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ÁGNES LUBLÓY–ESZTER TANAI

Operational Disruption and the Hungarian Real Time Gross Settlement System (VIBER)

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Operational Disruption and the Hungarian Real Time Gross Settlement System (VIBER)

(Működési kockázat és a hazai valós idejű bruttó elszámolási rendszer (VIBER))

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Abstract

Central bankers wish to ensure worldwide that large-value transfer systems, as a component of the key market infrastructure, exhibit sufficiently robust levels of operational resilience. We focus on the operational resilience of the Hungarian real time gross settlement system, known as VIBER. The goal of the research is the quantitative assessment of the ability of the system to withstand certain types of operational shocks. Systemically important participants are identified and it is argued that they overlap with endangered participants. An indicative list of participants who might be endangered by a liquidity shock is compiled by analysing proxies for liquidity risk. We shed light on the capacity of the system to function smoothly in the event of operational problems by simulating the technical default of one or two systemically important participants in VIBER. Altogether six plausible scenarios were formed, three entire-day incidents and three incidents involving less time (part-time incidents). The impact of behavioural reactions of technically non-defaulted participants and the application of existing back-up procedures are also considered. The disturbance in the payment system was measured by the value of initially not submitted payments, the value of rejected payments, the total value of queued payments, the maximum queue value, the average queue length and the settlement delay. By means of gross and net liquidity deficit indicators, liquidity assistance required to settle all previously rejected transactions is calculated. By comparing the value of unsettled payments with the value of eligible collaterals in the banks' balance sheet, we can gain insight into whether the liquidity deficit can be financed through normal monetary policy operations.

JEL: E50, G10, G21, L10, L14.
Keywords: real-time gross settlement, large-value transfer system, operational risk, shock-absorbing capacity.

Összefoglaló

A fizetési és elszámolási rendszereket kritikus infrastruktúrának tekinthetjük, hisz a rendszerek nem megfelelő működése veszélyeztetheti a pénzügyi szektor hatékony működését, szélsőséges esetben akár a rendszer egészének stabilitást is. Ezért a jegybankok világszerte nagy hangsúlyt helyeznek ezen kritikus infrastruktúrákban rejlő működési kockázatok megfelelő kezelésére. Tanulmányunkban a hazai valós idejű bruttó elszámolási rendszer (VIBER) résztvevőinek más rendszertagnál (illetve -tagoknál) bekövetkező működési kockázati esemény által kiváltott likviditási sokktűrő képességét vizsgáltuk meg. A tanulmány alapján kirajzolódik, hogy az egyes (elsősorban nagyforgalmú) résztvevőknél bekövetkező működési kockázati események által leginkább érintett szereplők egybe esnek azokkal a résztvevőkkel, akiknél bekövetkező technikai probléma leginkább befolyásolhatja a rendszer működését. Egész napos és napon belüli incidensek elemzésével vizsgáljuk, hogy miképpen érinti a VIBER többi szereplőjét, ha egy vagy két nagyforgalmú bank valamely technikai hiba folytán nem képes beküldeni tranzakcióit. Megnézzük azt is, hogy vajon a VIBER-tagok elegendő likviditással rendelkeznek-e a bejövő tételek egy részének elmaradása esetén is ahhoz, hogy aznapra vonatkozó összes (normál körülmények között tervezett) fizetési kötelezettségüknek eleget tegyenek. Összesen hat forgatókönyvet vizsgáltunk: háromszor egész napos, míg további háromszor részleges kiesést feltételeztünk. A technikai problémával küzdő résztvevőn kívüli szereplők esetében bizonyos reakciók (tételek küldésének leállítása), illetve egyes helyettesítő megoldások (kiválasztott tranzakciók papír-alapú benyújtása és manuális feldolgozása) hatását is elemezzük. A rendszer működésében keletkező hatásokat különböző statisztikai mutatószámokkal mértük, így például a technikai hibát elszenvedő résztvevő által be nem küldött tételekkel, a rendszer által fedezthiány miatt visszautasított tranzakciókkal, valamint a sorbanálló tételek nagyságával, a sorbanálló tételek maximális értékével, a sorbanállás átlagos idejével, illetve a késési indikátorral. Egyes forgatókönyvek esetében azt is számszerűsítettük, hogy vajon mennyi pótlólagos likviditásra lenne az egyes szereplőknek szüksége ahhoz, hogy valamennyi visszautasított tételük teljesülhessen.

