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* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

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A liquidity black hole: What is the impact of a failing participant in a large value payment system and does time matter?

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Abstract

This paper presents a methodology to detect potential failing participants in large value payment systems and measure the intraday impact of outages, considering Liquidity, Systemic, and Receiver Impacts. Medium and high risk thresholds are established to create a combined risk indicator. Outages of large banks can be detected within 10 minutes, while smaller banks may take over 30 minutes. Impact and risk levels vary by the size of the bank and the start time of the outage. Large banks can reach high-risk levels in 30 minutes, highlighting the need for timely detection, whereas smaller banks rarely reach high-risk levels.

Keywords: Financial market infrastructures, TARGET2, liquidity risk, operational risk, systemic risk, financial stability.
JEL classifications: E42, E50, E58, E59.

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1 Introduction

Financial Market Infrastructures (FMIs) play a crucial role in facilitating the clearing and settlement of financial obligations for both financial institutions and their clients. When an FMI encounters a disruption, it can have significant repercussions on the overall functioning of the economy. Therefore, FMIs are required to adhere to rigorous international standards outlined in the Principles for Financial Market Infrastructures (PFMI), established by international standard-setting bodies (CPSS-IOSCO, 2012).

In the context of a Large Value Payment System (LVPS), participants can encounter disruptions stemming from various sources, such as technical problems, IT infrastructure failure, or cyberattacks. When such disruptions occur, affected participants often become incapable of making payments. This not only affects the disrupted participant, but also has a ripple effect on the liquidity position of other participants. The other participants no longer receive payments from the disrupted one, which can be particularly significant if the failing participant generates substantial outgoing payment traffic. This is particularly relevant for LVPSs as they are very liquidity demanding systems; see, e.g., Bech and Hobijn (2007).

To mitigate potential disruptions in TARGET2, large participants are required to notify the operator if they experience an operational outage. The official TARGET2 information guide states that only outages lasting longer than thirty minutes are considered critical, requiring an incident report, see ECB (2022). It is important that operators can identify possible outages and assess the criticality of these outages, by having participant-specific knowledge on normal payment patterns. Detecting problems in a timely manner by operators can greatly reduce the impact on other participants and enhance the overall resilience of the system.

Our paper proposes a method to detect a failing participant (having an operational outage) and develops a combined risk indicator that measures the growing impact of the outage over the course of the business day in LVPS (such as TARGET2), specifically. Operators can use these to identify and assess the criticality of outages. To detect a potentially failing participant, we identify the intraday Minimum Outage Time Interval (MOTI) for each individual participant in TARGET2. This is the minimal time interval, based on regular payment patterns of an individual participant, during which no payments are sent to the system that could potentially indicate an outage of a participant. In other words, the MOTI is defined as an unusually long time interval between two payments for that participant, indicative of an outage. As this MOTI is participant-specific, it allows operators to signal possible outages as soon as possible. To capture intraday payment patterns, we establish the MOTI for each hour during daylight operating hours of TARGET2.

As part of the combined risk indicator, we assess the impact of a participant outage over time, starting from the last payment made. We distinguish three types of impact, 1) Liquidity Impact (LI) 2) Systemic Impact (SI), and 3) Receiver Impact (RI). LI is defined as the liquidity not sent by the participant that experiences an outage, or, in other words, the missing liquidity in the system. SI is the number of participants affected that would normally have received at least one payment from the failing bank during the outage. Lastly, RI is the number of participants that, under normal circumstances, receive at least 15% of their daily average liquidity from the failing participants[1] These are the participants who are severely affected by the outage and could potentially cause second-round effects.

In this paper, we examine the evolution of the three types of risk independently, for different types of participants and times during the day that the outage occurs. This distinction is crucial, as the impact can significantly vary at different times and among participants who possess distinct payment profiles in TARGET2, see, e.g. Glowka (2020). We also monitor the evolution intraday to assess the potential impact, depending on the duration of the outage. Finally, we combine LI, SI and RI into one single combined risk indicator (CRI), which indicates when during the day the outage of a participant causes medium or high risk. We propose a method how this CRI can be used by operators to assess the impact of an outage. We define thresholds for medium and high risk levels for both individual indicators and for CRI. Together with MOTI, to detect potential outages, this provides the operator with an extended toolkit to have a clear expectation of CRI's medium and high levels in the event of real-life outages based on bank-specific

[1]This percentage is based on the liquidity efficiency of TARGET2 based on Benos et al. (2014), as we see in Section 4.

historical data.

The paper is organized as follows. Section 2 gives an overview of the related literature. In section 3 we provide general characteristics of TARGET2 and data selection and filtering. Our method of identifying the MOTI of a single participant and the definition of the impact measures is described in section 4. In section 5 we discuss the results and section 6 zooms in how an operator can use our method to monitor the payment system. Finally in section 7 we conclude.

2 Related Literature

This paper adds to three strands of literature. The first two strands are closely aligned with two Principles of the PFMIs for LVPS, namely, operational risk and liquidity risk. The third strand concerns the detection of these risks by developing (risk) indicators.

The identification of operational risks in an LVPS was first addressed by Klee (2010), who developed a method to detect possible operational outages in the US LVPS called Fedwire. They state that a participant has an outage if it makes no payments for more than 15 minutes, assuming that participants in Fedwire normally make payments much more frequently. Glowka et al. (2018) improved Klee (2010) the detection of potential outages looking both at intervals without any transactions at all and with very limited amount of transactions in the European LVPS TARGET2. They, furthermore, investigate how often active participants have intervals with low or no payments beyond 30 and 40 minutes, as participants in TARGET2 are obliged to inform the operator in case they have an operational problem lasting longer than 30 minutes. Arjani and Heijmans (2020) implemented a similar method as Glowka et al. (2018) for the Canadian LVTS.[2] They compared their result with reported outages to the operators and found that the algorithm works best for the five largest banks. Although all above-mentioned papers develop a method to detect potential outages, their main goal is not to provide a real time risk indicators of potential outages, but to identify potential outages backward looking and linked to a generic outage time of 15 or 30 minutes instead of bank specific.

The literature strand concerning liquidity risk is more broad than the liquidity risk due

[2] In the Canadian LVTS outages have to be reported is they last more than 15 minutes in contrast to TARGET2.

to an operational failure. A historically important topic in this area is the delay in payments. The importance of timing (and delay) of payments in payment systems was first addressed by Bech and Garratt (2003, 2006), in which they study the impact of delay using a game theoretical model. At the bilateral level, a participant can delay payments due to free riding, i.e., a participant wants to receive money from a counterparty before it pays, see, e.g. Diehl (2013) for an investigation of free riding in the German part of TARGET2. Participants can also manage their liquidity position with respect to one single counterparty or the system as a whole using the so-called net bilateral limits or multilateral limits, respectively; see, e.g. Diehl and Müller (2015). An operational outage of a free rider during the day can potentially have stronger consequences as their hoarded liquidity will not flow into the system. Alexandrova-Kabadjovaa et al. (2023) compare the liquidity efficiency of many large value payment systems around the world, including TARGET2. They show that the liquidity efficiency of TARGET2 is roughly 6, which means every euro of liquidity available to the system (of all the participants) roughly 6 euros can be settled.

Benos et al. (2014) studies the impact of the global financial crisis on the use of liquidity in the UK LVPS CHAPS. They also study the impact of an outage and relate this to different types of liquidity management before and after the crisis. They find that the liquidity impact of an outage after the crisis was greater as a consequence of delayed payments to maximize liquidity.

The third strand of literature uses the risk measures developed in the aforementioned papers to develop risk indicators and measure the impact of a failing participant. Berndsen and Heijmans (2020) identify general quantitative risks in financial market infrastructures (FMIs), which are inspired by the Principles for Financial Market Infrastructures (PFMIs). These risk measures can be used by overseers and operators looking at the system as a whole. Heijmans and Wendt (2023) defines a measure to quantify the impact of the failing commercial bank or financial market infrastructure. In this measure, they combine both liquidity risk and systemic impact, based on an outage that lasts for the entire day.

This paper adds to all three strands of literature. First, it adds to the literature on operational risks by looking at participant-specific outage time intervals instead of fixed cutoffs, such as 15 or 30 minutes. Most papers that look at the liquidity impact of a disruption measure the impact over a fixed time period of an entire day. We add to the literature by looking at the intraday evolution of the impact of an outage. To this we add the impact to receiving banks individually, instead of solely focusing on the liquidity impact on the system as a whole. We use the three newly developed impact measures to develop a new combined risk indicator that operators can use to estimate the impact of a real-life operational outage of a specific participant and the speed with which it can evolve.

3 TARGET2 and data

3.1 The system and its participants

TARGET2, the large value payment system (LVPS) for euro-denominated transactions, is owned and operated by the Eurosystem. It enables the real-time gross settlement of payments using central bank money, ensuring immediate finality. Approximately six days in duration, TARGET2 processes transactions equivalent to the entire GDP of the euro area, making it one of the world's largest payment systems.

TARGET2 has approximately 960 direct participants, primarily credit institutions (banks). Other direct participants include Eurosystem central banks, some non-euro EU central banks, and national treasuries. Furthermore, 79 financial market infrastructures (FMIs) participated in TARGET2 as ancillary systems (ASs) to settle net cash positions from their clearing and settlement activities. The average transaction value is around EUR 5.5 million. Although it is a high-value payment system, 70% of the transactions were less than EUR 50,000, with only 9% exceeding EUR 1 million.

ASs can send payment instructions to TARGET2 to debit the accounts of other participants, such as banks. The debited bank does not need to send the payment instruction or maintain an active connection to the TARGET2 platform for the payment to be processed. This aspect is crucial for our paper, as we aim to measure the impact of a bank being technically unable to send payment instructions.

In March 2022, TARGET2 and TARGET2 Securities (T2S) were consolidated into a single platform named T2. The primary objective behind this consolidation was to integrate the technical and functional aspects of both TARGET2 and T2S, with the overarching aim of improving operational efficiency and reducing costs. Consequently, this consolidation led to some structural changes in the behavior of payments. Given the structural shift resulting from this consolidation and the limited availability of data for T2 at the time of this research, our analysis focuses on TARGET2 only to ensure statistically sound conclusions. However, it is important to note that the methodology developed in this paper remains applicable to the new system, but some adjustments in the thresholds may need to be made due to the changes in this new system.

3.2 Critical participants

A participant is considered critical according to the TARGET Information Guide (see ECB, 2022) for TARGET2, as it consistently settles more than 1% in terms of value of the TARGET2 turnover on a daily average in the first quarter of the year. This turnover excludes transactions submitted by ancillary systems and transfers between accounts of the same participant. The Eurosystem uses simulation techniques alongside turnover analysis to evaluate the impact of a participant's technical failure based on measurable criteria. Specifically, it simulates the failure of a credit institution and measures its effect on payment settlements in TARGET2. Generally, a credit institution may be classified as critical if simulations show that, on average, 1.5% of TARGET2's total turnover cannot be settled due to its technical outage.

We will use the critical participant exercise to derive a method to set thresholds for medium and high risks for the Liquidity Impact- of an outage; see Section 4.3.

3.3 Liquidity efficiency

Liquidity efficiency is a measure of the total value of outgoing payments made for each single euro of intraday liquidity. Or in other words, how many euros are settled using one euro of liquidity. The higher the liquidity efficiency, the more efficient a system is in terms of its liquidity reuse. At the same time, a more efficient system is more dependent on the incoming liquidity.

An exact measure for the liquidity efficiency Q of the entire system, was defined in

Benos et al. (2014), as the ratio between the aggregate payment value P and aggregate liquidity L used at system level,

$$Q = \frac{P}{L}. \tag{1}$$

Alexandrova-Kabadjovaa et al. (2023) uses this measure to calculate the liquidity efficiency of many large-value payment systems worldwide.They find that the maximum liquidity efficiency reached in TARGET2 is 6.71. This means that on average each bank makes its payments, sourced from a total amount of $1/Q_{max} * 100\% = 15\%$ of their total received payments. Banks reuse this amount during the day to be able to pay all their payments. We will use this percentage in our definition of the receiver impact of an outage in section 4.2.3. There we assume that participants who miss 15% of their incoming liquidity will no longer be able to make their own payments, due to the lack of incoming liquidity, causing spillover effects.

