicates window dressing. Lynch et al. (2014) use a large database on institutional trades and discover 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 & Scalia (2016) find that the low frequency (end-of-quarter) of Basel III Leverage Ratio reporting as mandated by EU rules facilitates window dressing. They conclude that banks have adjusted quickly to the new leverage framework, well in advance of the 2018 deadline, by improving their Leverage Ratio at quarter end. Munyan (2017) investigates the U.S. repurchase market and finds window dressing on a quarterly basis that spills over into broader market liquidity.

Second, the information lags one month, as the reporting deadline is currently set at 30 days after the ending of the reporting month. 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 the consequences are in case of failing liquidity coverage of one bank. 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.

The remainder of this paper is as follows: in chapter 2 we present our methodology, chapter 3 contains results, while chapter 4 contains conclusions and recommendations.

2 Methodology

2.1 Data used

We use historical payments data from the most important European payment system, TARGET2, which processes 350,000 transactions per day between 2,200 participants. The data set spans June 2008 to December 2016, comprising of 2,295 days and 786 million transactions. Though fast available (next day), these large and granular data sets are designed to store

historical transactions and are not suited for analysis. In order to maintain good performance this data is transferred into a data warehouse.

2.2 Simulating stress cascades

We define a set of the 100 largest institutions in the payments network, denoted by $\mathbb{L}100$. We first adopt the list of 'Systemically Important Financial Institutions', or SIFIs, as defined and published by the Financial Stability Board (FSB, 2016), denoted by $\mathbb{S}$. Further more we adopt the list of 'Critical Participants' as defined by the ECB[2], which we denote by $\mathbb{C}$. The list contains 66 institutions, which we then complete by selecting the largest institutions based, in turn, on the total value of outgoing payments or on the weighted Eigenvector centrality. For each of the banks in $\mathbb{L}100$ we simulate the failure of its liquidity management and follow what happens in the payments 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 LCR; 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 starting point of the simulation 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 stressed period. L is the ratio of the liquidity buffer B divided by the 30 day stressed net outflow, O_n;

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

$$L = \text{Liquidity Coverage Ratio},$$

$$B = \text{Liquidity Buffer},$$

$$O_n = \text{Outflow, netted during a 30 day period.}$$

The netted outflow O_n is the difference between total outflow O and total inflow I. One

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[2]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).

important restriction in the definition of L is the fact that the total inflow I is capped to 0.75 of the total outflow O;

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

$$I_c = \text{Inflow, capped,}$$
$$I = \text{Inflow during a 30 day period,}$$
$$O = \text{Outflow during a 30 day period.}$$

The netted outflow O_n is restricted to positive values. In case inflows are larger than outflows, the results must be zero;

$$O_n = max(0, O - I_c) \tag{3}$$

For the Basel III calculation of net outflow, a balance sheets 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% etcetera, see BIS (2013), 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 $L = 1$ it implies that a bank is able to fulfil all of its payment obligations for a maximum of a 30 day stressed period. When L is above 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 α denotes the additional amount of liquidity above $L = 1$. We take 0.1 as a starting value of parameter α.

In case we want to calculate which liquidity buffer B is needed for an L at this level we rewrite equations 1, 2 and 3 to

$$
\begin{aligned}
B &= LO_n \quad \text{, or} \\
B &= (1+\alpha)O_n \\
B &= (1+\alpha)max(0,O-I_c) \\
B &= (1+\alpha)max(0,O-min(I,0.75O)).
\end{aligned}
\tag{4}
$$

After calculating the liquidity buffer for all banks we start simulations of stress for each of the banks in the $\mathbb{L}100$ set of largest institutions, by decreasing each bank's L to a level below 1. For this we introduce a parameter for shortage, σ, and take 0.2 as the starting level. During each simulation the stressed bank therefore starts with a level of

$$
B = (1-\sigma)max(0,O-min(I,0.75O)).
\tag{5}
$$

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 below 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 L of the receiving banks below 1 the exercise is continued to the next round. We introduce parameter ρ 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.

The scenario of the simulation of L deterioration through the network rounds is visualized in figure 1:

- Round 0 is used for the calculation of the liqudity buffer in case $L = (1+\alpha)$ for all banks.

- From the initial list of stressed banks one bank is then picked (in this case bank ❶). The payment outflows from this bank to all receiving banks (❷, ❹ , ❺, ❻ and ❼) are decreased and the new L of the receiving banks is calculated and stored. The L of banks ❷ and ❹ 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 ρ is reached.

Viewing the simulation of stress cascades from a network perspective we start off with a weighted and directed network graph G, consisting a set of vertices (or nodes) V and a set of edges E; $G = (V, E)$. In our case, there are no loops, i.e. for all edges there's 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 ρ the result therefore is a set of connected subgraphs, $\{G'_n, \ldots, G'_n\}$. Each bank, including the initially stressed bank, is possibly part of one ore several subgraphs, with the exception that the initially stressed bank cannot be present in the first round.