1 Introduction

1.1 MOTIVATION

The Hungarian real time gross settlement system (Valós Idejű Bruttó Elszámolási Rendszer, hereinafter VIBER) is used mainly for settling large-value payments. The system can be considered as critical infrastructure for those transactions which assume settlement in Hungarian forint and the settlement or part of the settlement takes place in VIBER. The transactions include mainly large-value financial market deals and other time critical payments. The average daily turnover of VIBER accounts for approximately 10% of the annual GDP of Hungary. Given this scale of activity, if the system is inappropriately designed or poorly operated, it could expose its participants to risk potentially large enough to threaten their day-to-day business activity. In extreme cases, the financial soundness of the participants and the stability of the system as a whole might also be threatened. A smoothly functioning large-value payment system is crucial to the efficiency of the financial markets. Besides the assurance of financial stability, central bankers have an additional interest in a resilient payment system, as it can play a pivotal role in the implementation of monetary policy.[1]

A disruption to normal payment processing activity could result in the crystallization of liquidity risk. If an operational problem involving a settlement bank prevents the bank concerned from submitting payments to the system, then liquidity can accumulate on the defaulter's account (liquidity sink effect). As the bank is unable to redistribute liquidity in the system by submitting payments, the liquidity positions of the counterparties are also affected or even threatened. The counterparties may delay their payments or even worse, due to lack of funds they might become unable to settle their payments.

Analysing the resilience of VIBER is part of the MNB's[2] payment systems oversight duties. Act LVIII of 2001 on the MNB defines as one of the basic tasks of the MNB the development of the payment and settlement systems and monitoring their activities in order to achieve sound and efficient operation and smooth money circulation (MNB, 2001). In line with this, the MNB has to assess all risks that might have an impact on the system overseen. If the central bank finds that there is high risk, it should take steps to eliminate or to lessen it by proper risk management. The main risks include legal, liquidity, credit and operational risk, which are usually interrelated. Besides interrelations, systemic effects are also relevant when risks in payment and settlement systems are assessed.[3] Thus, systemic risk captures the fact that the impact of legal, liquidity, credit and/or operational risk is more widespread.

Accordingly, the goal of the current research is the quantitative assessment of the ability of the system to withstand certain types of operational shocks. We wish to shed light on the capacity of the system to function smoothly in the event of operational problems and highlight the mechanisms for mitigating the impact of such problems.

The paper is organised as follows. As for motivation, we review the recent large-scale operational incidents and then we elaborate on the importance of contingency arrangements and back-up facilities. The scope of the research is outlined in Subsection 1.4. Section 2 offers a brief review of previous empirical literature using the same simulation methodology as we do. Section 3 highlights the stylised facts of operational incidents having occurred in VIBER in the recent past. Section 4 presents the data used and discusses the simulation methodology. In Subsection 4.1 the functioning of RTGS systems in general and the specific features of VIBER are presented. In Subsection 4.2 the indicators used for describing the operation of an RTGS system, both under normal circumstances and in distressed periods, are explained. Subsection 4.3 provides a description of the normal functioning of VIBER. The benchmark case is characterised by usual statistical tools and by specific indicators. Critical periods of the business day, systemically important participants and endangered participants are also identified. We cluster the VIBER participants by analysing proxies for liquidity risk to get an indicative list of participants who might be endangered in

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[1] Note that, depending on the domestic payment and settlement infrastructure, countries might have different approaches concerning whether they settle their monetary policy operations in the RTGS or in another system. In Hungary the issuance and the redemption of the two-week MNB bills are settled in VIBER, while the settlement of other monetary policy operations (except the early redemption of the O/N collateralised loans) are booked in the bank's own system (called InFoRex).

