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Measuring counterparty risk in FMIs

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Abstract

This paper extends traditional payment system simulation analysis to counterparty liquidity risk exposures. The used stress test scenario corresponds to the counterparty stress scenario applied in the BCBS standard "Monitoring tools for intraday liquidity management" (BIS, 2013). This stress scenario is simulated for participants of the Finnish TARGET2 component with the new BoF-PSS3 simulator. Two liquidity deterioration indicators are introduced to quantify counterparty liquidity risk exposures. As comparison of liquidity risk projections to the available liquidity of participants in the system only yields a restricted and system-specific view of the severity of the scenarios, we compare the liquidity risks to high-quality liquid assets (HQLA) available at the group level to assess the overall liquidity risk that participants face in TARGET2. Our results generally comport with the literature and results reported elsewhere. Banking groups are exposed to a liquidity deterioration equivalent from 20 % to 60 % of their respective HQLA in just 0.35 % of the daily scenario observations. The exercise paper demonstrates that our proposed alternative form of payment system analysis can be helpful in banking supervision, micro- and macroprudential analysis, as well as resolution authorities' assessment of the effects of their actions on payment systems.

Keywords: payment systems, stress testing, liquidity risks, counterparty risks, systemic risk, computer simulation

1. Introduction

Payment and settlement systems are an essential element of Financial Market Infrastructure (FMI) (Kokkola, 2010; Manning, Nier & Schanz, 2009). Since financial transactions are settled in strongly interlinked payment and settlement systems, quantitative evaluation is an important tool for understanding the risks present in these systems.

While oversight lead research in this field generally focuses on aggregate-level systemicity of participants and performance of the system as a whole, we suggest that fuller use of payment system data is possible with participant-level analysis. Regulators, who have traditionally carried out their oversight duties with ongoing monitoring and assessing safety and efficiency of relevant FMIs, should appreciate that payments data offer a further opportunity for micro-level analyses to support their supervisory work and macroprudential analysis.

In the following discussion, we analyze the liquidity exposures of individual participants vis à vis other participants in the case of failure or payment incapacity. To obtain our liquidity projections, we run liquidity stress test scenarios using the new BoF-PSS3 simulator.[1] This approach lets us assess the sufficiency of liquidity buffers in the system and identify participants causing the biggest risks to other participants. It also helps identify participants showing the greatest vulnerabilities to the scenarios. Participant-level information is not given here for confidentiality reasons, but the information is naturally available for internal analysis purposes. Our methodology further allows identification of specific relationships between participants. It provides complementary input for other micro- and macroprudential liquidity risk analyses.

2. Data

This study uses a Finnish subset of the Trans-European Automated Real-time Gross Settlement Express Transfer System (TARGET2) data. The data consist of transactions, accounts, beginning of day balances, intraday credit limits, bilateral limits and reservations. Specifically, the subset is the TARGET2-Suomen Pankki component from April 2020, the latest available data when this research started. It covers 16 business days in April 2020. These days are presumably representative of all the business days of the year, and there is no obstacle to performing similar analyses on a regular basis. The TARGET2-Suomen Pankki component contains 25 participants. We run scenarios for 19 of them, excluding participants such as the central bank and state treasury.

We also incorporate group-level supervisory data for end of April 2020 on high-quality liquid assets (HQLA) available for eleven banking groups (BCBS 2019). HQLA figures are used to evaluate the severity of the liquidity impacts of each scenario.The participant-specific daily liquidity risk indicators are obtained from the stress tests run with the simulator. To understand the severity of the liquidity risk projections obtained from the simulations, we compare the projections to HQLA figures for each banking group at the end of section 4.

3. Methodology

The BoF-PSS2 simulator has been widely used for the quantitative analysis of payment and settlement systems. Many simulation analysis have been conducted and the topics cover stress tests (Bedford, Millard & Yang, 2005; ECB, 2013), liquidity saving mechanisms (LVMs) (Galbiati & Soramäki, 2013) and new feature analysis (Koponen & Soramäki, 1998, Laine, Korpinen & Hellqvist, 2013). The ESCB uses simulation-based indicators to round out its methodology for identifying critical counterparties (ECB, 2013).

There is a strong interest in handling liquidity risks of financial institutions in FMIs (BIS, 2008; BIS, 2010; BIS, 2013). In this paper, we quantify counterparty liquidity risks of Finnish participants in TARGET2. More specifically, we measure the liquidity risk exposures of TARGET2 participants in the case of liquidity sink scenarios (Bedford, Millard & Yang, 2005). A participant becomes a liquidity sink when it is unable to send its payments while still receiving payments. This can occur, for example, due to a technical disruption (Lacker, 2003), bankruptcy or a moratorium (FMLC, 2018) declared by a resolution authority. Technical disruptions are sudden, while the latter two cases require time for information to spread and possibly give participants opportunities to adapt their behavior.

To perform the analysis, we used the automated stress tester tool of the latest version of the Bank of Finland's simulator – BoF-PSS3.[1] The stress tester allows the automatic creation and running of scenarios. In one scenario, all the outgoing payments of a participant are removed for one full business day. This corresponds to a liquidity sink scenario (BIS, 2010) due e.g. to a technical failure in a participant's IT-system. From these results, we calculate the direct effects, the systemic effects (or contagion effects) and the liquidity risk indicators. These are the *maximum and minimum liquidity deterioration indicators* (MaxLD and (MinLD) presented below. All indicators are based on the difference between the scenario outcomes and a benchmark simulation that is the unaltered observed outcome for the simulation days. The indicators are computed for each scenario, simulation day and participant.