3.4 Data

The TARGET2 dataset available to us encompasses individual transactions settled in TARGET2 from its inception in 2007 to March 2023. For each transaction, the data set contains information on the sender and receiver, the entry and settlement time, the payment type, and the amount. For our analysis, we select the payment data from TARGET2 according to the following selection criteria:

Time period and holidays We take a single year to calculate MOTI as it may vary over longer time frames. This variability may be due to the increased activity of a participant. Many large banks, who also participate in EURO1, may also move payments from EURO1 to TARGET2 or vice versa.[3] We compare the MOTIs of 2022 with 2020 and 2021 to compare their stability over time. We do not compare our results with the results after consolidation, as differences in the system can have an impact on the number of payments banks make and therefore on their MOTI. We analyze all business days in 2022, except for certain holidays, where a large number of participants have only very limited activity. We also exclude days with a very small number of payments, as they

[3]EURO1 is the large value payment system for for euro denominated owned and operated by a commercial party.

might be indicative of a system disruption.[4] This leads to 251 out of 257 business days in 2022.[5] Note that due to our definition (see section 4.1), the MOTI is not influenced if we include a business day on which a specific participant makes fewer payments, such as local holidays. We chose this method, instead of explicitly excluding specific holidays per participant, as we might not be aware of all local holidays or other reasons that a participant could have a deviant payment pattern.

Opening hours We analyze all hours during daylight opening time, which is between 7:00 and 18:00 hours. The reason for this is that payment instructions can be sent at any time, but they will only be settled soon after the system opens in the morning.[6] Therefore, in case a participant cannot send payment instructions outside the daylight opening hours, there will be no impact on other participants until the opening of the system. We do not include payments made after 18:00 hours due to delayed closing hours, as these payments will not reflect payment behavior on a normal day.

Payment types Table 1 provides a detailed overview of all possible payment types in TARGET2.[7] We only select payment types that are actually sent in by the credit institutions themselves. This includes all payment types except 3.1, 3.2, 3.3 and 3.5 which are often generated by the ancillary system in which these participants are also active, and 0.0, which are technical payments generated by the system. These payments will still be executed even though a participant faces a technical outage and cannot send in payment instructions itself. In contrast to Glowka et al. (2018), we include transactions with central banks (2.1 to 2.5) and liquidity transfers (4.1 to 4.7). We include them as these transactions are often initiated by the participant itself, and consequently want to incorporate them into the calculation of the MOTI as we want to identify periods of time where the participant has not initiated a payment. When measuring the impact on other commercial banks in the system, we only include the 1.1 (client) and 1.2 (interbank) payment types. In our analysis, we do not include the Liquidity Impact that a failing participant has on central banks or other branches and subsidiaries of the

[4]Holidays, or other similar days with less payments we exclude are 03-01-2022, 06-01-2022, 26-05-2022, 06-06-2022, 15-08-2022 and 01-11-2022.

[5]2019 contains 255, 2020 contains 257 and 2021 contains 258 business days.

[6]There is also night time settlement, but those are within the payment types 3.1. and 3.2, which are out of the scope of our analysis.

[7]Table taken from Berndsen and Heijmans (2020).

disrupted participant.[8]

Table 1: Description of the different payment types in TARGET2.

Description	Category
Main transactions	
Customer payments	1.1
Interbank payments	1.2
Transactions with central bank	
Cash operation	2.1
Intraday repo and similar transactions	2.2
Payments sent and/or received on behalf of customers	2.3
Inter NCB payments	2.4
Other transactions	2.5
Transactions with AS	
Trade by trade settlement of SSS	3.1
Other settlement operations	3.2
EBA Euro1	3.3
CLS	3.4
EBA Step2	3.5
Liquidity transfers	
Intraday transfers with LVPS	4.1
Intraday transfers with retail systems	4.2
Intraday transfers with SSS	4.3
Internal transfers between different accounts of the same participant	4.4
Commercial transfer between different account of same participant	4.5
Transfers T2S	4.6
Transfers back to TARGET2 from T2S	4.7

Participants We define a participant as the collection of the same BIC8 of the account, which are the first 8 characters of the BIC11 of the total account name. In this paper, we focus on credit institutions. As TARGET2 contains many credit institutions that only initiate a few payments a day, we select a subset of them. We deem participants sufficiently active when they have on average at least 50 payments per business day in the year 2022. This corresponds to a time interval between two payments of 13.2 minutes. We choose this limit because we need enough hourly payments to be able to determine MOTI, but at the same time we want to include as many small participants

[8] Measuring the impact on Ancillary Systems could be a potential extension of the current approach. However, since these systems usually settle a set of netted payments in TARGET2, the economic impact of liquidity is not easily comparable to interbank and customer payments.

as possible to highlight the differences between different types of participants.[9] We further limit our selection to credit institutions that have at least one type 1.2 payment on average per day. We impose this restriction because we are interested in the impact of an outage on other credit institutions, which we will refer to as banks in the rest of this paper. Applying these criteria leads to a selection of 292 banks. These banks send payments to 1076 receiver banks, of which 987 receive payments of type 1.1 and 1.2.

Introduction time As the timestamp for payments, we use the introduction time for TARGET2 rather than the settlement time. The introduction time is the time when the payment enters the settlement queue and is therefore a better indicator than the settlement time when looking at payment outages. Because we only analyze daylight opening hours, we ignore all payments that are settled during opening hours but have been sent in when the system was closed.

4 Method

To construct a risk indicator capable of detecting critical outages and assessing the impact of a failing bank, we employ a two-step approach. Initially, we establish the MOTI at the bank level, as outlined in section 4.1. This interval denotes the shortest duration between payments that could qualify as an operational outage or an intentional delay. Subsequently, in section 4.2, we measure the evolution of the impact in terms of Liquidity Impact (i.e., liquidity not sent), Systemic Impact (i.e., participants directly affected), and Receiver Impact (i.e., participants missing substantial fraction of incoming liquidity). We combine these indicators into a combined risk indicator in section 4.3.

4.1 Minimum Outage Time Interval

In order to define a time interval, during which no payments are sent to the system, that is considered exceptionally long, we introduce the MOTI. We define the MOTI for each individual bank as the boundary between normal time intervals between two payments sent into the system and outliers for that specific bank. We, furthermore, calculate a

[9]Note that we do not select participants based on their average daily volume, such as done in Glowka et al. (2018).

separate MOTI for each business hour as we expect the MOTI to depend on the time of day, which is indeed the case, as we show in section 5.1.

To determine MOTI, it is important to realize that the set of time intervals between two payment instructions is not normally distributed. Instead, most time intervals are relatively short, and the distribution has a large positive tail of longer time intervals, leading to a distribution with large positive skewness and high kurtosis. It is not easy to identify outliers for this type of distribution. Furthermore, we expect the number of potential outages, or in this case outliers, to be independent of the size of the bank, and thus the number of payments it makes in a day.

For these reasons, we determine the MOTI using a two-step approach. As a first step, we define a set of intervals I_{bh} containing the largest payment interval $I^{\max}_{bhd}$ per bank b during business hour h for each business day d as

$$I_{bh} \equiv \{I^{\max}_{bhd}\}\,, \tag{2}$$

where

$$I^{\max}_{bhd} \equiv \max\left(t^{i+1}_{bhd} - t^{i}_{bhd}\right)\,, \tag{3}$$

with t^{i}_{bhd} the entry time of the ith payment into the system on day d during hour h from bank b. The size of I_{bh} is thus equal to the total number of business days D_b for each bank. As we calculate the MOTI on an hourly basis, the largest payment interval is maximum 60 minutes. This guarantees that we do not have any extreme outliers influencing our results. We then define the MOTI as

$$\begin{aligned}\mathrm{MOTI}_{bh} &\equiv \text{mean}\left(I_{bh}\right) + 3\cdot\text{st.dev}\left(I_{bh}\right)\,,\\ &= \frac{1}{D_b}\sum_{d=1}^{D_b} I^{\max}_{bhd} + 3\sqrt{\frac{1}{D_b}\sum_{d=1}^{D_b}\left(I^{\max}_{bhd} - \frac{1}{D_b}\sum_{c=1}^{D_b} I^{\max}_{bhc}\right)^2}\,.\end{aligned} \tag{4}$$

This is equivalent to considering each longest time interval on a daily base with a z-score of 3 or more a potential outage, as is a common method for identifying outliers.

We use the z-score instead of the Inter Quartile Range (IQR), which is another common method to determine outliers, since the latter identifies an unrealistic large number of potential outages. The main reason for this is probably that I_{bh} is still slightly positively skewed. This might be due to seasonal effects that cause certain banks to have different payment behavior on certain days. As it is more sensitive to outliers, the IQR method identifies a lower MOTI than the z-score method, and thus a larger number of possible outages.

Note that with this definition of MOTI_{bh}, MOTI is not significantly affected if we accidentally include a business day on which that specific bank makes fewer payments, such as a local holiday. The inclusion of such a day will only amount to one bad data point in I_{bh}. This is an important advantage of our method, as we might not be aware of all local holidays or other reasons a bank could have a deviant payment pattern.

To be able to classify banks according to their MOTI we define an average MOTI$_b$ between 9:00 and 16:59 hours per bank as

$$\text{MOTI}_b = \frac{1}{8} \sum_{h=9}^{16} \text{MOTI}_{bh}. \tag{5}$$

As we will show in section 5.1, the MOTI can deviate a great deal outside these hours, and therefore we do not include them in the average. We classify all banks into six groups with similar MOTI_b, to be able to draw general conclusions.

4.2 Impact of an outage

We quantify the impact of a possible bank outage using three different measures, namely LI (section 4.2.1), SI (section 4.2.2) and RI (section 4.2.3). These provide a measure of the Liquidity Impact to the system, the number of receivers affected, and the degree to which these receivers are impacted, respectively. Each of these measures are time dependent, meaning that they depend both on the time of day the outage starts and on the duration of the outage. In addition, we define risk thresholds associated with these impact measures, indicating the severity of the impact. In the remainder of this section we define and discuss each measure in detail.

4.2.1 Liquidity Impact

We define LI as the total amount of liquidity not sent by the disrupted bank during the outage period. As such, LI is a measure of the missing liquidity in the entire system as a consequence of the outage. As we do not have information on the amount of liquidity a disrupted bank planned to send, we use historical data to determine the most likely impact, based on previous payment behavior. The LI on a specific day d is defined as

$$LI_{bd}^{t_S,T} = \sum_{\substack{j=1 \\ j \neq b}}^{N} a_{bjd}^{t_S,T}, \tag{6}$$

where b is the bank that has been disrupted, t_S the start time of the outage, defined as the time of the last payment made, T the duration of the outage, defined as the time between t_S and the first payment after the outage, N the number of banks in the system and $a_{bjd}^{t_S,T}$ is the total payment flow from bank b to bank j between t_S and $t_S + T$ on day d. As we want to investigate the impact of an outage on other banks in the system, we ignore payments from and to the same bank. In contrast to Heijmans and Wendt (2023), we look only at the incoming value and do not take a net position between the incoming and outgoing payments. This illustrates the speed with which the system deals with the growing liquidity shortage and provides better insight into how quickly the operator and the receiving banks have to react to a potential outage of the failing bank.

To define the general $LI_b^{t_S,T}$ of bank b we take the set of $\{LI_{bd}^{t_S,T}\}$ and determine the 10th, 50th and 90th percentile of all days during the year. We do not solely look at the median as the impact can vary over days, and we want to provide an operator with information on all likely scenario's. To track the intraday evolution of the outage starting at t_S, the duration T must be consistently increased until the end of the day.