[2] MNB stands for Magyar Nemzeti Bank, the central bank of Hungary, hereinafter MNB.

[3] The definition of *Bank for International Settlements* regards systemic risk as the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default with a chain reaction leading to broader financial difficulties (Kaufman, 1996, pp. 17-18).

the case of liquidity shocks. A simple sensitivity analysis is also carried out to see what happens to participants if they do not receive some of their incoming funds. The overlap between systemically important participants and endangered participants is also investigated. In Subsection 4.4 assumptions are reviewed. The scenarios are based on different assumptions in relation to behavioural reactions of technically non-defaulted participants, the timing and length of operational failures, the number and list of technically defaulted participants, and the application of existing back-up procedures. The scenarios are hypothetical. We carry out thought experiments by answering 'what if' types of question. Section 5 summarises the simulation results. We simulated altogether six scenarios, three entire-day incidents and three part-time incidents. The disturbance in the payment system is measured by the value of initially not submitted payments, the value of rejected payments, the total value of queued payments, the maximum queue value, the average queue length and the settlement delay. By means of the gross and net liquidity deficit indicators, we also make an attempt to calculate the additional liquidity that would be required to settle all rejected transactions (Subsection 5.4). Section 6 compares the simulation results prepared by other central banks with the Hungarian outcomes. Finally, Section 7 presents the conclusions and highlights the area for further research.

1.2 OPERATIONAL INCIDENTS

The smooth operation of payment and settlement systems assumes the availability of resources (premises, staff, IT equipment, power, etc.) required for their operation. These resources are exposed to operational risk. They can be endangered by both internal and external factors which could lead to operational disruption. The spectrum of internal and external factors is diverse; it includes power outages, disruptions to telecommunication networks, IT failures (software or hardware problems), natural disasters and terrorist attacks. Resources can be protected by different means (e.g. back-up sites and procedures or, in the case of outsourcing, by service level agreements). Nevertheless, a considerable amount of money has to be allocated for their protection. Due to the high variety of operational incidents, the unforeseen nature of such events and the low probability of large-scale events, the costs can often offset the expected benefits of the protection.

As a consequence of various international incidents in the recent past, increasing attention has been devoted to business continuity planning and operational risk management.

The consequences of a *power outage* on the payment system can be highlighted by analysing the impact of the blackout of 14-15 August 2003 in the U.S (FBIIC, 2003). On 14 August at approximately 4:11 pm, large areas of the northeast lost power, including New York City. The two primary retail and wholesale payment system operators were able to quickly switch over to back-up generators and there was no interruption in their services. However, several depository institutions had to close all operations because their head offices or operations centres did not have back-up power arrangements or they experienced some problems with their back-up generators. The 14 August blackout disrupted trading in federal funds.

The impact of *natural disasters* could perhaps best be demonstrated by the flood in the tunnels below the Chicago business districts. On 13 April 1992 the Chicago Board of Trade was shut down completely and resumed trading only at small volume in subsequent days (Pelant, 1992).

The damaging role of *terrorist attacks* can be highlighted by analysing the disturbance in the U.S. financial system after 11 September 2001 (McAndrews and Potter, 2002; Lacker, 2003). It has been reported that, due to the widespread damage to property and communication systems in Lower Manhattan, the banks experienced difficulties in making their payments. The inability of some banks to send payments resulted in an unexpected shortfall of liquidity for other banks. This was significant, as banks rely heavily on incoming funds to make their own payments. The level and timing of activity on Fedwire were also severely disturbed. To mitigate the effects of the terrorist attacks, the Federal Reserve supplied abundant liquidity to the banking system through discount window and open market operations.