Figure 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 deterioration of banks' L. 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.

2.3 Storage and analysis of simulation outcome

During each round, for each of the outgoing payment flows, the L of the affected banks is recalculated.

Each calculation of L results in a record containing:

- 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 (wich will be added to the list of stressed banks in case $L < 1$)
- current inflow
- current outflow
- current L.

In doing so we are able to analyze the outcome of a cascade from different perspectives. Further more, by performing series of simulations on the same payment networks, we are able to compare different values of liquidity shortage, σ, of the stressed banks as well as liquidity addition, α, 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. Figure 3 is an example of such a network of deterioration, in which the nodes represent the institutions and the edges (or links) represent the amount of damage. The size and darkening of colors of nodes reflect the institutions' outgoing strength, indicating the power to cause damage [3]. The size and darkening of colors of edges reflect the value of damage caused and therefore visualize paths of destruction.

Figure 3 about here.

2.4 Taking a subset of the network

There are 1,236 institutions present during the full period spanning June 2008 till December 2016. As calculation of stress cascades would take too long, it was 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, separate tests were conducted

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[3]Kleinberg's hub centrality measure has been applied, which highly ranks nodes having outgoing links to most central nodes.

using network subsets of 200 and 150 institutions. As this turned out not to be the case, it was decided that for the remainder of this paper the stress cascades were conducted using the $\mathbb{L}100$ subset of the network.

3   Results

3.1   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. Figure 4 contains the total of the outgoing payment flows of all institutions and the calculated liquidity buffers at four levels of additional liquidity α.

Figure 4 about here.

The graph shows that there is a linear relationship between the total value of payments and the calculated Buffers. This indeed follows from

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

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

$B = L\,0.25\,O$

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

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

3.2   High frequency networks

As the data from the large value payment system is timely and granular, it is possible to generate stress cascades on a daily basis containing transactions of the most recent 30-day period. This enables to explore more granular versions of LCR damage networks. Figure 5 gives an example of daily generated LCR damage. The amount of damage differs significantly. Further more, the amount of concentration of damage caused by the institutions is calculated using the Herfindahl index, which is the sum of the squares of the institutions' proportions of damage;

$$HHI = \sum_{i=1}^{n} p_i^2 \quad , \text{ where} \tag{6}$$

$$p = \text{proportion of damage caused.}$$

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 value of the damage.

Figure 5 about here.

3.3 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, in case their L drops below 1, in which case, during the following rounds, their outflows become decreased as well. Figure 6 gives an example of the effects of stress through 6 rounds. In this example it is clear that the largest part of the damage already occurs during the first rounds, most probably as the parameters were set at a relatively high liquidity shortage and minimal liquidity addition ($\sigma = 0.50$, $\alpha = 0.05$).

Figure 6 about here.

3.4 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 most damage when their liquidity management has failed, while on the other hand it is interesting to know which institutions are most vulnerable to damage caused by others, despite of 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 also 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 might not suffer easily from stress caused by smaller institutions, but again centrality cannot be ignored. Figure 7 shows the amount of damage per institution, at causing and suffering side. The left-hand side shows the damage caused, while 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. The red dot shows the difference between the causing and suffering side and, indeed, shows that the largest 3 institutions cause far more than they suffer.

Figure 7 about here.

In order to further explore the network topology of the damage, figure 8 presents the network adjacency matrices. Each row in an adjacency matrix represents the damage caused by one institution; 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 an other institution. In the right graph the coloring is used to represent communities found in the network.

Figure 8 about here.

3.5   The relation between liquidity shortage and addition

In order to analyse the relation between liquidity shortage, σ and liquidity addition, α, series of stress cascades have been conducted containing parameter values $(0.05, 0.15, 0.25, 0.35, 0.50)$. This results in 25 damage networks of which the total damage is visualized in figure 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, while the right hand figure shows an applied surface grid. As expected, we can 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 becomes clear that the most important changes in damage occur when σ is decreased (and not when α is increased). Therefore we conclude

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that in our model it is more important to prevent liquidity shortfall than to add more liquidity.

Figure 9 about here.

3.6 Monthly cylicality

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 cyclicality the period length was brought down to 14 days. Damage networks were then generated for the period January 2016 to July 2017, resulting in 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. We therefore conclude that the damage networks contain significant monthly cycles, which is in correspondence with literature as described in subsection 1.4.