To give an indication of the risk that comes from LI, we define LI_{risk} as the risk level associated with LI, which can be low, medium or high. To determine these levels, we use a 1% threshold, in line with the exercise of critical participants (see section 3.2 for details). For type 1.1 and 1.2 payments one percent of the total daily turnover of the first quarter of 2022 corresponds to EUR 8.11 billion. We set this as the limit for high risk and 0.3% as the limit for medium risk. There is no clear guideline available to set this threshold. However, we set this limit such that it is lower than the one percent of the total daily turnover for critical participants, but still a a substantial absolute value. Here there is clear trade off between obtaining too many (false positives) or too few (false negative) alarms. We apply this limit to the 90th percentile of $LI_b^{t_S,T}$, which in practice means that the risk level increases when the limit is reached 10% of the days. This leaves a 10% chance that if the outage had not occurred, more liquidity would have flowed into the system. Thus, we define the risk levels as

$$LI_{b\,risk}^{t_S,T} = \begin{cases} low & \text{if } P_{90\%}\left(LI_b^{t_S,T}\right) < \text{EUR } 2.43 \text{ bln}, \\ medium & \text{if EUR } 2.43 \text{ bln} \leq P_{90\%}\left(LI_b^{t_S,T}\right) < \text{EUR } 8.11 \text{ bln}, \\ high & \text{if } P_{90\%}\left(LI_b^{t_S,T}\right) \geq \text{EUR } 8.11 \text{ bln}. \end{cases} \tag{7}$$

Given the reuse of liquidity in large value payment systems, one could argue that these limits are rather high. However, given the current state of ample liquidity available in TARGET2 Alexandrova-Kabadjovaa et al. (2023), there is less risk associated with missing liquidity in the system as a whole. In periods of stronger liquidity constraints, these boundaries should be adjusted. It is important to note that some receivers could be severely affected, even when the LI is low. For this reason, we define the RI in section 4.2.3.

4.2.2 Systemic Impact

The SI is defined as the number of banks that are affected by the failing bank. This is also known as the out-degree of that bank, as defined by Dorogovtsev and Mendes (2003). SI is a measure of the number of participants that would normally receive at least one payment during the outage time. To calculate SI, we first define the out-degree $o_{bj}^{t_S,T}$ as

$$o_{bjd}^{t_S,T} = \begin{cases} 1 & \text{if } a_{bjd}^{t_S,T} > 0, \\ 0 & \text{if } a_{bjd}^{t_S,T} = 0. \end{cases} \tag{8}$$

The SI on day d is then defined by:

$$SI_{bd}^{t_S,T} = \sum_{\substack{j=1 \\ j \neq b}}^{N} o_{bjd}^{t_S,T}. \tag{9}$$

As for LI, to define the general $SI_b^{t_S,T}$ of bank b we take the set of $\{SI_{bd}^{t_S,T}\}$ and determine the 10th, 50th and 90th percentile of all business days. A high out-degree, i.e. a large SI, indicates that many banks will not receive a share of their incoming liquidity from this outage bank. Consequently, an outage bank with a high out-degree will have a larger impact on the system than a bank with a low out-degree.

As there is no commonly used guideline that we can use to determine the risk levels for SI, we choose the thresholds such that medium- and high-risk levels are reached sufficiently often for the larger banks but will not cause constant alarms for the system operator. This leads to a threshold of 7.5% and 15% of the total of around 1000 receiver banks in our sample for medium and high risk, respectively. In line with the LI there is no clear guideline to set these values and a trade off needs to be made by the expert in charge by the number of alarms in prefers to get. We thus define SI_{risk} as

$$SI_{b\ risk}^{t_S,T} = \begin{cases} low & \text{if } P_{90\%}\left(SI_b^{t_S,T}\right) < 75, \\ medium & \text{if } 75 \leq P_{90\%}\left(SI_b^{t_S,T}\right) < 150, \\ high & \text{if } P_{90\%}\left(SI_b^{t_S,T}\right) \geq 150. \end{cases} \tag{10}$$

4.2.3 Receiver Impact

We define RI as the number of receiver banks that miss a significant part of their incoming liquidity, as a consequence of the fact that they do no longer receive payments from the failing bank. These banks potentially rely on this incoming liquidity to make their own payments, causing a delay in their own outgoing payments. This could lead to a snowball effect that affects the entire system. We use the liquidity efficiency measure, defined in section 3.3, to quantify what is a significant part of the incoming liquidity of a bank. As explained in section 3.3, using Q_{max}, we assume that participants who miss 15% of their total incoming liquidity will no longer be able to make their own payments due to the lack of incoming liquidity. We can then define RI as

$$RI_{bd}^{t_S,T} = \sum_{\substack{j=1 \\ j \neq b}}^{N} r_{bjd}^{t_S,T}, \tag{11}$$

with

$$r_{bjd}^{t_S,T} = \begin{cases} 1 & \text{if } a_{bjd}^{t_S,T}/R_{jd} \geq 0.15, \\ 0 & \text{if } a_{bjd}^{t_S,T}/R_{jd} < 0.15. \end{cases} \tag{12}$$

and R_{jd} is the total received liquidity for bank j on day d, defined as

$$R_{jd} = \sum_{\substack{i=1 \\ i \neq j}}^{N} a_{ijd}^{7,18}. \tag{13}$$

Thus, $r_{ijd}^{t_S,T}$ is only equal to 1 if the amount of liquidity received from bank i is more than 15% of the total incoming liquidity of bank j on day d.[10] As forLI and RI, to define the general $RI_{b}^{t_S,T}$ of bank b we take the set of $\{RI_{bd}^{t_S,T}\}$ and determine the 10th, 50th and 90th percentiles of all business days.

When RI is non-zero, it indicates the number of banks that are likely to start delaying payments, due to their missing incoming liquidity. As this will lead to second-order effects, we set the risk thresholds of RI_{risk} relatively low. However, we do take into account that having a non-zero RI is not always problematic as some of the receivers do not make a large amount of payments or have enough available liquidity on their balance sheet to compensate for the missing incoming liquidity. We define the threshold for medium and high risk as

$$RI_{b\ risk}^{t_S,T} = \begin{cases} low & \text{if } P_{90\%}\left(RI_{b}^{t_S,T}\right) \leq 2, \\ medium & \text{if } 3 \leq P_{90\%}\left(RI_{b}^{t_S,T}\right) \leq 6, \\ high & \text{if } P_{90\%}\left(RI_{b}^{t_S,T}\right) \geq 7. \end{cases} \tag{14}$$

The liquidity efficiency measure and, consequently, the threshold at which a participant reaches its threshold, could be calculated for each individual bank in TARGET2.

[10] It would technically be possible to define a liquidity efficiency measure per bank. The aim of this paper is to have the same general measures that apply for all banks.

However, it is out of the scope of this paper to carry out this exercise.

4.3 Combined risk indicator

We combine the risk levels of LI, SI, and RI into one combined risk indicator (CRI). The CRI gives an overall assessment of the evolution of the total level of risk when a bank faces an outage and supports the system operator in managing the risks associated with that specific outage. Especially, it provides key information on how long after the start of an outage medium and high risk levels are reached. This general assessment should be seen as complementary to the individual indicators of LI, SI, and RI. We define CRI as

$$CRI = LI_{risk} + SI_{risk} + RI_{risk}, \tag{15}$$

where we assign a value of 0, 1 and 2 for low, medium and high risk for the individual risk indicators, respectively. As for the individual risk indicators, we also associate medium and high risk thresholds with CRI as

$$CRI_{risk} = \begin{cases} low & \text{if } CRI \leq 1, \\ medium & \text{if } 2 \leq CRI \leq 3, \\ high & \text{if } CRI \geq 4. \end{cases} \tag{16}$$

This means that CRI reaches a medium risk level when two of the individual risk levels of LI, SI, and RI reach the medium level, or when at least one of the three indicators reaches a high level. The CRI reaches a high risk level when two of the individual risk levels are at medium risk and the third is at high risk, or when two of the individual risk levels are at high risk.

Figure 1 illustrates the evolution of CRI over time. In each figure, the outage starts at 8:00 hours and continues until the end of the day. A jump of one in CRI (purple line) is caused by an increase in LI_{risk}, SI_{risk}, or RI_{risk}, moving from low to medium risk or from medium to high risk. The green, orange and red background colors indicate when CRI is low, medium or high, respectively, and the asterisks indicate the start of a new risk level. In this example, MOTI is well before any alleviated risk levels occur. This gives an indication of how much time an operator has between potential detection of an outage and the need to respond.

Figure 1: Schematic examples of the evolution over the remainder of the business day of the combined risk levels for outages that start at 8:00 hours. The purple line shows the evolution of CRI starting at 9.00 hours. The green, orange, and red background colors indicate when the CRI is low, medium, or high, respectively. The red and yellow asterisks are the starting points of high and medium risk, respectively. The blue dashed line is the MOTI.

(a) High risk. (b) Medium risk. (c) Low risk.

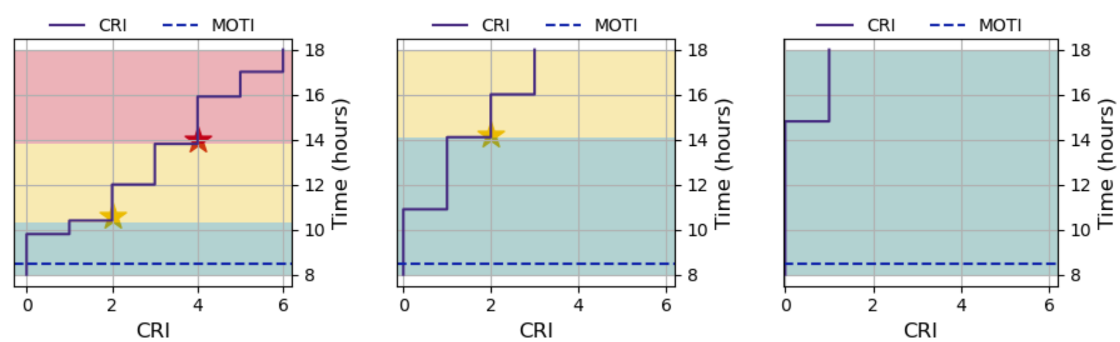


Figure 1a illustrates a situation where CRI reaches a medium risk level just after 10:00 hours (orange asterisk), i.e., 2 hours after the outage starts, and a high risk level around 14:00 hours, i.e., 6 hours after the outage starts. Figure 1b shows a situation in which the impact of the failing bank reaches a medium risk level around 14:00 hours (6 hours after the start of the outage) and never reaches a high level. Figure 1c shows a situation in which the risk level CRI remains low until the end of the business day.

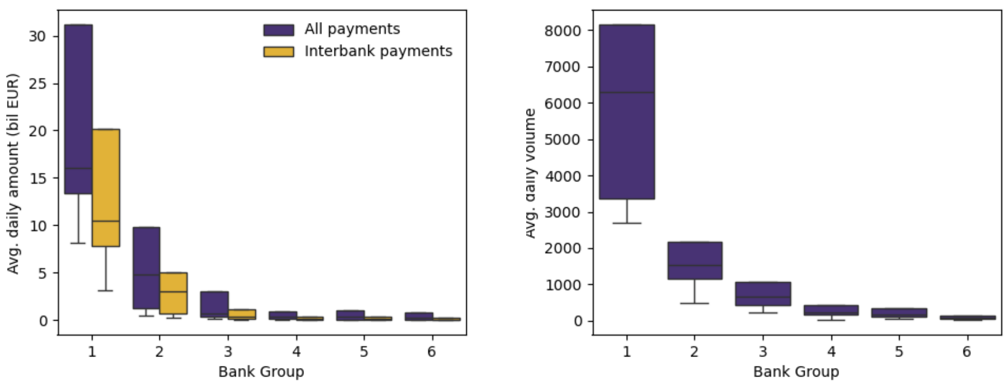
5 Results

In this section we discuss the results of our analysis. Section 5.1 provides the results of the MOTI analysis based on the payment characteristics of the banks. In section 5.2 we show the liquidity, systemic, and Receiver Impact for different types of banks and starting times of the outage.