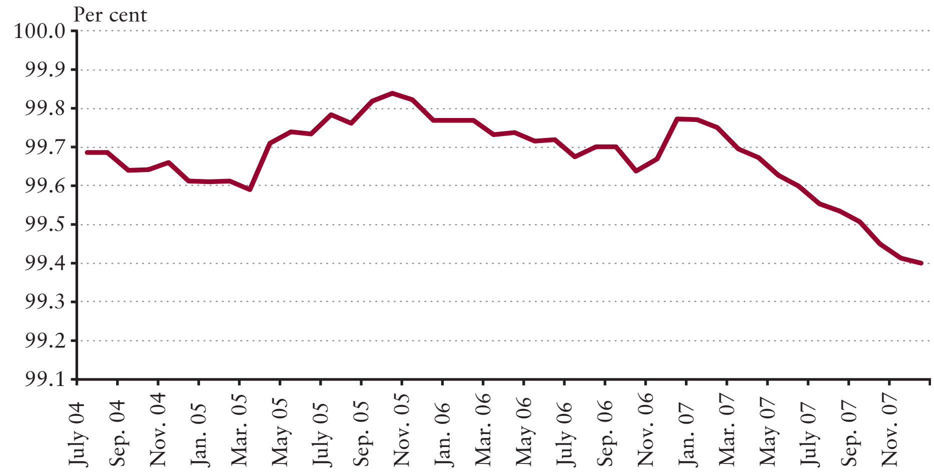
The *Hungarian real time gross settlement system* fortunately has never suffered from any similar large-scale natural disaster or terrorist attack. The incidents occurring in the recent past had a much smaller impact on the operation of the payment system. The events either affected the *components of the central settlement infrastructure* or the *participants' facilities.*

The service level of VIBER can be illustrated by the availability ratio. On a yearly basis the system was usually available for settlement in 99.6 per cent of the business hours (Chart 1). In order to define the weak points of the system and to improve the service level, the MNB regularly monitors the availability of VIBER.

Chart 1

The availability ratio of VIBER

(12-month moving average)



The *components of the central settlement system* are operated by the central bank and its service providers. Reliable statistics are accessible about the operational incidents affecting these central components. The database of incidents affecting the central components can be considered as complete. Nevertheless, processing of payments also requires the constant ability of *VIBER participants* to send and receive payment messages. However, the technical problems of VIBER participants are not always reported to the MNB. Exceptions include when the participant asks for the prolongation of operating hours. In this case the participant is obliged to report to the MNB the reason for the prolongation. In many cases technical problems were cited as the justification for lengthening. Unfortunately, the database of external failures (incidents affecting the participants) is not complete, and the sample itself is not representative.

Despite the incomplete database the MNB is aware that in the recent past several serious operational incidents have occurred. From April 2003 until May 2007 the MNB recorded 71 external incidents (including problems with monitoring facilities or incidents involving ancillary systems like retail ACH or CSD/SSS), which are evidently far less than the number of real occurrences. In twenty cases the MNB has information concerning how long those problems lasted. The average length of the operational problems was 2 hours and 21 minutes, the maximum 5 hours and 50 minutes, and the minimum 14 minutes. Twenty-six of the 72 cases occurred due to the unavailability of the messaging network, known as SWIFT. In the remainder of the cases there is no detailed information about the source of the technical problem. Although it is hard to draw any conclusion from this incomplete database, it is clear that failures arose both at small and at big credit institutions. The incident database shows that failures happen from time to time. Regardless of the low probability of incidents, once they hit it, they could have a large impact on functioning of VIBER and its participants. Some of the incidents (credit and debit turnovers) will be analysed in detail in Section 3.