Each participant can have from one to three accounts, i.e. a TARGET2 main account, an account for STEP2 payments and an account for TARGET2 Securities. In each scenario, the outgoing payments of all three of the participant's accounts are blocked simultaneously. The rest of the payments system i.e. the transactions between the other accounts not under stress are kept unchanged. This gives us 19 simulated scenarios. The simulator system setup used in the simulations is a system setup tailored to replicate TARGET2.

In central bank payment systems, participant liquidity is usually defined as the available credit limit and the account balance. We define the intraday liquidity capacity as the sum of beginning of day credit limit (BoDCredLimit) and beginning of day balance (BoDBalance). Notably, incoming transactions are an important factor affecting the available liquidity during the day.

[1] https://www.suomenpankki.fi/en/financial-stability/bof-pss2-simulator/

These are payments received from other large-value payment system (LVPS) participants and ancillary systems.[2]

Traditional liquidity indicators are the upper bound (UB) and the lower bound (LB) for a given system (Koponen & Soramäki,1998). The UB corresponds to the liquidity needs of a participant to allow immediate settlement of all transactions. The UB can be calculated by running a benchmark simulation with free intraday credit limits and then subtracting the minimum balance of the day from the beginning of the day balance of an account during a business day. UB can only have positive values. When no liquidity is needed or all outgoing transactions can be funded with incoming payments, it receives the value 0.

The LB of an account is the net liquidity need of the account during a business day. It is the theoretical minimum amount of liquidity needed to settle all transactions from an account by the end of the business day. In this case, the minimum liquidity needed for successful settlement of all of a bank's payments is equal to the excess value of outgoing over incoming payments. When an account is a net receiver, the LB is considered to be 0.

Direct effects of a scenario are the amount of liquidity not transferred to recipients due to the removal of the transactions. *Systemic effects* are the other participants' transactions becoming unsettled in the scenarios due to the direct effects. Systemic effects reflect the contagion of liquidity issues in the system as every participant with additional unsettled payments in a scenario spreads the liquidity issue within the system.

To our best understanding, these two liquidity deterioration indicators introduced here are novel. We first presented them at the Bundesbank seminar on International Conference on Payments and Settlement in 2015 (Korpinen & Laine, 2015). The aim of the indicators is to measure the liquidity risk that participants face in various scenarios. The indicators are based on different scenario assumptions regarding the capacity of participants to react to the stress of each failure scenario. The indicators form a value band with a maximal theoretical exposure ceiling and a minimal exposure floor. The *maximum liquidity deterioration* is the amount of extra liquidity the participant needs to keep its end-of-day balance unchanged from the benchmark end-of-day balance in the case that other participants are unable to adapt to the altered scenario situation on an intraday perspective. The *minimum liquidity exposure* assumes that other participants are able to bring in extra liquidity and perform their payments regardless of the stress.

Finally, because the available liquidity in TARGET2 does gives an incomplete picture of each participant's financial situation, we extend our analysis to find a better way of assessing the severity of our scenarios. As in traditional system-level analysis, e.g. identification of systemically important counterparties, the focus is on the relative size of the unsettled transactions to all transactions at the system level. While this makes sense to a certain level for the

[2] More information on intraday liquidity need dynamics can be found in Hellqvist, M & K. Korpinen (2021), "Instant payments as a new normal: Case study of liquidity impacts for the Finnish market."

identification of critical counterparties for example, we find it inadequate for our purpose of assessing the liquidity risks that counterparties face within the payment system.

To get a better understanding of the severity of the liquidity risk projections, we compare them to the high-quality liquid assets (HQLA) of each counterparty. As HQLAs are only collected for our eleven banking groups, comparison with all participants is not possible here.

3.1 Maximum Liquidity Deterioration

Maximum liquidity deterioration (MaxLD) is defined as follow:

Needed extra maximum liquidity to keep the end-of-day (EOD) balance unchanged
= EOD balance in benchmark simulation
- EOD balance in scenario
+ value of participant's unsettled transactions in scenario
- value of unsettled transactions in benchmark

Thus, MaxLD is the participant's needed extra liquidity to keep the end-of-day balance unchanged when compared to the benchmark end-of-day balance. It assumes that the participant is bound by its obligations and pays out all its payments, including the unsettled ones in the scenario. It is assumed that other participants are unable to bring in extra liquidity and unsettled incoming payments from other participants remain unsettled for this participant. If the value is negative, it is a liquidity improvement and these observations are disregarded. A negative value for MaxLD means that the participant is proportionally either receiving more payments or sending less during the scenario day, so its end-of-day balance increases compared to the benchmark scenario. This could be because the participant was a net sender to the failing participant. In this scenario, the liquidity flow deficit decreases.

3.2 Minimum Liquidity Deterioration

Minimum liquidity deterioration (MinLD) is defined as follows:

MinLD = MaxLD - value of incoming unsettled payments from other participants (systemic, indirect) in the scenario.

Here it is assumed that other participants are able to compensate for the deteriorated liquidity conditions and perform their observed unsettled transactions in the scenarios. This assumption is the same as supposing that the other participants have sufficient liquidity buffers, and they are able to bring in the required extra liquidity. The buffers assimilate any contagion effects.

4. Results

Figure 1 gives an overall liquidity situation overview in an *unaltered benchmark situation*. Total available liquidity in central bank money for each participant is defined here as the sum of the beginning-of-day credit limit (BoDCreditLimit) and beginning-of-day balance (BoDBalance). From Figure 1, we can see that the required liquidity for the immediate settlement of the payments, i.e. the upper bound (numerator in y-axis), is much less for most of participants than available total liquidity. The upper bound (UB) relative to total liquidity is below 40 % for most of the participants. The banks are on the left side and the non-banks on the right side. The lower bound (LB), i.e. daily net liquidity needs, are not reported but are found to be 0 for most participants.