Figure 2: Payment statistics per banks group. The whiskers denote the 10th and 90th percentile.

(a) Average daily amount.

(b) Average daily volume.



5.1 Minimum Outage Time Interval

To analyze the characteristics of MOTI and the corresponding impact of an outage, we have divided all banks into six groups of banks depending on their MOTI_b, see Table 2. We find that banks with the smallest MOTI_b of 10 minutes or less are banks with a high daily amount and a high number of daily payments, as can also be seen in Figure 2. In contrast, we find that for bank groups with higher MOTI, MOTI_b is less correlated with the total daily amount of the bank, but is still highly correlated with the number of transactions. In general, we find that MOTI is mainly related to the number of transactions, which is not unexpected, since the average payment interval is inversely proportional to the total number of daily payments.

Table 2: MOTI statistics for 2022.

Bank group (nr)	MOTI range (min)	Number of banks	Median daily amount (billion EUR)	Median daily volume	Median MOTI (MM:SS)
1	0-10	28	16.1	6297	7:22
2	10-20	32	4.7	1531	15:30
3	20-30	30	0.7	655	24:56
4	30-40	51	0.3	241	35:14
5	40-50	75	0.3	160	46:48
6	50+	76	0.2	90	53:24

Figure 3 shows the average MOTI_{bh} for each bank group. We find for banks in BGs 1 to 3, that on average their MOTI is significantly higher during the first two hours and final opening hour than during the rest of the day. This seems counterintuitive, as large banks often make a significant portion of their payments just after the system is opened. Further investigation shows that most of these payments are often made in the first 20 to 30 minutes after opening. After this, the number of payments is on average less than during the rest of the day. As we determine MOTI_{bh} based on the longest payment interval throughout the hour, it is mainly driven by the period in which the least payments are made. One could potentially correct for this by having a separate MOTI for the first half-hour after opening; however, we deem this a too detailed approach for an operator. The higher MOTI in the last hour is caused by the fact that during this time only interbank payments (1.2) are allowed in the system, leading to a smaller number of transactions. Figure 3 shows that all bank groups have a similar MOTI during this hour, which is a consequence of the fact that banks that settle more payments on average during this final hour often send these payments into the system within a short time interval and have relatively little activity during the rest of the hour.

For banks in BGs 4 to 6, we find a different pattern. Here, the MOTI values during the first two hours and the final hour are not significantly different from the other hours, indicating a stable payment frequency during the day.

We find that of the 292 banks in our sample, for 90 banks, i.e. BG 1 to 3, an interval between two payments of less than 30 minutes can already be indicative of an outage. An earlier warning of a potential outage can significantly reduce the impact.

To verify that our definition of MOTI makes sense in practice, we have identified all occurrences in 2022 where the payment interval of a bank was larger than MOTI. Figure 4a shows the distribution of the number of potential outages per bank.[11] It shows that most banks experience no more than 5 potential outages per year, which we consider to be a reasonable number. Note that this does not mean that each bank experiences up to five outages per year, but only that these are indications of possible disruptions, since the time between payments was exceptionally long. As there is no database of all actual reported outages, we cannot verify how many of these potential outages were real.

[11] In case the outage lasts for multiple hours it is only counted once.

Figure 3: Average MOTI_{bh} per bank group.

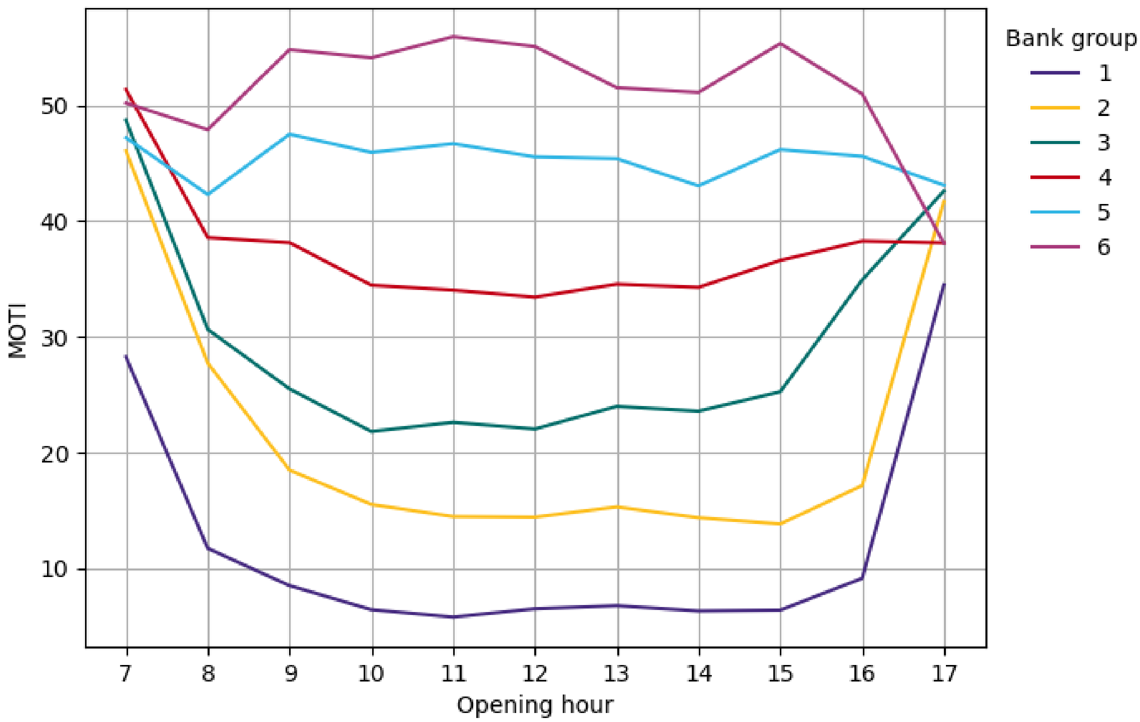


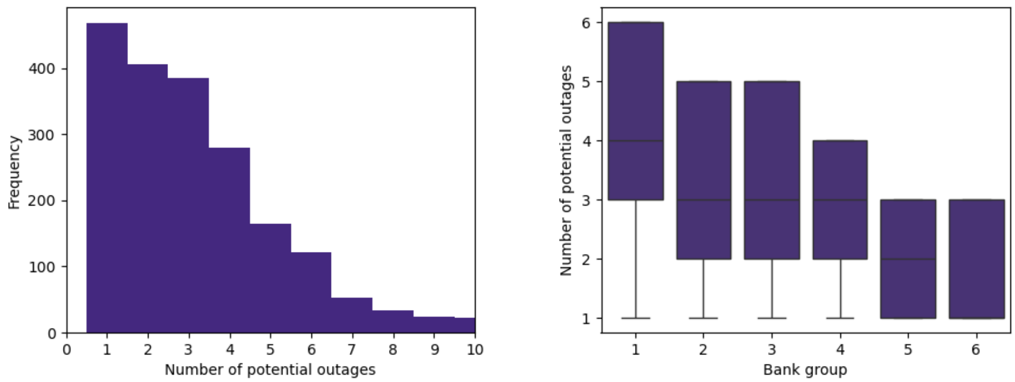
Figure 4b shows that the number of potential outages during 2022 is not much larger for banks with a lower MOTI than for banks with a large MOTI, which was one of our assumptions. The fact that the number is slightly higher for banks in BG1 could be explained by the fact that these banks are more prone to enter a manual payment during an outage, leading to two consecutive exceptionally long intervals without payments. However, for banks with fewer payments, we do not expect multiple potential outage intervals within the same hour.

We check the stability of MOTI over time by comparing the MOTIs of 2022, with those of 2021 and 2020. We find that MOTI fluctuates over the years, observing changes of on average 1 minute for banks in group 1 and up to 5 minutes for banks in group 6. In general, MOTIs become shorter in each subsequent year. This can be explained by the fact that more payments were processed each year, which led to a shorter average time interval between two payments in 2022, compared to earlier years.[12] This shows the importance of recalculating MOTI on a regular basis, accounting for changes in

[12]According to the TARGET Annual Report the volume of payments increased with 6.5% in 2022 and 8.7% in 2021 compared to the previous years, see ECB (2023).

Figure 4: Number of intervals longer than MOTI per bank in 2022.

(a) Histogram. (b) Average per bank group.



payment patterns of both the entire system and individual participants.

The banks in BG1 experience the largest relative fluctuation. This is because large outliers have a stronger impact on the MOTI for banks with shorter payment intervals. As we split the data into hourly intervals, we never see time differences of more than one hour, leading to fewer outliers for banks with a large MOTI. In years with many outliers for a specific bank, we are likely to overestimate MOTI. However, since the difference is only a couple of minutes for all bank groups, the overall impact is not too large.

5.2 Liquidity, Systemic and Receiver Impacts

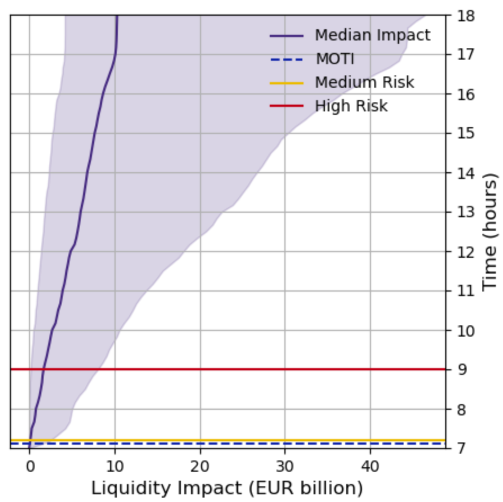
This section shows the evolution of the Liquidity Impact (5.2.1), Systemic Impact (5.2.2) and Receiver Impact (5.2.3. All results are on the bank group level. Later, in section 6, we illustrate how an operator can use these impact indicators to monitor its participants individually.

5.2.1 Liquidity Impact

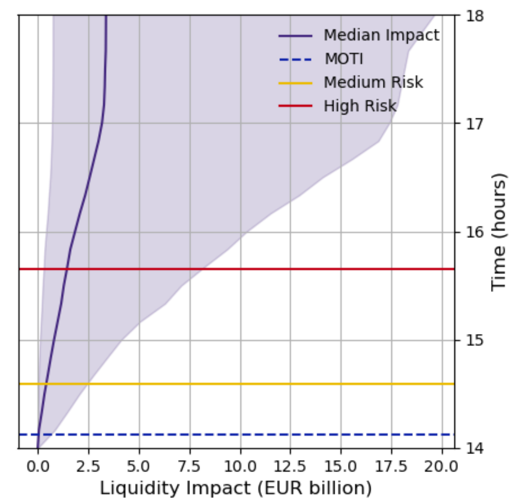
To study the impact of an outage during the day, we look at the evolution of LI over time. Figure 5 illustrates the LI for BG1 and BG4 for an outage that starts at 7:00 and 14:00 hours. The median (solid purple line) shows the amount of liquidity not sent by a bank in the respective bank group on a median business day. The yellow and red horizontal lines mark the medium and high risk levels, respectively, based on the thresholds defined in Section 4.2.

Figure 5: Liquidity Impact per bank group. The solid line represent the median and the shaded area the 10th and 90th quantile per bank and business day. The blue dotted line is the MOTI. The outage starts at 7:00 or 14:00 hours.

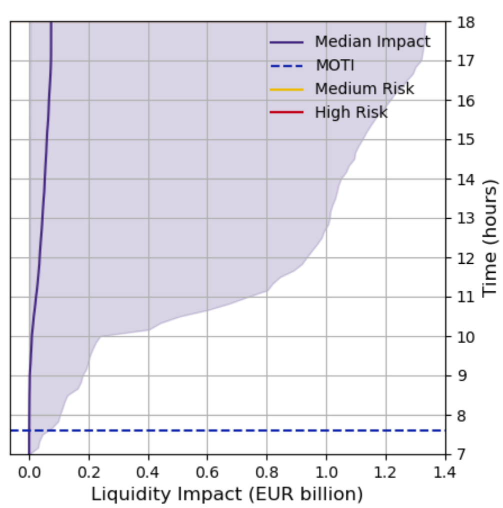
(a) BG1 - 07:00.