1.3 CONTINGENCY ARRANGEMENTS AND BACK-UP FACILITIES

Due to recent operational incidents more emphasis is put on national and cross-border strategies related to business continuity planning and operational risk management. Though there have been a range of controls and procedures in place to reduce the likelihood of disruption from internal sources of operational risk, they proved to be insufficient in many cases. By defining critical functions and infrastructures, trading and post-trading infrastructures (covering payments and settlement systems) have been reviewed. The real time settlement systems (hereinafter RTGS system) were considered as critical infrastructure. After mapping the infrastructures which play pivotal roles in the society and the economy, the decision makers set up guidelines, expectations or even standards for business continuity planning and operational risk management of such critical infrastructures. Those expectations (BoE, 2003; BoE, 2004; BoE, 2005; ECB, 2006 and FED, 2003) usually include the following:

- required redundancy of resources essential for the operation of such infrastructures (e.g. the requirement of back-up facilities),
- conditions of redundancy (e.g. the minimum requirement on the geographic separation of the live and remote sites),
- the regular testing of redundant resources in order to ensure that back-up resources are capable of substituting the primary resources if the latter experience some problems.

Besides critical infrastructures, critical participants were defined in many cases as well. This is in line with the fact that the normal functioning of the RTGS system supposes that not only the central settlement processing operates properly but also the facilities of critical participants.

At the same time, the interrelations of various risk types (e.g. operational and liquidity risks) and the importance of technical liquidity assistance of the central bank was also pointed out. As the central bank is the residual liquidity provider and the residual liquidity absorber of the banking system, it should always be aware how an operational incident would influence its counterparties. The central bank should also be able to judge whether the liquidity effects can be handled within the framework of the usual operations or it has to act as a lender of last resort.

Despite all the efforts to improve the resilience of the payment infrastructure, it is clear that the risk that normal operations will be disrupted anyhow cannot be eliminated entirely. As a consequence, it is important to assess how operational risk in systemically important payment systems could be controlled and mitigated.

1.4 SCOPE OF THE RESEARCH

An *operational incident,* either historical or hypothetical, can be characterised by *two dimensions:* by the probability of the occurrence and by its impact (Chart 2). The *probability* of the incident can either be estimated from an incident database covering a long time horizon or from an appropriate theoretical distribution, e.g. by means of extreme value theorem. By measuring the *impact* of an operational incident, there is a need to distinguish between first and second round effects. *First round effects* can be directly observed in the payment system. Appropriate indicators of the severity of first round effects include the indicator of payment delay or the volume of unsettled transactions. The analysis is ex post, if the first round effects are measured by means of historical payment system data. The analysis is forward looking, if the disruption of the system is measured by means of simulated payment data. *Second round effects* cannot be directly observed in the payment system. Second round effects materialise in delaying time-critical payments or other contractual obligations. Besides the severity of the incidents, the costs related to those incidents should also be estimated.

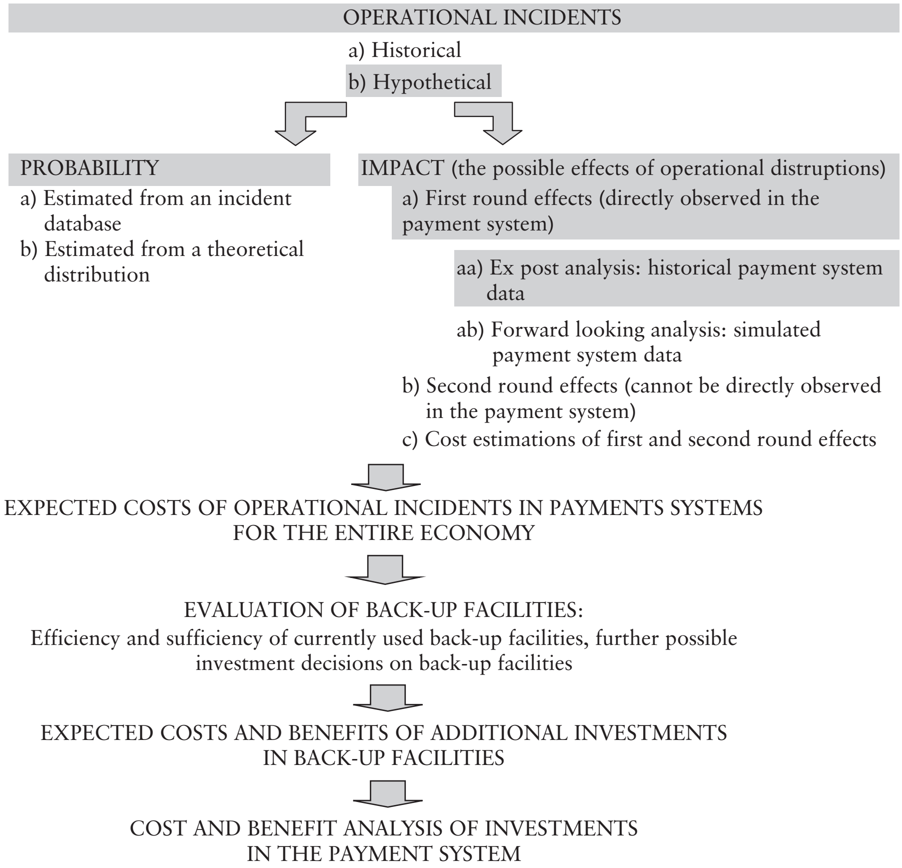
After estimating the expected costs of operational incidents in the payment system for the entire economy, we should evaluate the role of the *back-up facilities* currently in place. The efficiency and the sufficiency of the currently used back-up facilities should be analysed. If the currently used back-up options prove to be insufficient, investment decisions related to additional back-up options should be considered. The investment decision should rely on a detailed cost-benefit analysis. At the same time, the appropriateness of the *payment system design* should also be evaluated, and a cost-benefit analysis of the possible investments should be carried out.[4]