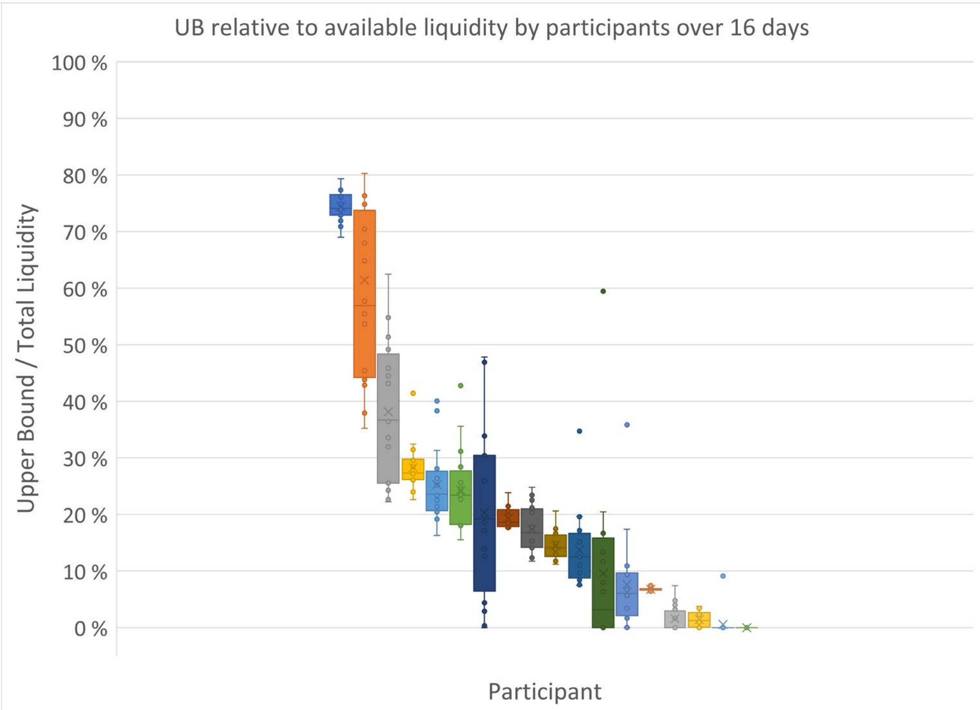

Figure 1. Box plots of upper bound (UB) relative to total liquidity by participants over 16 days. A special case has been removed. Source: Bank of Finland calculations.

Figure 2 is a histogram presentation of the system level direct effects of the 19 scenarios for each of the 16 days. From Figure 2, we see that the sum of outgoing payments for a certain participant on a certain business day is less than 1 billion euros in the most cases. In a few case, however, certain participants and certain days experience direct effects as large as 20 billion euros.

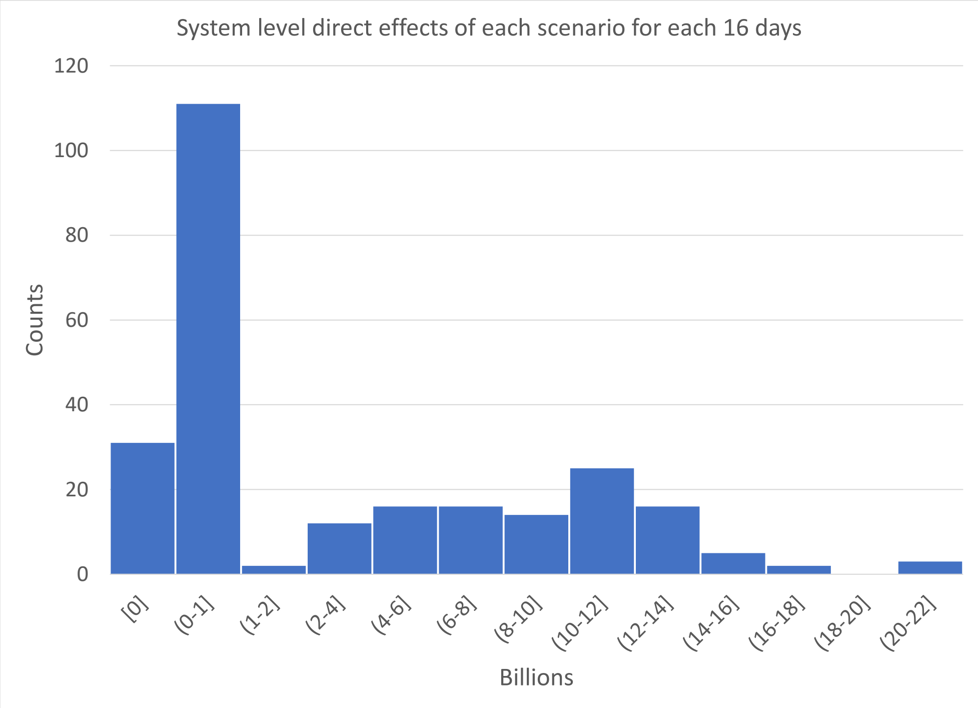

Figure 2. Distribution of system level direct effects of each scenario per 16 days by effect magnitude in billions of euros. Source: Bank of Finland calculations.