4 Conclusions

Using payment flows from the major European payment system TARGET2 we generate daily approximation of the LCR and focus on what happens to the other institutions when we stress each bank. In doing so we generate and store a network 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. Further more 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 banks LCR. Our model shows that the most important driver is the the shortfall of LCR of the stressed bank; once a bank becomes stressed, cascades can and will soon occur. A short version of the contagion network based on a 14-day period reveals monthly cyclicality, which is in line with literature that can be found on window dressing.

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 as well as the

consequences of banks' liquidity coverage failure. Due to the timeliness and granularity, this can be done on a daily basis.

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5 Tables and figures

Table 1: Daily turnover of the main large value payment systems in the world.

In USD billions						
Country	System	2013	2014	2015	2016	2017
Japan	BOJ-NET	1,146	1,131	1,072	1,214	1,229
United Kingdom	CHAPS	430	439	410	400	424
United States	Fedwire	2,797	3,469	3,273	3,008	2,902
European Union	TARGET	2,914	2,594	2,213	2,108	2,148
As % of GDP						
Country	System	2013	2014	2015	2016	2017
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	TARGET	22.1	19.2	18.9	17.6	17.0

Source: BIS (2019).

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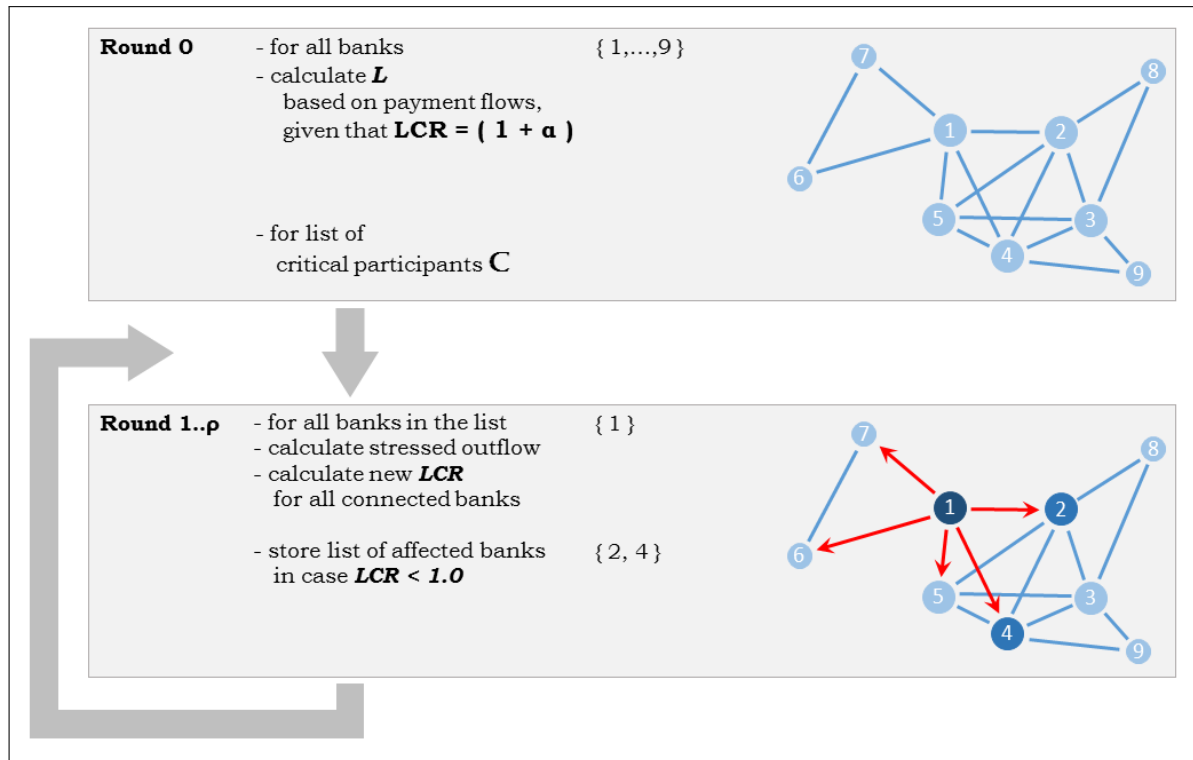
Figure 2: Example of a stress cascade caused by one bank.
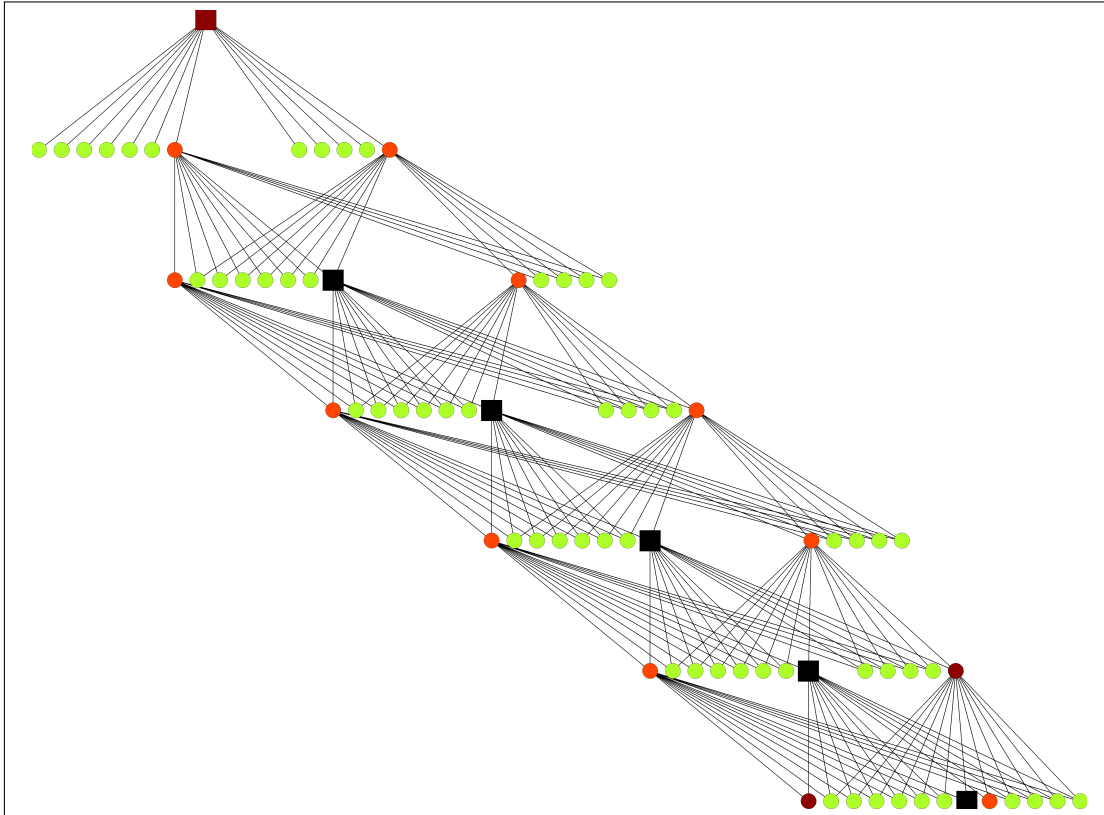
Notes: Each level in the graph represents a round in the cascade (starting at the top with level 0, and ending at the bottom with round 6). The stressed bank is represented by a square. Darkening of nodes reflects the deterioration of L at four levels (1.1 - 1, 1 - 0.7, 0.7 - 0.35 and 0.35 - 0). Used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