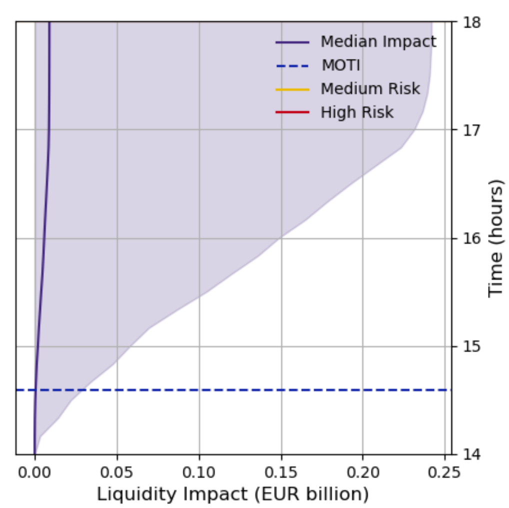
(b) BG1 - 14:00.



(c) BG4 - 07:00.



(d) BG4 - 14:00.



When the outage starts at 7:00 hours, for BG1, a medium risk level is reached in roughly 15 minutes and a high risk level after approximately 2 hours. In case the outage starts at 14:00 hours, the medium risk is reached after more than half an hour. High risk is reached in more than 2.5 hours. In all cases, medium and high risks are reached after MOTI. Later, in section 6, we will see that it is also possible for certain banks that a risk level is reached before MOTI. This shows the importance of early detection of outages. For banks in BG4, we see that they never reach a medium or high risk level according to our thresholds. See Appendix A.1 for an overview of the LI of the other bank groups. We observe that the spread (the shaded area ranging from the 10 to 90 percentile) is large for a whole bank group. Looking at a single bank, this spread will likely be much lower. Another observation is that the missing liquidity increase in the last business hour (from 17:00 to 18:00 hours) is very low for all bank groups. This is due to the fact that client-related payments are only sent until 17:00 hours and that banks use the last business hour primarily to manage their account balance.

We conclude that the evolution of LI differs substantially between different bank groups. The timing of the outage also has a significant impact on LI and when medium and high risk levels are reached. Given the spread of LI (a shaded area in purple around the median), the impact also differs between different business days.

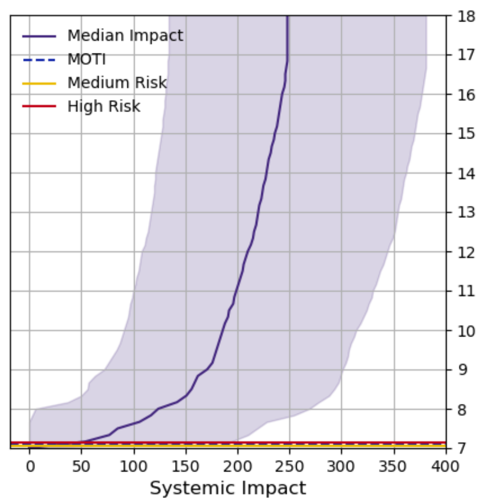
5.2.2 Systemic Impact

Figures 6 depict the evolution of SI for BG1 and BG4 for an outage that starts at 7:00 and 14:00 hours. In line with the figures for LI, the median (solid purple line) illustrates the median number of participants who do not receive liquidity from the failing bank during the duration of the outage. The yellow and red horizontal lines mark the medium or high risk, respectively, based on the thresholds defined in section 4.2.2.

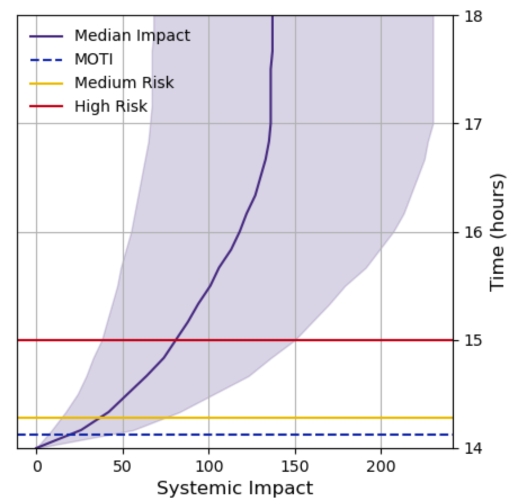
Our results indicate that the SI or the payment network of the banks in BG1 is much larger than for BG4. For BG1 and in case the outage starts at 7:00 hours the medium and high risk are reached after about 5 minutes and 15 minutes, respectively. When the outage starts at 14:00 hours these levels will be reached at roughly 45 minutes and almost three hours, respectively. This is completely different for BG4, for which medium and high risk levels are never reached. See Appendix A.2 for an overview of SI of the other bank group. The increase in SI for all bank groups slows down over time in contrast to LI. The reason is that the SI (or degree) only increases if the outage bank would make a payment to a bank that it has not yet made any payment to before. As

Figure 6: Systemic Impact per bank group. The solid line represent the median and the shaded area the 10th and 90th quantile per bank and business day. The blue dotted line is the MOTI. The outage starts at 7:00 or 14:00 hours.

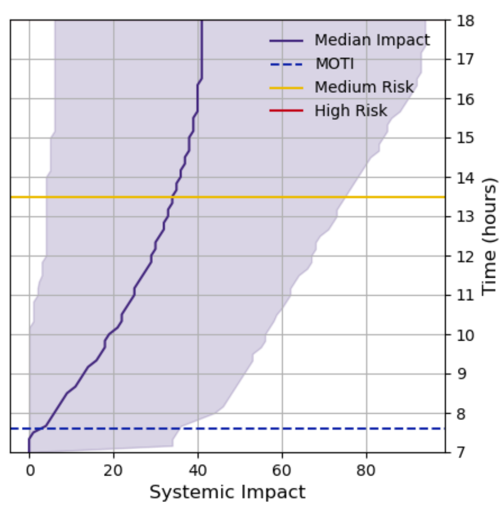
(a) BG1 - 07:00.



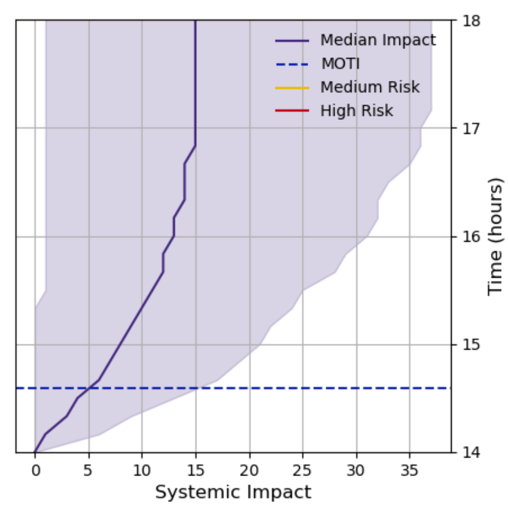
(b) BG1 - 14:00.



(c) BG4 - 07:00.



(d) BG4 - 14:00.

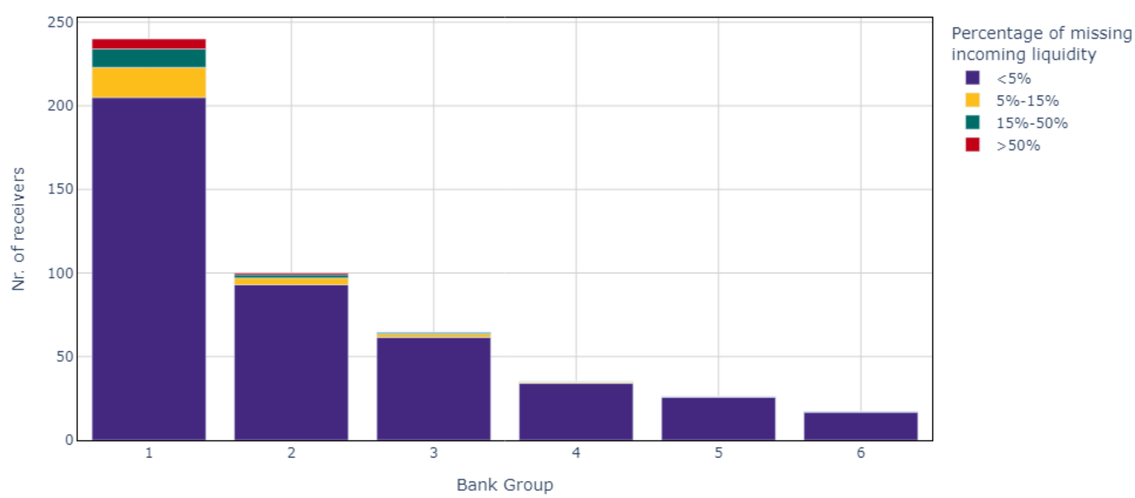


for LI, we observe a rapid increase in SI when the outage begins at 7:00 hours, as banks tend to make a relatively large share at the beginning of the business day.

5.2.3 Receiver Impact

LI is the total amount of liquidity missing from the system during an outage. However, the impact on the liquidity of individual participants can be much larger or smaller depending on the relationship with the bank that has an outage. Figure 7 shows the median distribution of the percentage of missing liquidity for all receivers in the event that a bank in each bank group experiences an outage that lasts for the entire day, which is the maximum RI reached during the day. For example, it shows that for BG1 a median outage that lasts all day will affect 236 receivers, which is equal to the SI in the previous section. For 204 of those receivers less than 5% of their daily incoming liquidity is affected due to the outage, while for 5 receivers more than 50% is missing. The figure shows that BG1 has the largest number of receivers that miss a significant portion of their liquidity, while receivers of banks in BG4 and higher on average do not have receivers that miss more than 5% of their incoming liquidity. Similarly, we find that on average only receivers of BG1 and BG2 have more than 50% of their incoming liquidity affected by an outage.

Figure 7: Median number of affected receivers of an outage that starts at 7.00 and ends at 18.00 hours per bank group. Receivers are grouped depending on the percentage of missing liquidity due to the outage.

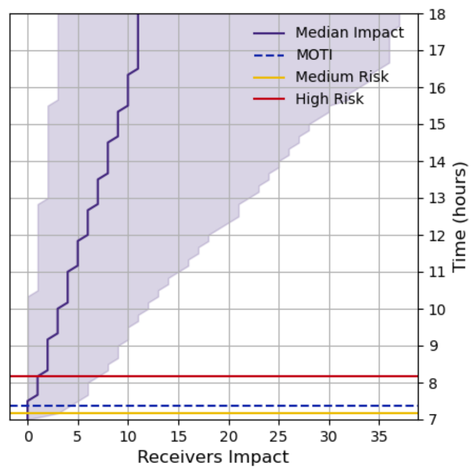


As for SI and LI, we study the impact of an outage on receivers over time. Recall that

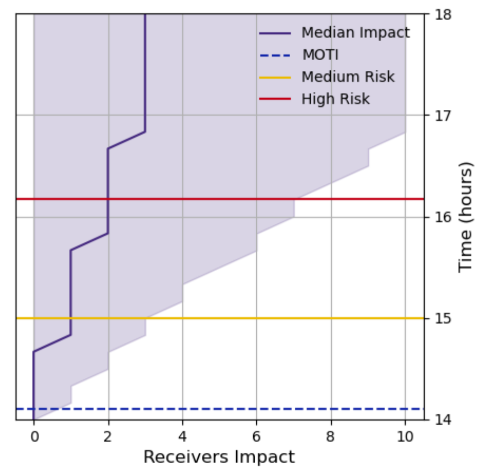
RI is defined as the number of receivers that have at least 15% of their daily incoming liquidity missing due to the outage. The results for BG1 and BG4 for an outage that starts at 7.00 and 14.00 hours, respectively, are shown in Figure 8. All results can be found in Appendix A.3.