In fact, the research carried out can be considered as a first step towards evaluating *the ability of the payment system to withstand certain types of operational shocks.* In order to judge adequately the appropriateness of system design from a risk perspective, further research is needed. We set up hypothetical scenarios for operational incidents and examine how severe the disruption of the payment system is. Note that the market participants do not doubt the creditworthiness of the institution in trouble. We do not aim to estimate the probability of operational incidents. If the MNB had a detailed database including all the operational incidents that occurred over a long time horizon, the database could serve as useful input to estimate the probability. Moreover, the severity and costs of second round effects are also disregarded; they could only be estimated by

[4] Two prominent examples of shifts in payment system design include the switch from net to gross systems and the introduction of liquidity saving features in RTGS systems.

Chart 2

Operational incidents and the payments system design from the risk perspective



obtaining information directly from the economic agents. Thus, the in-depth analysis of the probability and severity dimensions of operational incidents requires further research.

The paper assesses exclusively the severity of *first round effects* of an operational incident by carrying out an *ex post analysis*. Although the interrelation between operational and liquidity risk in an RTGS system is well-known, *the impact of operational risk on liquidity risk depends on many factors which are unique to all systems*. These factors include the characteristics of the payment network (e.g. concentration of turnover), available liquidity, behavioural patterns followed by system participants (e.g. timing of payments) and payment system design. Previous studies (Kiss–Tanai, 2004; Lublóy, 2006) showed that VIBER has many specific features that might influence the interrelation between operational and liquidity risks in extreme situations. In the paper we also make an attempt to assess *how much additional liquidity is required to ensure the smooth functioning of the system in the case of an operational incident*. We provide a rough estimate for the additional liquidity need by comparing the value of unsettled payments with the value of eligible collaterals in the banks' balance sheet. In this way we can gain insight into whether the liquidity deficit can be financed in the framework of normal monetary policy operations (usual open market operations and/or overnight collateralised loans).[5] If not, the central bank might intervene in its lender of last resort role as the financial stability of the banking system might be threatened.

[5] In Hungary the central bank provides liquidity only against collateral. If one of the participants wishes to take longer term or O/N credit, it has to post additional collateral if the eligible assets already pledged do not cover the collateral requirement. In Hungary both intraday and monetary policy loans are collateralised.

2 Previous studies

There are several studies prepared by central banks that assess the affects of various operational failures in *RTGS or hybrid systems*.[6] These are reviewed in this section. In RTGS and hybrid systems the transactions are settled immediately when submitted if there are enough funds to cover the payment. The funds usually consist of the current account balance and the intraday credit line. The participants have to post collateral to obtain intraday credit.