Figure 3: Example of a network of LCR Deterioration.
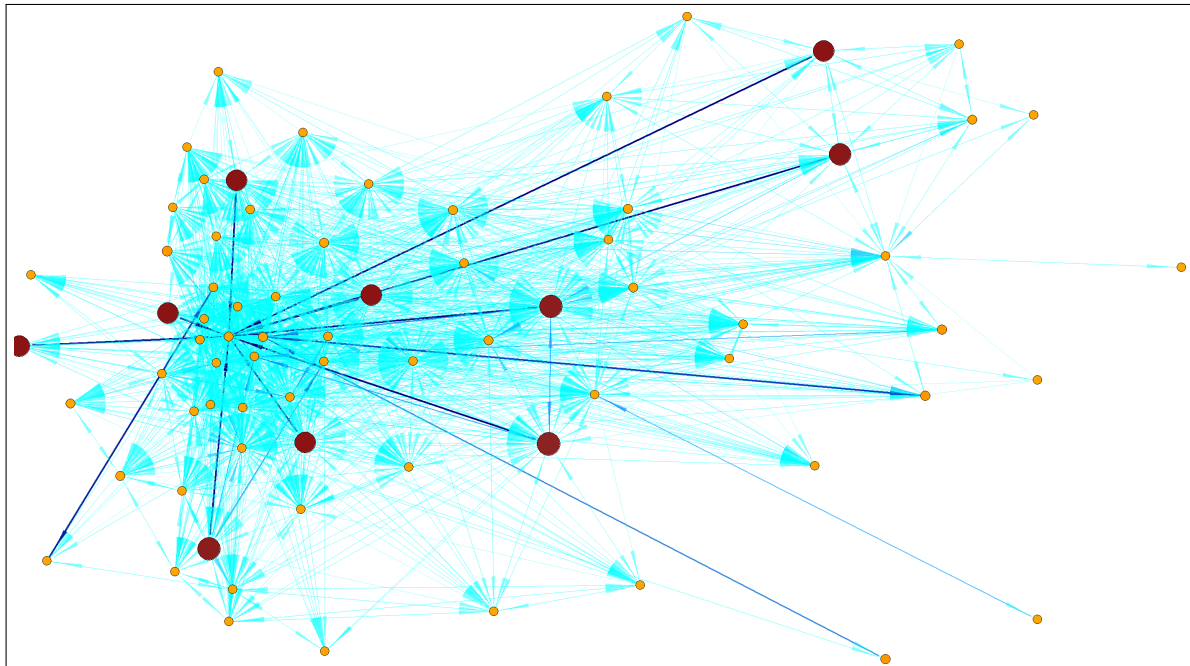
*Note: The size and darkening of colors of **nodes** reflect banks' outgoing strength, indicating the power to cause damage [3]. The size and darkening of colors of **edges** reflect the value of damage caused and therefore visualize paths of destruction.*