Figure 8: Receiver Impact per bank group. The solid line represent the median and the shaded area the 10th and 90th quantile per bank and business day. The blue dotted line is the MOTI. The outage starts at 7:00 or 14:00 hours.

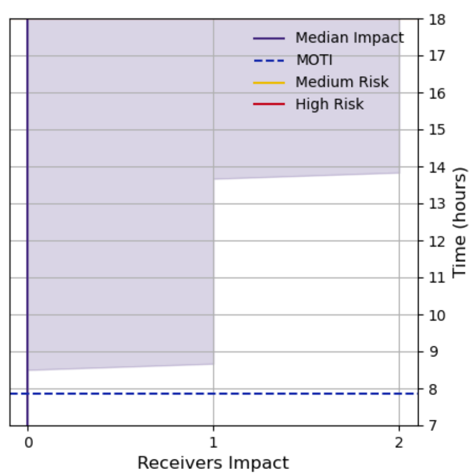
(a) BG1 - 07:00.



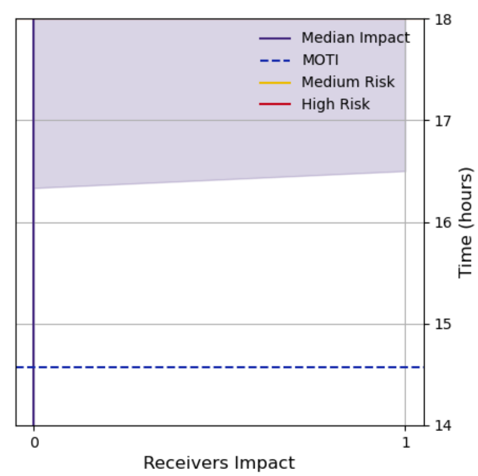
(b) BG1 - 14:00.



(c) BG4 - 07:00.



(d) BG4 - 14:00.



We find that the evolution of RI is more or less linear during the day, with the exception of the last hour. For BG1 a median RI of 10 is reached for an outage that lasts all day, while if the outage starts at 14:00 hours, the RI is only 3. In general, we find that in case an outage starts later in the day, even on extreme days, only a few receivers are significantly affected. This is because a significant part of the incoming liquidity is received during the morning hours.

We, furthermore, find that for BG3-BG6 for most banks during most days, none of the receivers miss a significant amount of their incoming liquidity and a medium risk level is never reached, regardless of the starting time of the outage. The only cases in which high risk levels are reached is when a bank in BG1 has an outage, or a bank in BG2 has an outage early in the morning lasting the entire day. In the latter case, a high risk level is only reached after several hours. From this we can conclude that for most banks an outage does not pose a risk for further contagion of the system, as other banks will still have enough liquidity to make their own payments.

In case of BG1, the high risk level can already be reached within an hour after the start of the outage, showing the importance of a timely detection of a potential outage for these banks. The fact that the MOTI for these banks is less than 10 minutes means that timely detection is possible when using this method to detect potential outages.

6 The view of the system operator

6.1 The Combined Risk Indicator dashboard

Section 5 presented the evolution of the liquidity, systemic, and Receiver Impacts for different bank groups over time. However, the primary concern for an operator monitoring a large-value payment system is the impact of an outage of a single participant within the system. This section demonstrates how an operator can utilize the MOTI combined with these three indicators and the combined risk indicator (CRI) in daily practice.

First, an operator is alerted to the presence of a potential outage. To achieve this, the operator receives an alarm whenever a bank has not made a payment for longer than its MOTI. For banks in BG1 to BG3, this MOTI is shorter than the TARGET2 outage reporting time of 30 minutes. Having a MOTI signaling system in place does not exempt banks from reporting an outage to the operator if they experience one. When an operator receives a 'MOTI' signal, they can decide to either monitor the bank to see if the issue persists or contact the bank to confirm if there is indeed an outage.

Second, at the time the MOTI signal is triggered, the operator views the CRI dashboard for that specific bank, which shows the graphs CRI, LI, SI and RI for the respective hour the outage started, as illustrated in Figure 9 to Figure 12.[13] The dashboard provides immediate information on the likely evolution of the different risk levels and the time available before a medium or high risk level is likely to occur. This allows the operator to estimate the potential impact of the outage and determine the appropriate response, whether it be immediate action or a wait-and-see policy. In each case, the operator will also be informed when CRI reaches medium or high risk levels. In this way, the operator will be signaled without having to constantly monitor the dashboard.

6.2 Combined Risk Indicator results

The CRI dashboard allows us to draw some general conclusions on the impact of an outage for each bank group. Figures 9 and 10 clearly show that the evolution of risks depends on the start time of the outage (hour). Although a high risk for an outage

[13] To ensure confidentiality, the data shown are the results for the entire bank group. The operator would see the results for a single bank.

Figure 9: CRI, LI, SI, RI, for 7:00 hours of a bank in bank group 1.

(a) CRI. (b) LI. (c) SI. (d) RI.

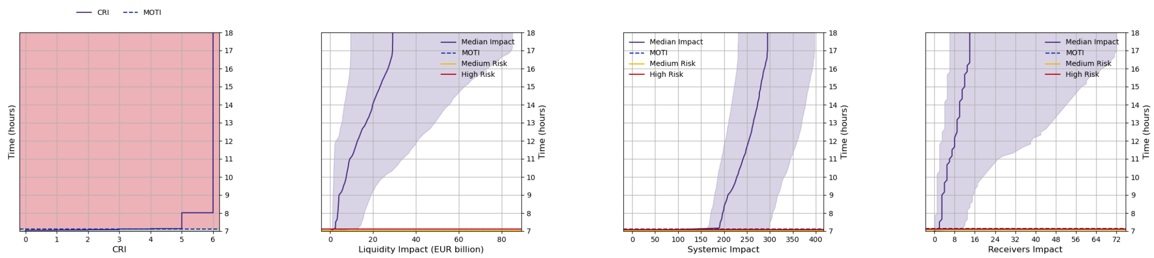


Figure 10: CRI, LI, SI, RI, for 14:00 hours of a bank in bank group 1.

(a) CRI. (b) LI. (c) SI. (d) RI.

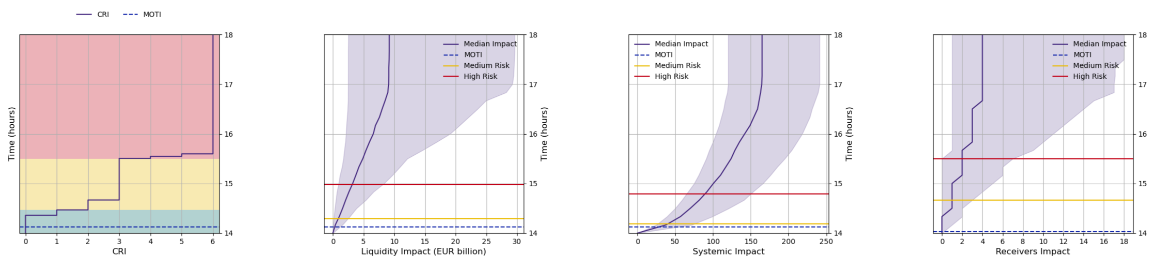


Figure 11: CRI, LI, SI, RI, for 7:00 hours of a bank in bank group 4.

(a) CRI. (b) LI. (c) SI. (d) RI.

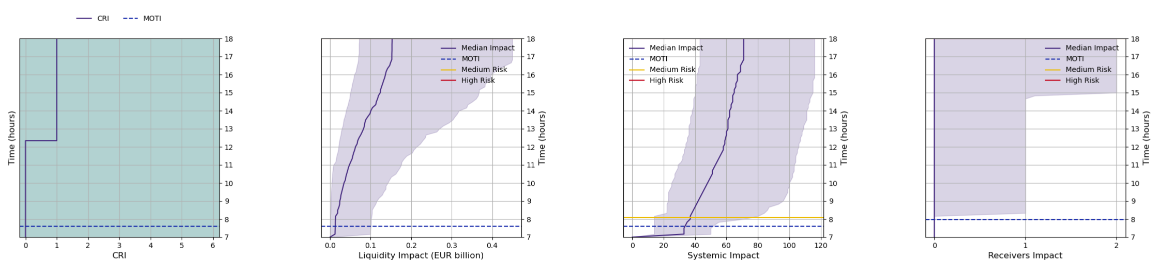
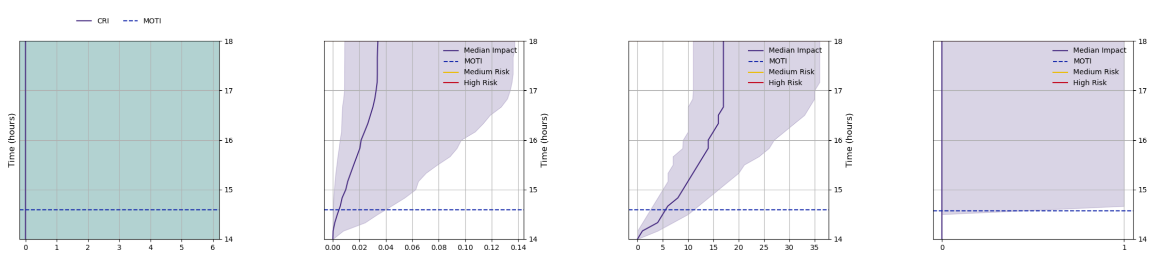


Figure 12: CRI, LI, SI, RI, for 14:00 hours of a bank in bank group 4.

(a) CRI. (b) LI. (c) SI. (d) RI.



starting at 7:00 hours is reached within thirty minutes for BG1, it takes more than one and a half hours for an outage starting at 14:00 hours. Interestingly, the dashboard also shows that medium and high risk for separate indicators can be reached simultaneously, indicating a relationship between the evolution of the indicators.

Figures 11 and 12 show that BG4 never reaches a medium risk level. Only the SI reaches a medium level after more than five hours. When the outage starts at 14:00 hours, none of the indicators reach an increased risk level. It should be noted that when the outage starts at 14:00 hours, there are only four hours remaining in the operational day.

7 Conclusions

We have developed a Combined Risk Indicator (CRI) that identifies possible critical outages and measures the impact of a failing bank by combining the Liquidity, Systemic, and Receiver Impacts over the remainder of the business day. As part of this CRI, we have identified a Minimum Outage Time Interval (MOTI) for each bank, reflecting the varying payment behaviors of the banks in TARGET2. Our findings indicate that MOTI not only varies significantly between banks but also between different business hours. For banks with a high volume of daily transactions, a MOTI of less than 10 minutes is common, indicating that outages can already be detected in a very early stage. This early detection is crucial, as our analysis of the impact indicators shows that for some of these banks situations of medium and high risk can occur within 30 minutes. Smaller banks often have MOTIs that exceed 30 minutes and never reach medium risk levels. Consequently, from a policy point of view, it is essential that the current Eurosystem critical participant exercise identifies all critical participants in the system given their potential impact on others.

The method developed in this paper offers two applications for LVPS operators. First, we provide a method for operators to detect outages as soon as possible, using MOTI. Secondly, we have developed a Combined Risk Indicator dashboard which can be used by operators to monitor a detected outage. This dashboard provides information on the evolution of risk indicators and the time it takes for an outage to escalate to medium and high combined risk levels. In addition, our method can identify critical participants within an LVPS by offering a bank-specific measure of impact evolution during outages at various times of the business day. This information is valuable not only for operators, but also for payment policy and financial stability experts, as it quantifies the impact of a failing systemically important bank.

We identify three potential areas for further improvement. First, the current thresholds for medium and high risks of LI, SI, and RI could be refined by consulting the system operator. Second, the current setup relies on averaged historical data to predict the evolution of LI, SI, and RI. This could be improved by employing a prediction model based on specific historical patterns for the day, accounting for cyclical trends in the data. Such an enhancement would provide more accurate predictions of the durations before medium or high risks are likely to be reached on a given day. Third, the liquidity efficiency measure at the system level could be calculated for each individual participant, enhancing the receiver impact indicator.