For analytical purposes *simulations based on historical data are carried out*. These experiments operate with the payment system simulator developed by the Bank of Finland (BoF-PSS) or Banque de France. With their built-in functionalities these simulators can replicate the functioning of various types of large-value payment systems. The goal of performing the simulations is to shock the payment system and to see what would have happened if the payment system had experienced *an unanticipated operational incident*. The possibility of *insolvency is ruled out*. The market participants do not doubt the financial soundness of the institution in trouble; the default is exclusively operational in nature.

All the studies considered address the question whether the inability of a single participant or multiple participants to submit payments leads to serious disturbances in the system. For analysing these effects *three features of the incident* are given: (1) the set of technically defaulted or affected participants, also named stricken banks; (2) when the incident starts (the timing of the incidents) and (3) how long it takes (the length of the incidents). These parameters are usually set by searching for the worst-case scenarios with some constraints (e.g. the length of the incident should be two hours). Besides these features the severity of the failure depends also *on the assumptions related to the liquidity available in the system,* the payment *system design* (e.g. the existence of back-up procedures) and whether the non-defaulting (or unaffected) *participants react to the incident* by applying stop sending rules or adjusting bilateral limits.

The inability of one or more participants to send payments may cause serious liquidity and settlement problems. The characteristics of liquidity shortages, unsettled payments, queues and delays can be measured by *various indicators*.

In general, all studies aim at analysing how operational risk might lead to the crystallization of liquidity risk. However the studies differ in the parameters of the stylised incidents, the assumptions made on the system design and behavioural reactions of non-defaulting participants, as well as the indicators measuring the impact of the operational incidents.

2.1 ASSESSING OPERATIONAL RISK IN UNITED KINGDOM'S CHAPS STERLING (Bedford et al., 2004)

Based on February 2004 data, Bedford et al. (2004) assess the impact of different types of operational incidents that could affect the United Kingdom's CHAPS Sterling. The authors examined *three shock scenarios:* the operational failure of one settlement bank, multiple settlement banks and the central payment processing infrastructure. Instead of using the actual liquidity available, the authors used five *hypothetical liquidity levels* resulting from linear combinations of upper and lower bounds of liquidity.[7]

In the study several *assumptions were made concerning the behaviour of the unaffected settlement banks and the timing of the incident*. In the first scenario it was assumed that the unaffected settlement banks do not change their behaviour; they wish to settle all previously planned transactions. Concerning the timing, it was supposed that the problem could not be sorted out until the end of the business day. In the second case the settlement banks were not passive economic agents; they stopped sending payments to the bank experiencing the technical default in ten minutes. The authors aimed to identify the point of time at which the operational failure of one of the settlement banks would potentially cause *the most serious disruption of the payment activity*. In order to determine the potentially most problematic scenarios, the authors introduced the terminology of the *virtual credit balance*. The virtual credit balance equalled the sum of the actual balance of the current account plus the

[6] Hybrid systems dispose of more advanced liquidity saving features by applying, for example, continuous bilateral or multilateral offsetting or netting. The Paris Net Settlement (PNS) is a prominent example of hybrid systems.

[7] For definitions of lower and upper bounds of liquidity see Subsection 4.2 part b).

gross inflow of funds over the next ten minutes. In the worst-case scenario the authors assumed that the operation failure occurs when the virtual credit position reaches its maximum for any settlement bank or for the randomly selected settlement banks, subject to the condition that the failure should occur before 12:00 noon.[8]

The system's shock-absorbing capacity is measured by *indicators related to unsettled transactions between unaffected settlement banks, queuing and delay*. Bedford et al. (2004) found that, except in the case of the lower bound of liquidity, the operational failure of one of the CHAPS Sterling settlement banks did not lead to any significant amount of unsettled transactions (either in value or volume terms). At the same time, the average queue length and the delays did not increase significantly. The impact of operational disruption involving three randomly selected settlement banks became significantly greater than in the scenario of single failure. In this case at the upper bound of liquidity there were no unsettled payments. As the actual amount of liquidity is typically higher than the upper bound of liquidity, it is claimed that CHAPS Sterling is able to withstand an operational failure affecting one or multiple settlement banks.