Figure 4: Value of outgoing payment flows and calculated liquidity buffers at different levels of α .
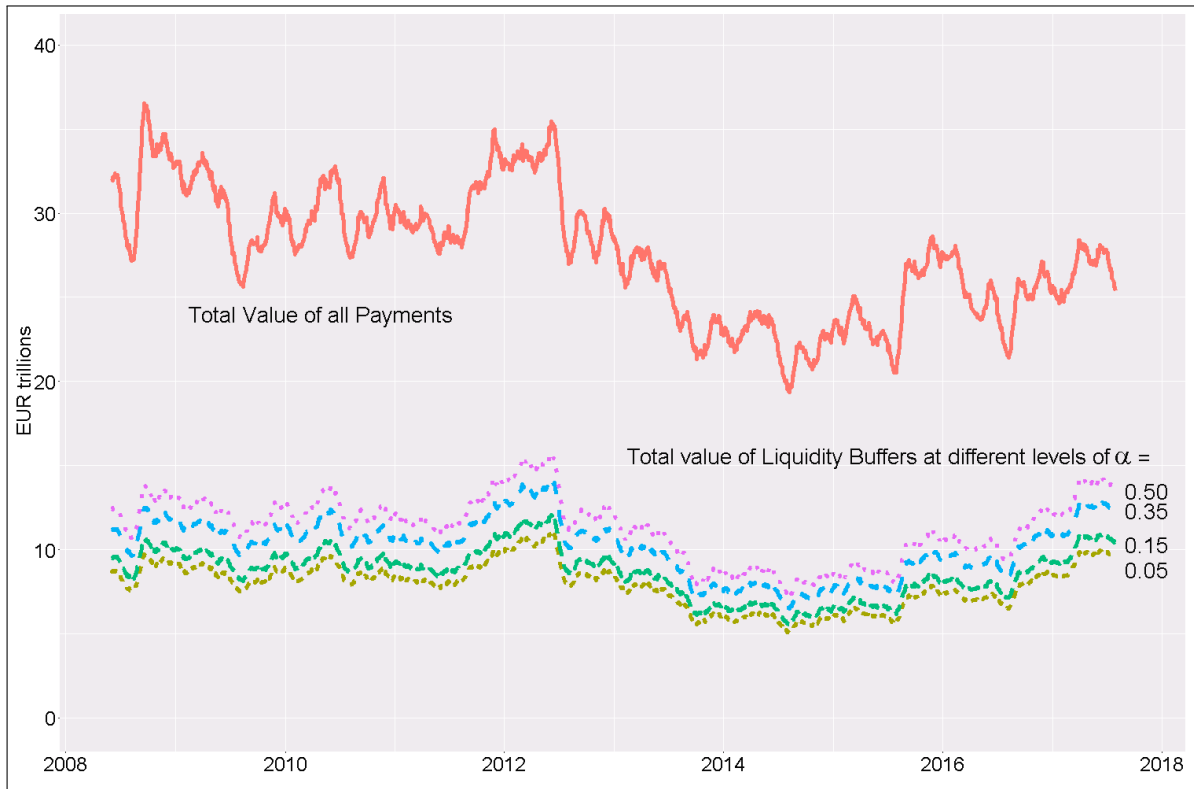
Figure 5: Example of High frequency LCR Damage networks.
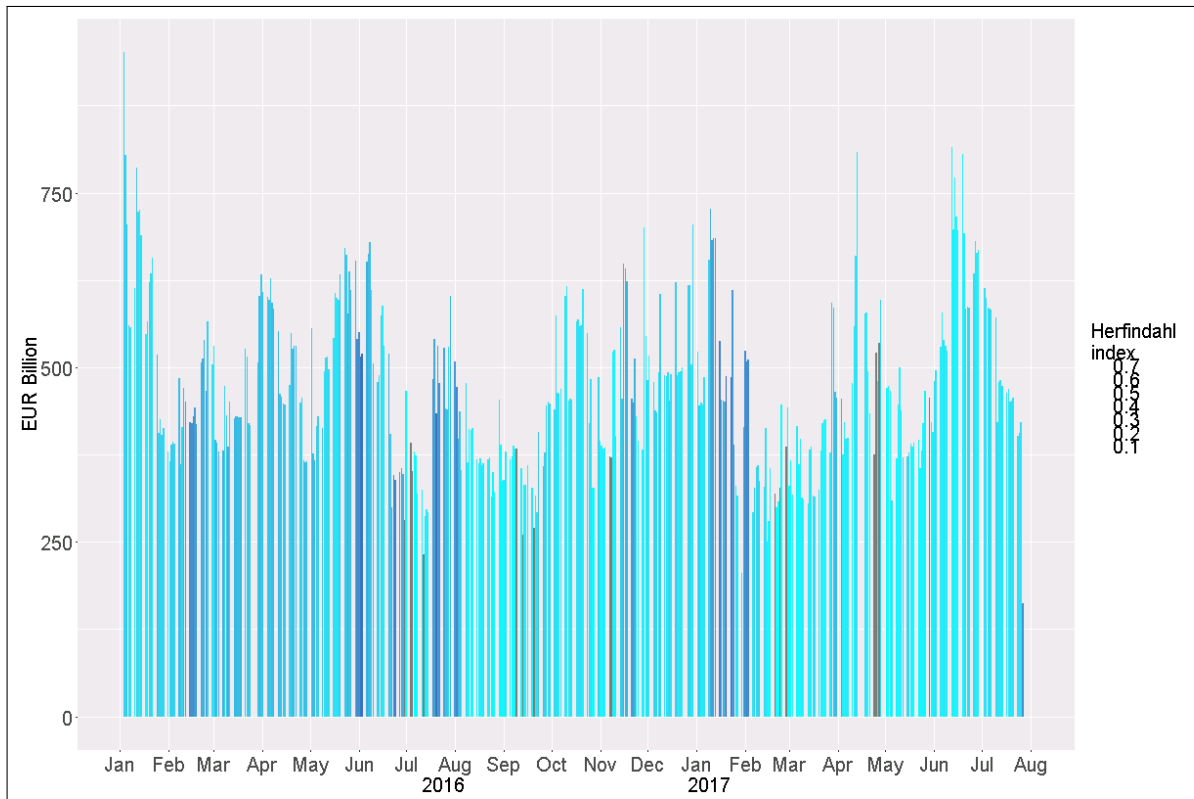
Note: The figure shows the amount of deterioration at daily frequency. The darkening of color reflects the increase of centrality of the deterioration network.