It is immediately striking how these scenario specific liquidity shocks are distributed among other participants and the kind of systemic effects they induce. Figure 3 shows that some participants transmit liquidity shocks forward in the form of subsequent unsettled payments. Figure 4 gives an idea of the magnitude of the liquidity risks some participants face. While confidentiality compels us to hide information that would identify the participants, such information is naturally available for regulators' own internal analyses.

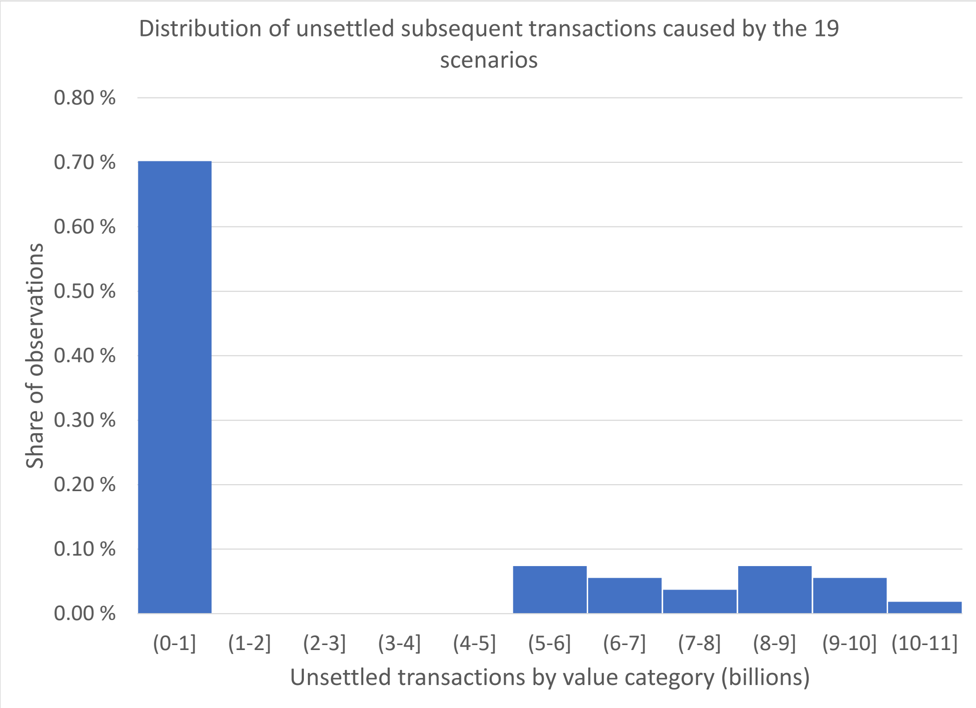

Figure 3. The observations are the value of the systemic unsettled transactions for each participant in each 19 simulated scenarios per 16 days. 99 % of the cases generate no contagion effect, and therefore are not included in the figure. Source: Bank of Finland calculations.

From Figure 3, we see that the scenarios do not generate contagion effects in the vast majority of cases. Indeed, less than 1.0 % of the daily scenarios cause any subsequent effects. In only 0.7 % of observations, other participants spread the shock forward for a total value less than a billion euros. In 0.3 % of cases, other participants spread a shock ranging from 5 to 11 billion euros in value of unsettled subsequent payments. From the relatively small amount of observations in Figure 3, we can conclude that the initial liquidity level in most of the cases are sufficient to absorb the liquidity shock. From the confidential granular data, it is easy to see which participants spread shocks and how much excess liquidity is available for settlement of payments.

The other indicator shown in Figure 4, the maximum deterioration indicator, tells how much extra liquidity a certain participant needs to bring in from its own funds to keep its end-of-day balance unchanged and still meet its obligations and absorb contagion effects from other counterparties not sending all of their payments. We observe that in 99 % of the cases there are no liquidity deteriorations. In just 1.0 % of the cases does the liquidity deterioration exceed 500 million euros. However, there are still 32 observations (0.6%) that exceed 5 billion euros.

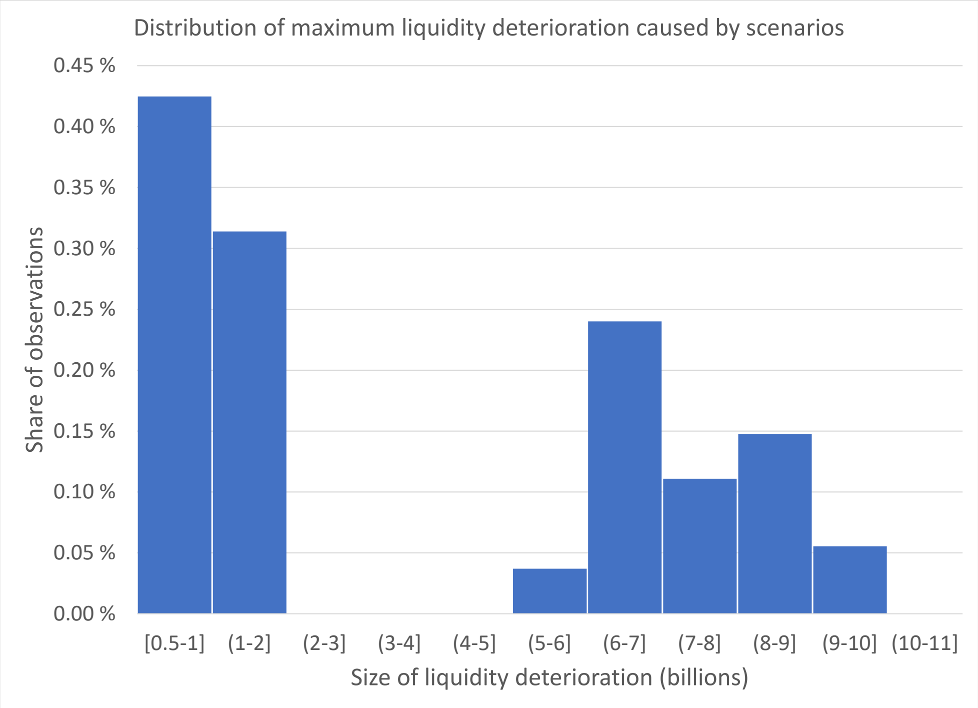

Figure 4. The value of the maximum deterioration indicator for all 19 scenarios. The x-axis shows the amount of liquidity deterioration caused by the scenarios. The y-axis shows the share of observations. The 99 % of observations that generate no effect are left out. Source: Bank of Finland calculations.