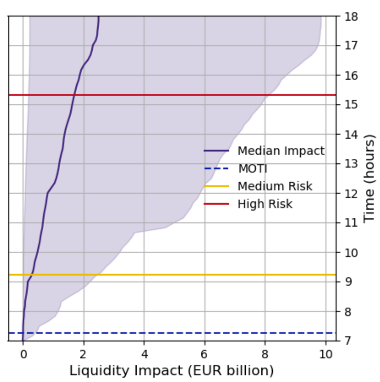
A Liquidity, Systemic and Receivers impact vs time

A.1 Liquidity Impact

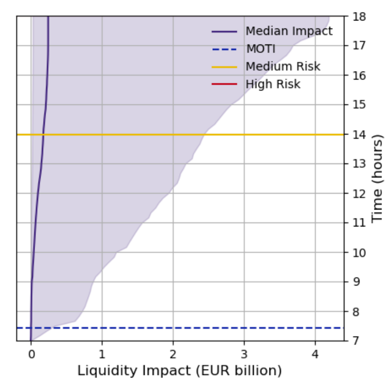
Figure 13 and Figure 14 show the Liquidity Impact of BG2, BG3, BG5 and BG6 for outages starting at 7:00 and 14:00 hours, respectively.

Figure 13: Liquidity Impact per bank group for an outage starting at 7:00 hours. The solid line represent the median and the shaded area the 10th and 90th quantile per bank and business day. The blue dotted line is the MOTI.

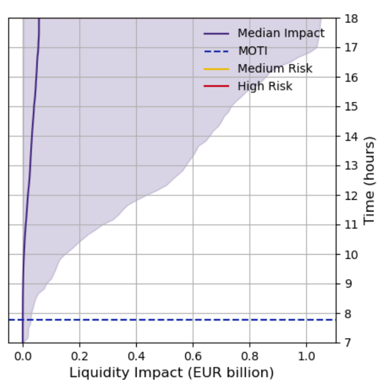
(a) BG2.



(b) BG3.



(c) BG5.



(d) BG6.

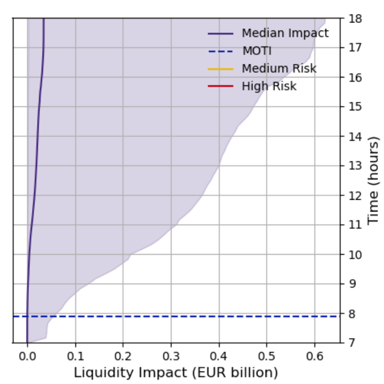
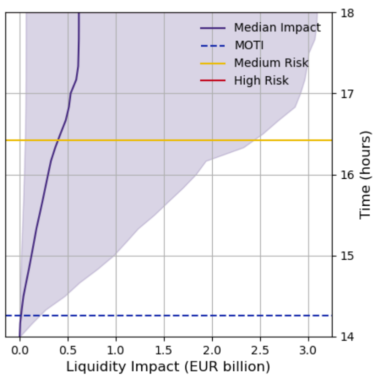
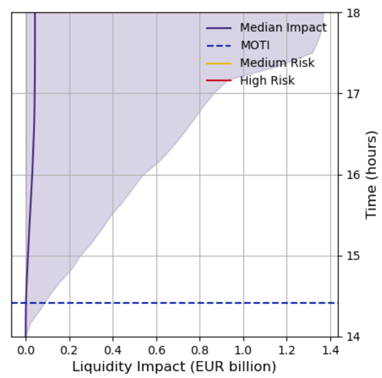


Figure 14: Liquidity Impact per bank group for an outage starting at 14:00 hours. The solid line represent the median and the shaded area the 10th and 90th quantile per bank and business day. The blue dotted line is the MOTI.

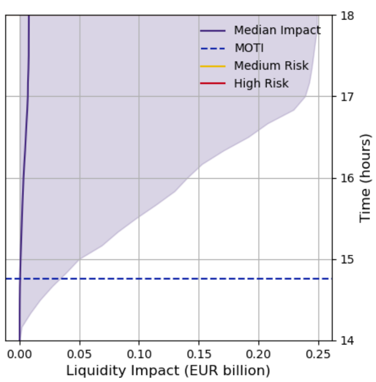
(a) BG2.



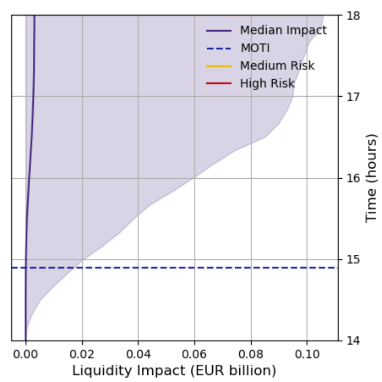
(b) BG3.



(c) BG5.



(d) BG6.

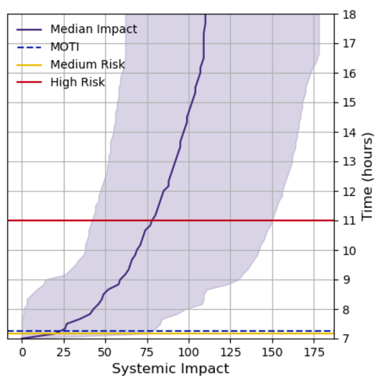


A.2 Systemic Impact

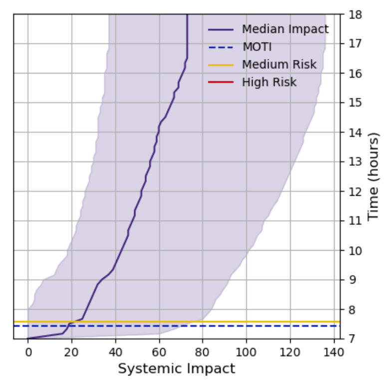
Figure 15 and Figure 16 show the Systemic Impact of BG2, BG3, BG5, and BG6 for outages starting at 7:00 and 14:00 hours, respectively.

Figure 15: Systemic Impact per bank group for an outage starting at 7:00 hours. The solid line represent the median and the shaded area the 10th and 90th quantile per bank and business day. The blue dotted line is the MOTI.

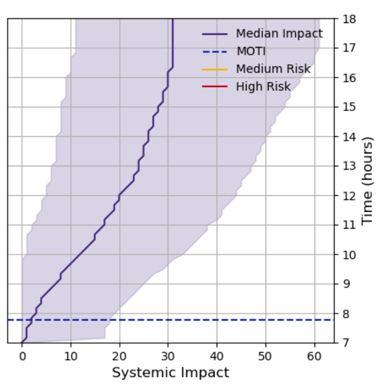
(a) BG2.



(b) BG3.



(c) BG5.



(d) BG6.

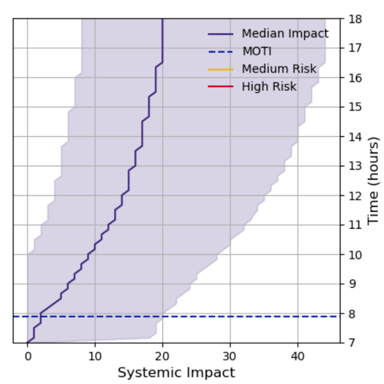
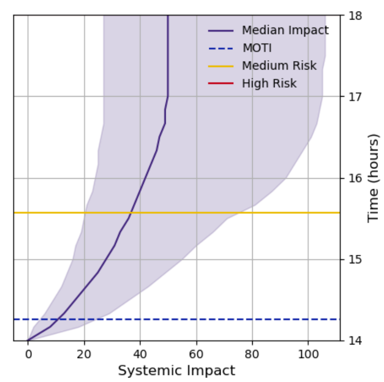
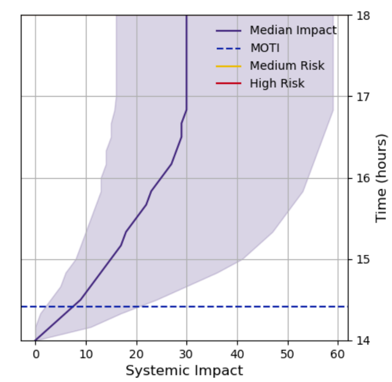


Figure 16: Systemic Impact per bank group for an outage starting at 14:00 hours. The solid line represent the median and the shaded area the 10th and 90th quantile per bank and business day. The blue dotted line is the MOTI.

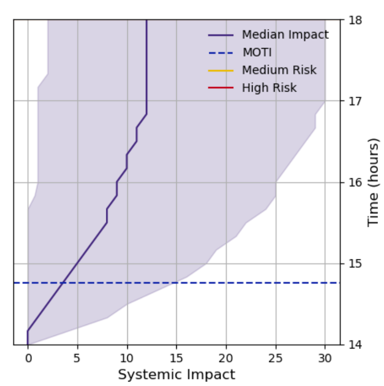
(a) BG2.



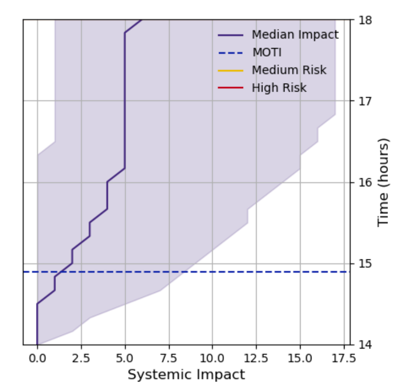
(b) BG3.



(c) BG5.



(d) BG6.

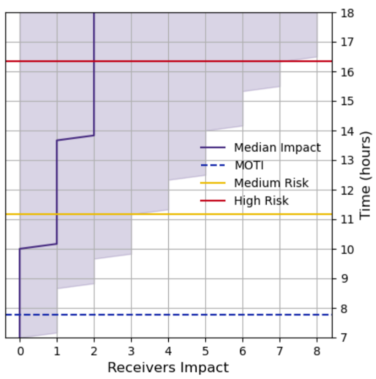


A.3 Receivers Impact

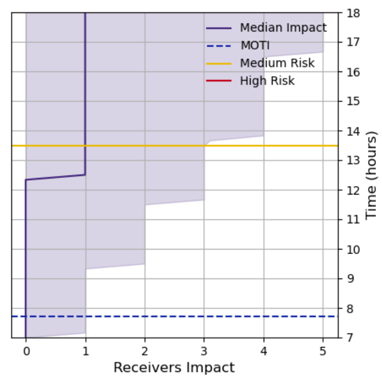
Figure 17 and Figure 18 show the Receiver Impact of BG2, BG3, BG5, and BG6 for outages starting at 7:00 and 14:00 hours, respectively.

Figure 17: Receivers Impact per bank group for an outage starting at 7:00 hours. The solid line represent the median and the shaded area the 10th and 90th quantile per bank and business day. The blue dotted line is the MOTI.

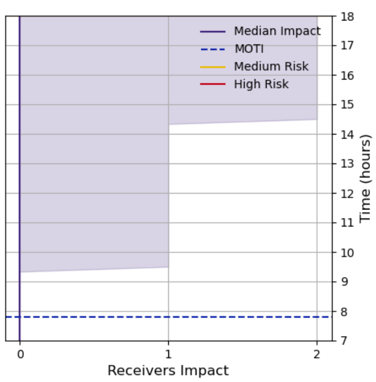
(a) BG2.



(b) BG3.



(c) BG5.



(d) BG6.