Figure 6: Damage per round.

(a) Percent value

(b) Number of Institutions

LCR Deterioration
Above 1.0
1.0 - 0.60
0.60 - 0.30
0.30 - 0.20
Below 0.20
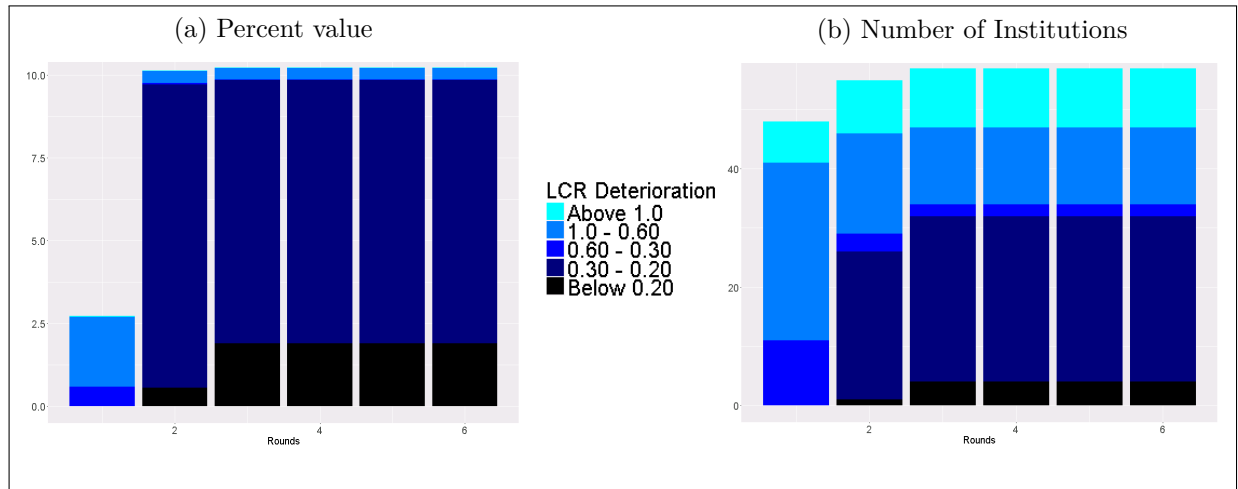
Note: Parameters: $\alpha = 0.05$, $\sigma = 0.50$, $\rho = 6$.