Comparing the Figures 3 and 4, we notice that these give a very different picture of the effects of scenarios. Focusing on subsequent unsettled payments caused by the scenarios in the simulation does not show how participants are actually affected. We only observe which participants and how often they are affected severely enough to potentially cause settlement failures. In a neat and concise manner, we can see which participants are likely to be part of the contagion channel in a crisis.

By focusing on liquidity deterioration, we get a more holistic understanding on how severely liquidity conditions are affected at the participant level overall. We also see that liquidity deterioration occurs more often than settlement failures. The data presented in Figures 3 and 4 can also be grouped in another way. Figure 5 shows how participants are affected by the scenarios. The position of the dots in the bar includes variation over different scenarios and different business days. From Figure 5, we see that the biggest liquidity deteriorations are experienced by participants 7, 10, 13, 14 and 17. Participant 14, in particular, seems to experience difficulties in settling payments more often.

Figures 3 and 4 can also be combined and presented the same way as Figure 5. This would give a clear indication as to which scenarios cause the biggest liquidity deteriorations and which cause the biggest contagion effects. Figure 5, in contrast, tells more about the vulnerabilities and exposures from a participant-centric perspective. The blue dots on the x-axis are daily liquidity deteriorations experienced by participants. The orange dots indicate how much the same participants spread the problem in terms of unsettled payments (systemic effect). Again, we see that participant 14 experiences moderate liquidity risks, but is more prone to disseminate problems to others.

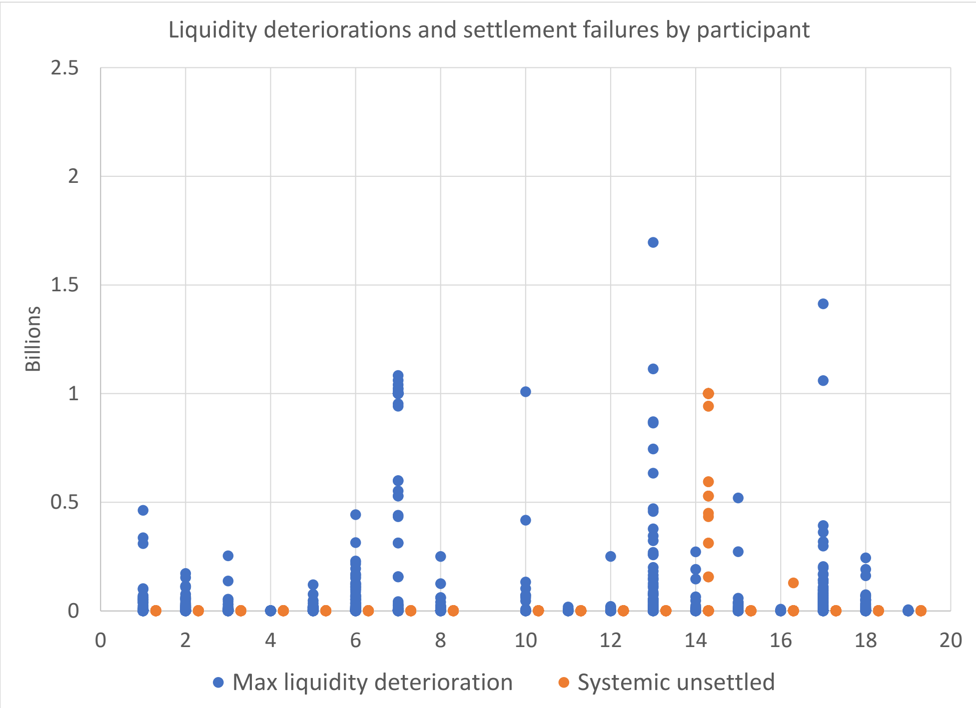

Figure 5. Box plots of systemic unsettled transactions (orange dots) and maximum liquidity deterioration indicator (blue dots) by participants. The boxes squeeze to the zero line. The few extremely high values are not shown for confidentiality reasons. Source: Bank of Finland calculations.