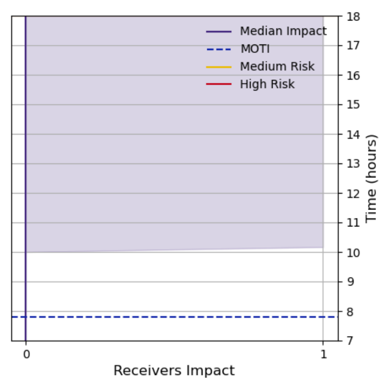
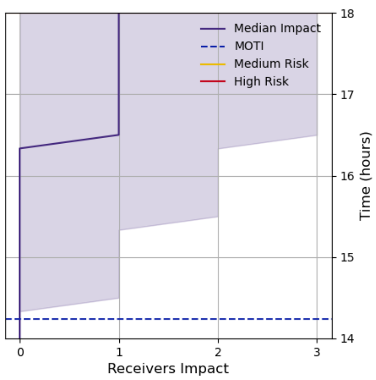


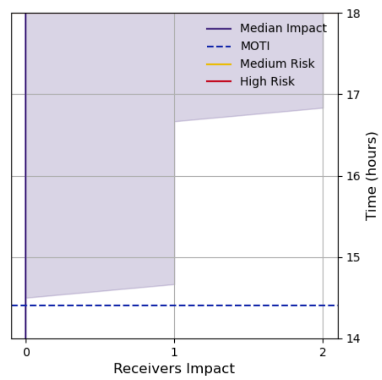
Figure 18: Receivers Impact per bank group for an outage starting at 14:00 hours. The solid line represent the median and the shaded area the 10th and 90th quantile per bank and business day. The blue dotted line is the MOTI.

(a) BG2.

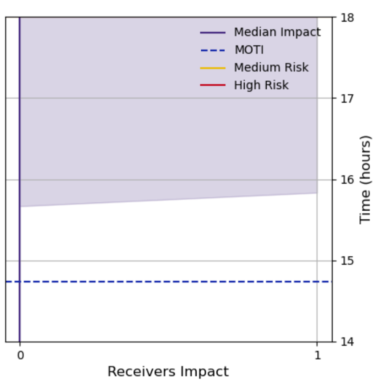


35

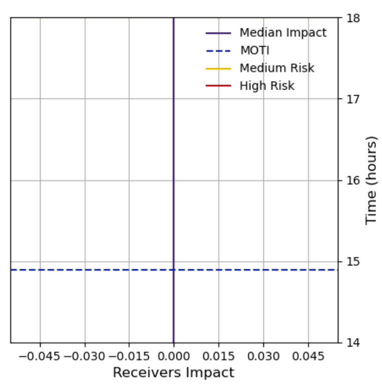
(b) BG3.



(c) BG5.



(d) BG6.



A.4 Operator's view

Figure 19 and Figure 20 show the BG2 Combined Risk Indicator dashboard for outages starting at 7:00 and 14:00 hours.

Figure 19: CRI, LI, SI, RI, for 7:00 hours bank group 2

(a) CRI. (b) LI. (c) SI. (d) RI.

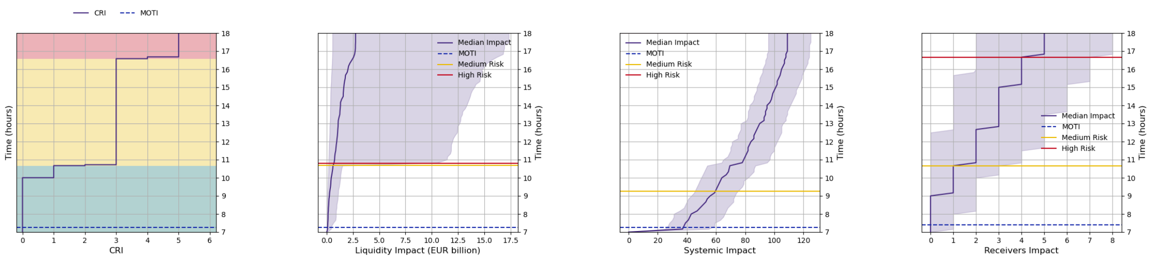


Figure 20: CRI, LI, SI, RI, for 14:00 hours bank group 2

(a) CRI. (b) LI. (c) SI. (d) RI.

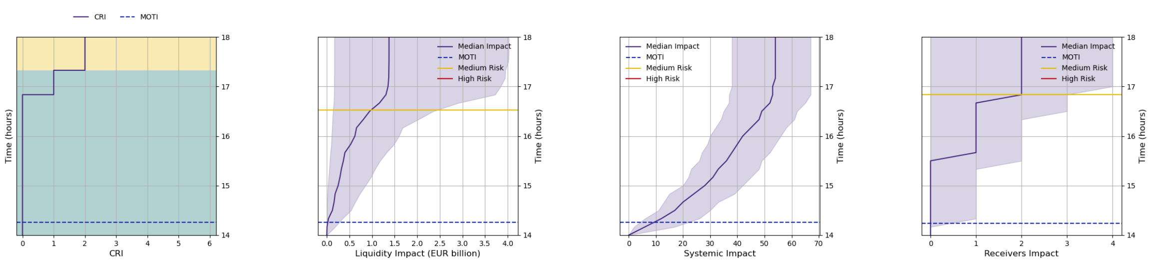


Figure 21 and Figure 22 shows the BG3 combined risk indicator dashboard for outages starting at 7:00 and 14:00 hours, respectively.

Figure 21: CRI, LI, SI, RI, for 7:00 hours bank group 3

(a) CRI. (b) LI. (c) SI. (d) RI.

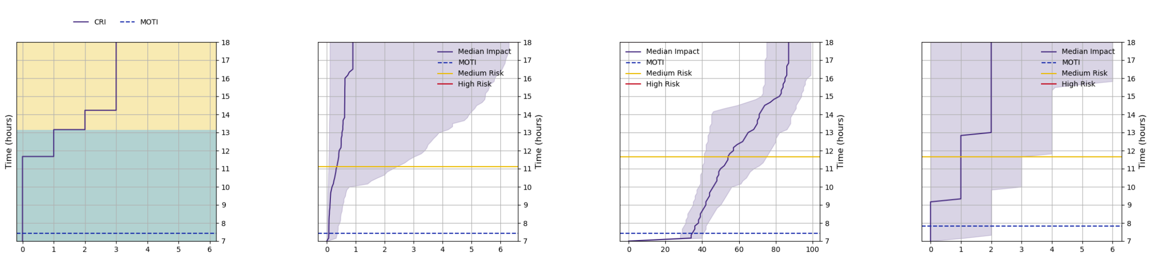


Figure 23 and Figure 24 show the BG5 combined risk indicator dashboard for outages starting at 7:00 and 14:00 hours, respecively.

Figure 22: CRI, LI, SI, RI, for 14:00 hours bank group 3

(a) CRI. (b) LI. (c) SI. (d) RI.

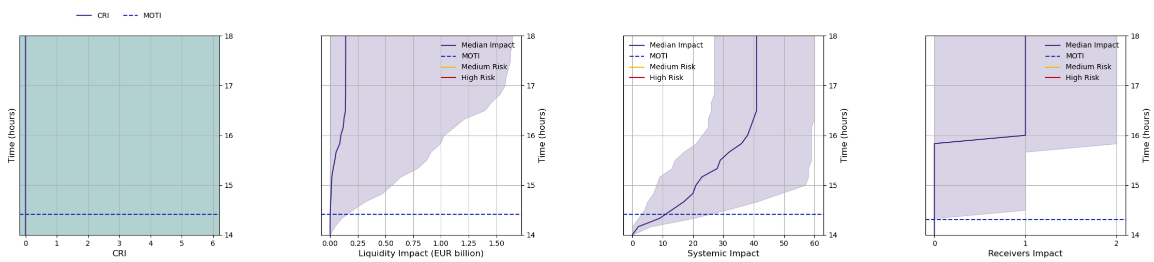


Figure 23: CRI, LI, SI, RI, for 7:00 hours bank group 5

(a) CRI. (b) LI. (c) SI. (d) RI.

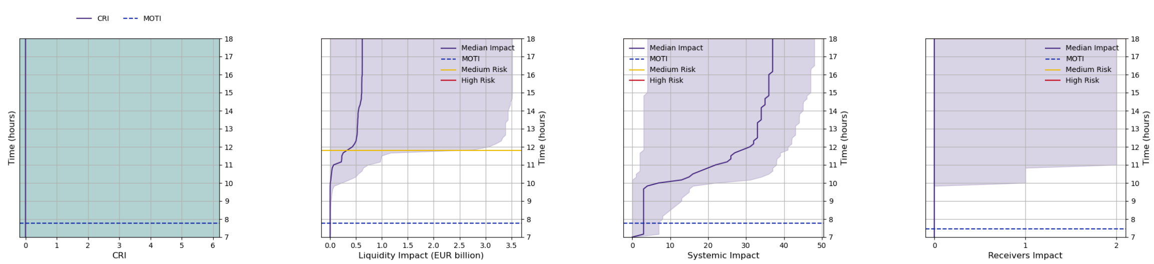


Figure 24: CRI, LI, SI, RI, for 14:00 hours bank group 5

(a) CRI. (b) LI. (c) SI. (d) RI.

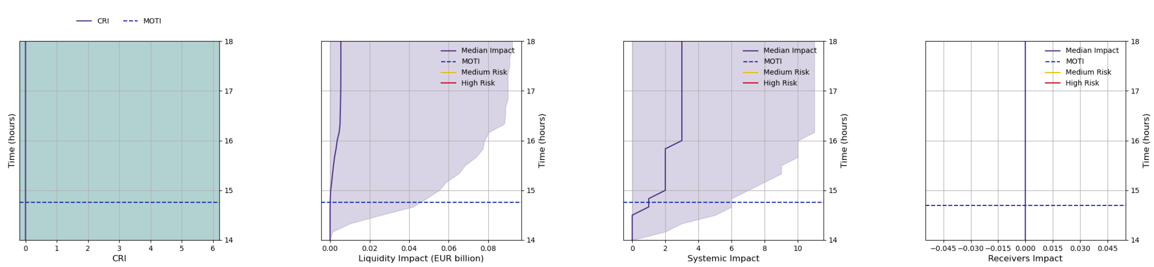


Figure 25 and Figure 26 show the BG6 combined risk indicator dashboard for outages starting at 7:00 and 14:00 hours, respectively.

Figure 25: CRI, LI, SI, RI, for 7:00 hours bank group 6

(a) CRI. (b) LI. (c) SI. (d) RI.

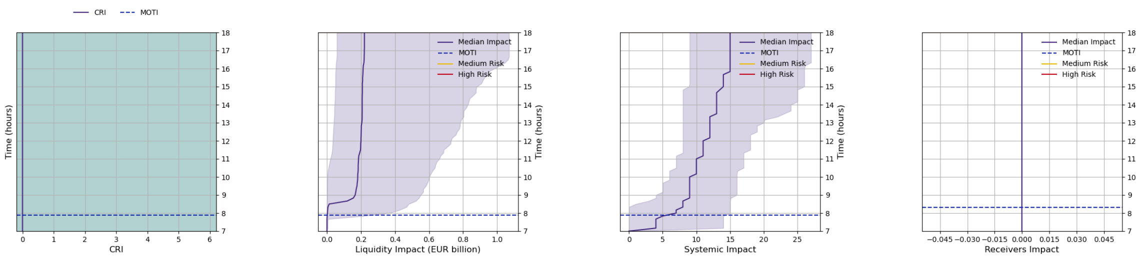
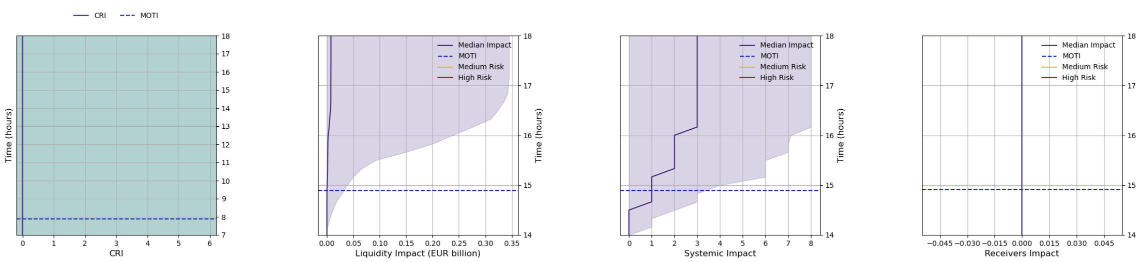


Figure 26: CRI, LI, SI, RI, for 14:00 hours bank group 6

(a) CRI. (b) LI. (c) SI. (d) RI.



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