Figure 7: Damage caused and suffered by the banks, network graph.

Damage caused (left side), and suffered (right side), as percent of outgoing payment value

Rounds
1
2
3
4
5
6

Netted value
of caused
and suffered
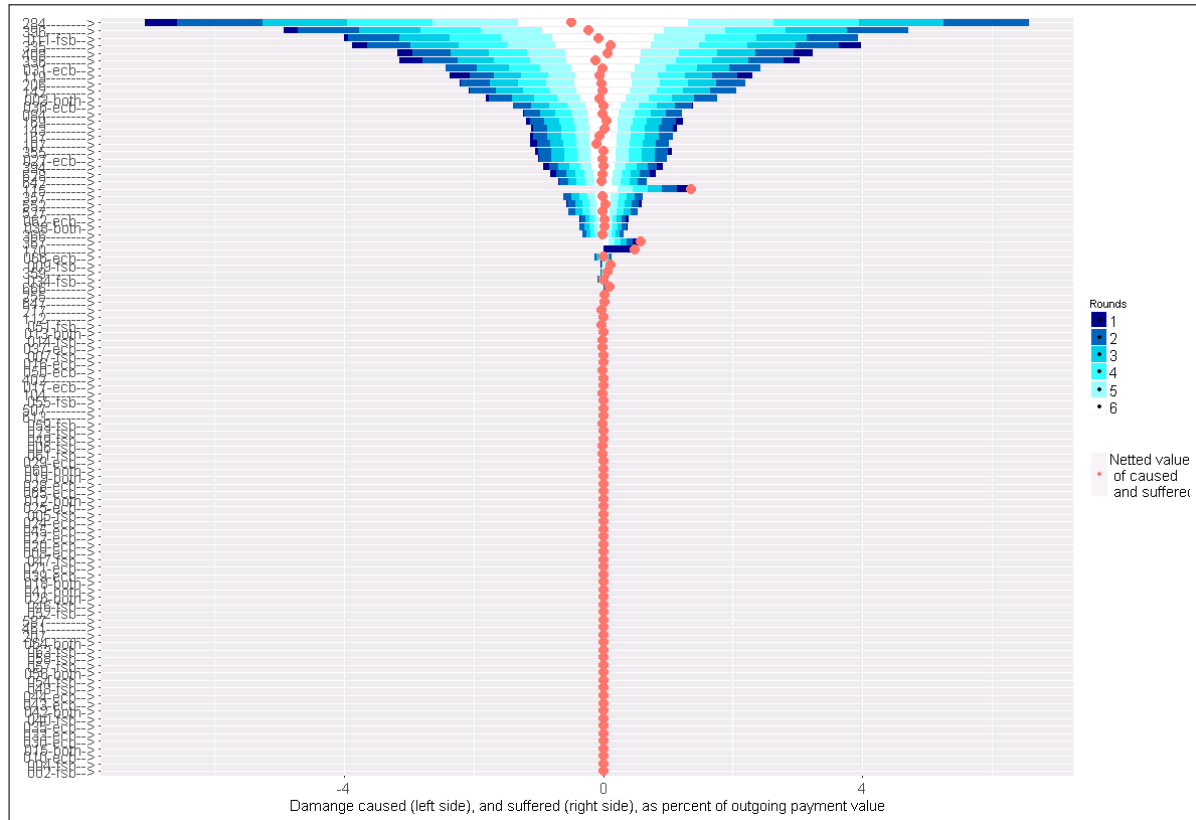
Figure 8: Adjacency matrices of damage caused and suffered by the banks.