Table 1 presents the liquidity risks each participant is exposed to in each scenario. Each row represents the liquidity exposure figures associated with a specific scenario. Because the scenarios are counterparty-specific, the matrix gives an idea on the counterparty risks existing between the participants. The values are peak maximum liquidity deterioration values relative to available total liquidity (similar to Figure 1). The rows show the scenarios and the columns, show the hit counterparties take in each scenario.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1		38 %	0 %	0 %	10 %	0 %	11 %	0 %	0 %	0 %	1 %	0 %	0 %	4 %	0 %	0 %	0 %	2 %
2	18 %		0 %	0 %	0 %	5 %	5 %	0 %	0 %	0 %	0 %	0 %	1 %	0 %	0 %	1 %	0 %	0 %
3	0 %	0 %		0 %	0 %	5 %	0 %	23 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	1 %
4	0 %	0 %	0 %		0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
5	4 %	0 %	1 %	0 %		5 %	0 %	0 %	0 %	0 %	1 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
6	0 %	14 %	1 %	0 %	19 %		0 %	0 %	0 %	17 %	1 %	0 %	8 %	0 %	0 %	2 %	0 %	0 %
7	0 %	3 %	1 %	0 %	5 %	4 %		0 %	0 %	0 %	1 %	0 %	0 %	0 %	0 %	2 %	0 %	0 %
8	0 %	0 %	39 %	0 %	0 %	0 %	0 %		0 %	0 %	0 %	100 %	0 %	0 %	0 %	0 %	0 %	0 %
9	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %		0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
10	0 %	0 %	0 %	0 %	0 %	21 %	0 %	0 %	0 %		0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %
11	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %		0 %	0 %	0 %	0 %	0 %	0 %	0 %
12	0 %	0 %	0 %	0 %	0 %	0 %	0 %	12 %	0 %	0 %	0 %		0 %	0 %	0 %	0 %	0 %	0 %
13	4 %	0 %	6 %	0 %	2 %	12 %	0 %	0 %	0 %	0 %	1 %	0 %		0 %	0 %	7 %	1 %	0 %
14	86 %	0 %	0 %	0 %	0 %	2 %	11 %	0 %	0 %	0 %	0 %	0 %	0 %		0 %	0 %	0 %	0 %
15	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %		0 %	0 %	0 %
16	63 %	41 %	67 %	0 %	1 %	10 %	11 %	0 %	0 %	0 %	9 %	0 %	12 %	32 %	6 %		1 %	0 %
17	14 %	7 %	4 %	0 %	1 %	14 %	11 %	0 %	0 %	0 %	1 %	0 %	1 %	2 %	0 %	1 %		0 %
18	0 %	0 %	1 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	0 %	

Table 1. Maximum values of the maximum liquidity deteriorations relative to total available liquidity over the 16 days. Each row corresponds to a scenario and indicates the number failing participants in that scenario. The columns show the other counterparties. The values are the maximum liquidity impact experienced over the 16 days by the participants in the columns. The maximum values are capped at 100 % for the sake of presentation. The 100% cap is needed to be able to show the fine structure of the matrix below 25% with the yellow colour code. Source: Bank of Finland calculations.

Row 8, for example, represents the scenario where participant 8 is failing. In each cell on the same row, we see the peak relative liquidity deterioration value for each counterparty. Values are capped at 100 % which means all available liquidity (or more) has been lost. We see that the worst relative liquidity deteriorations are caused to participant 12 by participant 8. Overall, the liquidity pressure due the different scenarios is modest, there are only few cells where the percentage value exceeds 50 %. From the matrix with the underlying data, we can see that small participants can also cause headaches for other participants. This matrix visualization approach allows us to depict special relationships between participants.

The presentations of counterparty liquidity risks in a matrix form allows us to see which participants generate the biggest liquidity deteriorations to others and which participants are the most exposed under the various scenarios. The matrix representations reveal properties of the payments network. Specially, if we substitute the subsequent systemic unsettled transaction values in the matrix, we see which participants are most likely to spread problems in each scenario.

In Figure 6, we relate the maximum liquidity deterioration indicators to the high-quality liquid assets (HQLA) of the banking groups. The comparison can only be done for banking groups that report their HQLA figures to the Finnish authorities. The result show that around 6 % of the ratio MaxLiqDet / HQLA observations have values greater than zero and below 20 %. Some scenarios lead on certain days to a liquidity deterioration to HQLA ratios of up to 58 %.

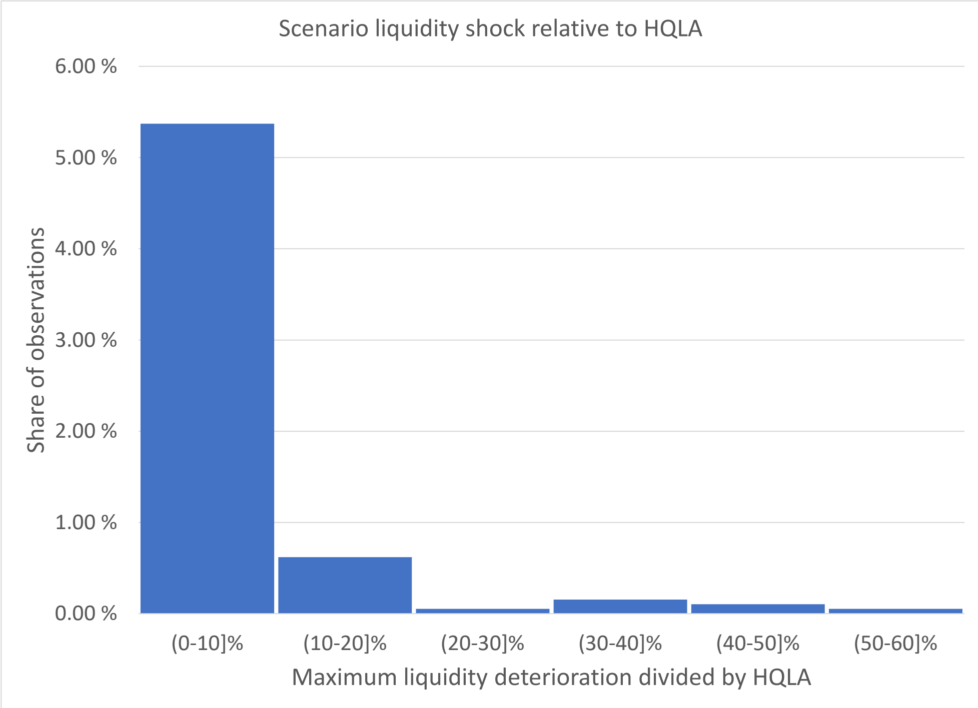

Figure 6. The maximum deterioration indicator divided by the available group-level high-quality liquid assets (HQLA). Only 6.35 % of the scenario outcomes are shown and above 0. Source: Bank of Finland calculations.

5. Discussion

This study offers a different focus from traditional oversight-driven payments system simulation studies. Rather than examining system-level risks or settlement performance of a system under stressed conditions, we study participants liquidity risk exposures in TARGET2.

To quantify the liquidity risks of counterparties, we introduced minimum and maximum liquidity deterioration indicators that define a value band. With the minimum liquidity deterioration indicator, we assume that other counterparties are able to mobilize extra liquidity to overcome the scenario effects and manage to send all of their payments despite a stress event. For maximum liquidity deteriorations, we leave all the subsequent settlement failures in the outcomes. All direct and systemic liquidity effects are taken in full.

There are several limitations worth addressing here. First, our scenarios ignore possible effects in the interbank markets. In the 2008 global financial crisis, for example, interbank lending patterns were severely distorted. Such effects clearly alter scenario outcomes. In a liquidity contraction, a participant might scale back on its interbank lending. While this eases the lender's situation, it could create additional liquidity contractions that propagate foreward.

Second, interbank lending could be incorporated to the model with Agent-Based Modeling (ABM). Indeed, the BoF-PSS3 simulator already supports ABM modeling and has rudimentary algorithms that allow participants to postpone payments in tightened liquidity conditions.

Both interbank-effect enhanced scenarios and modelling require that the various types of payment obligations are considered. Obligations related to proprietary business and interbank lending, ancillary system obligations and customer payments are likely to have different timing constraints.

Third, we should remember that the liquidity risk calculations here only cover TARGET2. Scenario counterparties can experience the same issues in other systems inside or outside the eurozone. At a group level, the creation of liquidity pressures in these other systems means that the liquidity projections might well be undermined and lacking other effects coming through other channels. This holds especially true for international players likely to be counterparties to each other in international FMIs, including central counterparty clearing houses (CCPs).

Fourth, comparing the liquidity risk projections only to available liquidity in TARGET2 may give an overly narrow view. While, as in most earlier studies, this is not an issue if we are only interested in the sufficiency of liquidity currently available in the system, the overall seriousness of a scenario for a participant and its resilience or capacity to bring in extra liquidity still depends on HQLA availablity. An advantage of HQLA is its ready convertibility to central bank liquidity.

The Group on TARGET2 Stress Testing paper “Stress-testing of liquidity risk in TARGET2” (Group on TARGET2 Stress Testing, 2017) is based on simulation analysis with collateral value deterioration scenarios. The analysis takes into account the structure of the collateral pool used for credits in TARGET2. The results are measured in terms of unsettled transactions, payment delays and queuing, end-of-day balances and collateral usage. Our approach extends the analysis by quantifying the meaning and severity of liquidity risks to individual participants. This is done by comparing the liquidity risk projections to banking groups’ total available HQLAs. Without HQLA figures or other balance sheet data, we do not know how much the liquidity committed in a payment system is from the total assets of the participant.

The Group on TARGET2 Stress Testing concluded that settlement performance remained fair in TARGET2 even in high collateral valuation deterioration cases. From this perspective at least, liquidity levels were optimal. Our results comport with the results of the group. The liquidity already present in TARGET2 is sufficient to absorb most shocks (see Figure 3).

The liquidity deterioration indicators on the other hand show that even if subsequent settlement failures are not experienced in the scenarios, liquidity deteriorations are still possible (see Figure 5). From Figure 6, we see that 6 % of the observations lead to a HQLA consumption of 0–20 % and that 0.35 % of the observations lead to HQLA consumption between 20 % and 58 %. Overall, these results are hardly alarming, but some cases certainly raise eyebrows. We must remember that there could be simultaneous exposures in other systems and markets as well.

The 2018 Paper of Ferrara, Langfield, Liu and Ota on short-term systemic liquidity identifies “liquidity SIFIs” (systemically important financial institutions), the failure of which would have a significant impact on other banks through liquidity contagion (Ferrara et al., 2015). They find that the systemic importance in terms of liquidity is not necessarily correlated with the size of the bank. This again lines up with our findings that the largest participants do not necessarily pose the biggest exposure risk to other participants. Instead, a small or mid-size participant can generate big exposures if the participant has a mediation role, i.e. it is a central node of the payments network or otherwise has a special relationship with a specific counterparty.

Our findings on participant-level liquidity exposure comport with the BCBS papers (BIS, 2013; BIS, 2010) which aim for an international framework for liquidity risk measurement, standards and monitoring. Section IV of the BCBS standard: Monitoring tools for intraday liquidity management (BIS, 2013) describes four types of stress scenarios of which the second is the same as the technical outage scenario used in this paper.[3]

Such analysis could also be useful for resolution authorities when deciding on declaring a moratorium. In a moratorium, the resolution authority blocks outgoing payments for a participant. The situation is fairly similar to the scenarios simulated in this paper. The methodology used in this paper could be used to evaluate the liquidity shock a moratorium might cause to other participants.