(a) Value of damage

(b) Communities
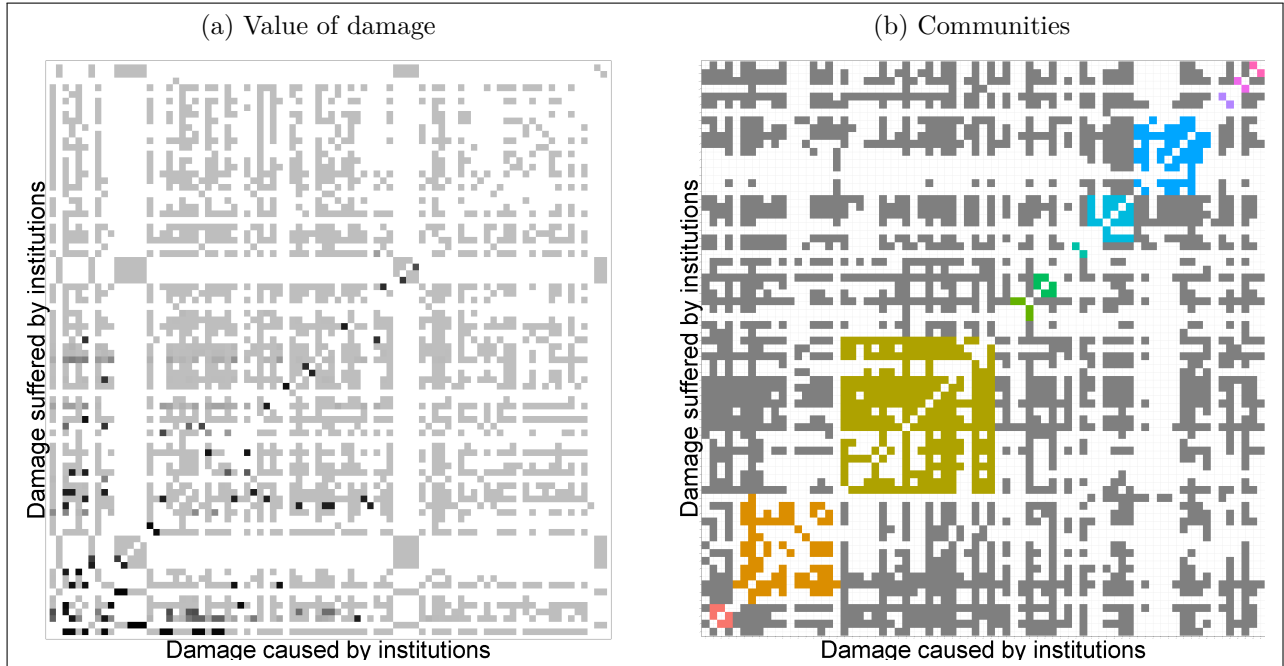
Note: The figures show the networks of damage caused and suffered. Each institution is visualized by one row and one column. Each cell represents one connection. In the left graph the institutions are ordered by their value of damage caused (columns) and suffered (rows). Dark colors represent high values of connections. In the right graph the institutions are ordered and colored according to their presence in communities, found by an optimization algorithm (Brandes et al., 2008), resulting in the maximal modularity score of 0.52.

Figure 9: Relation between liquidity shortage and addition.

(a) As measured

(b) Fitted Grid
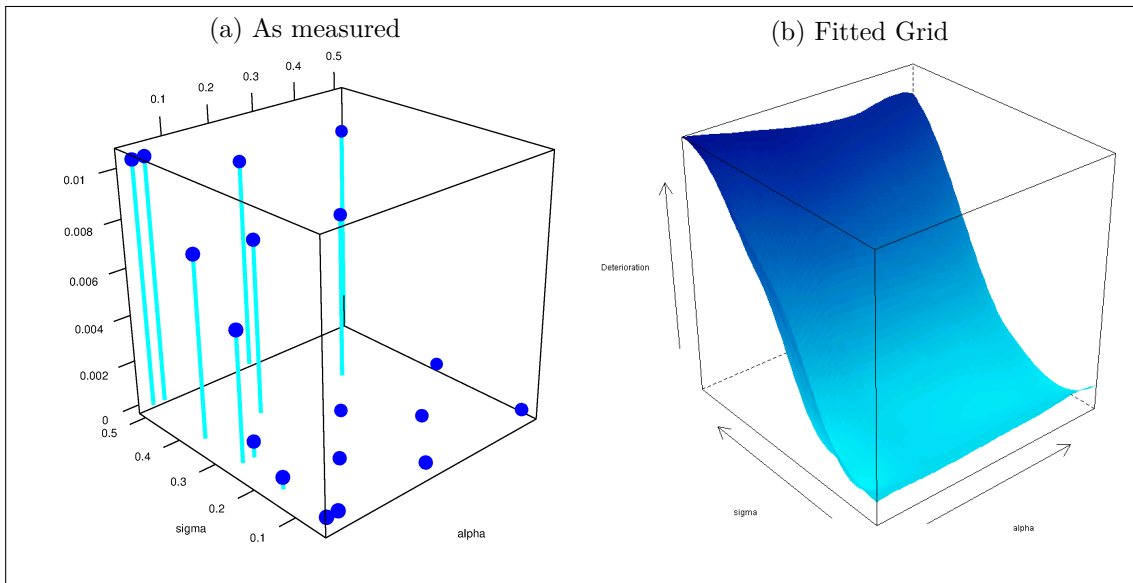
Note: The figures show the amount of deterioration (Y-axis), caused by the liquidity shortage $\sigma = sigma$ on the left axis, or prevented by the liquidity addition $\alpha = alpha$ on the right hand axis. The left figure shows the measured combinations of σ and α while the right hand figure shows an applied surface grid.

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