6. Conclusion

In this work, TARGET2-Suomen Pankki data were analyzed with the BoF-PSS3 simulator. We introduced two new indicators, maximum and minimum liquidity deterioration indicators, to quantify the liquidity exposures of participants. The results show that the upper bound of the liquidity relative to the total liquidity is clearly below 40 % for the vast majority of participants. In other words, the liquidity levels in the system are relatively high for pure settlement of payments. This is also reflected as a relative low amount of subsequent settlement failures associated liquidity shock scenarios. The maximum deterioration indicator indicates some high values for the observed scenarios. In 6 % of cases, the liquidity deterioration ranged between 0 % and 20 % of available HQLA. In some scenarios, the liquidity deterioration amounted to 60 % of available HQLA.

Focusing on the counterparty level and liquidity deterioration, we see that liquidity deterioration in scenarios are more common by far than in settlement failures. The matrix presentation of indicators allows studying special relationships and exposures between participants. Our data also show which participants are spreaders of risk, which are most exposed and which are in special liquidity relationships with each other.

In most of the studied scenarios, the liquidity pressure is generally modest. However, in operational usage, it seems wise to monitor the peak scenarios where the maximum liquidity deterioration indicator gets high values.

[3] Section IV ii) Counterparty stress: a major counterparty suffers an intraday stress event which prevents it from making payments.

References

Arjani, N.M. (2007). Examining the tradeoff between settlement delay and intraday liquidity in Canada's LVTS: A simulation approach. In Leinonen, H. (ed.), Simulation studies of liquidity needs, risks and efficiency in payment networks. Bank of Finland Publications, pp. 87-121.

Bedford, P., Millard, S. and Yang, J. (2005). Analyzing the impact of operational incidents in large-value payment systems: a simulation approach. In H. Leinonen (ed.), Liquidity, risks and speed in payment and settlement systems − a simulation approach. Bank of Finland Publications, pp. 247-274.

BIS (2008). Principles for sound liquidity risk management and supervision. BCBS Publication No. 144, September, http://www.bis.org/publ/bcbs144.pdf.

BIS (2010). International framework for liquidity risk measurement, standards and monitoring. BCBS Publication No. 188, December, http://www.bis.org/publ/bcbs188.pdf.

BIS (2013). Monitoring tools for intraday liquidity management. BCBS Publication No. 248, April, http://www.bis.org/publ/bcbs248.pdf.

BIS (2019). LCR30 High-quality liquid assets. December, BCBS Publication.

ECB (2013). The TARGET2 simulator. Target Newsletter No. 7, https://www.ecb.europa.eu/paym/t2/shared/pdf/newsletter/TARGET_Newsletter_issue_number_7.pdf.

Ferrara, G., Langfield, S., Liu, Z., and Ota, T. (2018). Systemic illiquidity in the interbank network. Bank of England Publications, https://www.bankofengland.co.uk/-/media/boe/files/working-paper/2016/systemic-illiquidity-in-the-interbank-network.pdf.

FMLC (2018, April), Bank Recovery and Resolution Directive: Legal Uncertainties in the Proposal to Amend Moratorium Powers, http://fmlc.org/wp-content/uploads/2018/05/moratorium_report.pdf.

Galbiati, M. and Soramäki, K. (2013). Liquidity saving mechanisms and bank behavior in payment systems. Simulation in computational finance and economics: tools and emerging applications. IGI Global, pp. 103-119.

Group on TARGET2 Stress Testing of the Market Infrastructure Board, Market Infrastructure and Payments Committee (2017). Stress-testing of liquidity risk in TARGET2. ECB occasional paper series No. 183/ February.

Hellqvist, M and Korpinen, K. (2021). Instant payments as a new normal: Case study of liquidity impacts for the Finnish market. BoF Economics Review 7/2021

Kokkola, T. (ed.) (2010). The Payment System. European Central Bank Publications.

Koponen, R. and Soramäki, K. (1998). Intraday liquidity needs in a modern interbank payment system − a simulation approach. Bank of Finland Publications E14, http://www.suomenpankki.fi/fi/julkaisut/tutkimukset/erillisjulkaisut/Pages/E14.aspx.

Korpinen, K. and Laine, T. (2015). Deepening Counter Party Risk Analysis in FMIs, presentation at 1st International Conference on Payments and Settlement, Eltville, Germany, September 2015.

Lacker J.M. (2003). Payment System Disruptions and the Federal Reserve Following September 11, 2001. WP 03-16, Federal Reserve Bank of Richmond.

Laine, T., Korpinen, K. and Hellqvist, M. (2013). Simulations approaches to risk, efficiency, and liquidity usage in payment systems. Simulation in computational finance and economics: tools and emerging applications. IGI Global, pp. 69-83.

Laine, T. and Korpinen, K. (2015). Exploiting parallelization to increase the performance of payment systems simulations. Analyzing the economics of financial market infrastructures. IGI Global, (pp. 91-101).

Leinonen, H. and Soramäki, K. (1999). Optimizing liquidity usage and settlement speed in payment systems. Bank of Finland Publications, http://www.suomenpankki.fi/fi/julkaisut/tutkimukset/keskustelualoitteet/Pages/dp1999_16.aspx.

Leinonen, H. and Soramäki, K. (2003). Simulating interbank payment and securities settlement mechanisms with the BoF-PSS2 simulator. Bank of Finland Publications, http://www.suomenpankki.fi/fi/julkaisut/tutkimukset/keskustelualoitteet/Documents/0323.pdf.

Manning, M., Nier, E. and Schanz, J. (2009). The economics of large-value payments and settlement: Theory and policy issues for central banks. Oxford University Press.

Murphy, D., Vasios, M. and Vause, N. (2015). A comparative analysis of tools to limit the procyclicality of initial margin requirements. Bank of England Publications.

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