2.2 THE IMPACT OF TECHNICAL DEFAULT OF PAYMENT SYSTEM PARTICIPANTS IN THE PARIS NET SETTLEMENT (PNS) (Mazars and Woelfel, 2005)

Another prominent study using January 2004 data assesses the impact of a technical default in the French PNS large-value transfer system. The authors used both *actual and hypothetical levels of liquidity*. The hypothetical liquidity levels included the lower bound of liquidity and four other liquidity levels obtained by the linear combinations of the actual and the lower levels of liquidity. PNS applies bilateral limits. The *bilateral limit* is the net amount of funds a participant is willing to pay to another participant before being paid back. The theoretical lower bound of bilateral limits corresponds to the minimum value of bilateral limits necessary to settle all payments between two banks. The simulations were carried out by the actual limits, by the theoretical lower bounds and by six other hypothetical values in between.

Mazars and Woelfel (2005) analyse the impact of the technical default of the largest debtor, defined as the participant with the highest value of total payments. The technical default *occurs at the opening of the system and lasts for the entire day*. In the simulations it is assumed that the submitting behaviour of the initially unaffected participants is unchanged and the participants do not adjust their liquidity levels. Nevertheless, the settlement banks are not totally passive economic agents across all scenarios. In certain simulations the settlement banks could *change their bilateral limits* vis-à-vis the defaulter and set them at their theoretical lower bound. On the one hand, this behaviour decreases liquidity flows to the defaulter, while on the other it ensures that all payments to the defaulter could be settled if the latter were also able to submit payments.

The metrics used to describe the impact of the default on the overall functioning of PNS overlap with the indicators used by Bedford et al. (2004). The authors found that PNS could function smoothly with significantly lower liquidity levels and bilateral limits than their actual values. However, if a major participant is unable to submit payment orders to the system, it could result in almost 10% of payments being unsettled among participants not affected by the technical incident. At the same time, the technical default leads to a considerable increase in the delay indicator, almost doubling it. In the study it is argued that contagion effects can be mitigated if the participants lower their bilateral sender limits vis-à-vis the defaulter shortly after the operational incident. The authors concluded that lower bilateral limits reduced the liquidity loss in the event of default, while having an insignificant impact if the system operates normally.

2.3 OPERATIONAL RISK ANALYSIS OF THE AUSTRIAN ARTIS (Schmitz et al., 2006)

Schmitz et al. (2006) also operate with real transaction data (recorded in November 2004) to quantify the contagion effect of an operational incident at one of the participants in ARTIS on the other participants of the system. The liquidity data used corresponds to actual statistics and disregard the possibility of adjustment by posting extra collateral when the incident happens.

[8] Measuring the liquidity sink effect by the virtual credit balance is not feasible in Hungary as minimum reserve requirements are in place. In the recent past in the toolkit of the Bank of England's monetary policy operations there was no minimum reserve requirement, thus the authors could assume that the end-of-day balance of the RTGS participants should be close to zero. If minimum reserve requirements are in place, the participants would not necessarily aim at disposing of zero balance at the end of the day. Thus, in this case it could not be assumed that the virtual credit balance equals the liquidity sink effect. Recently, the Bank of England has also introduced a reserve requirement regime with voluntary participation.

In the simulations operational incidents happen to *one or more participants*. Schmitz et al. (2006) examined the effect of the operational failure of the *most active participants*. The most active participants were defined on the basis of liquidity and payment concentration. The authors assumed that the participants are incapacitated by a technical problem *for the entire business day*. In the simulations various *assumptions were made concerning 'stop sending' behaviour and the usage of back-up procedures* (debt-authorization[9] or paper-based submission). It was supposed that effective business continuity arrangements are in place and back-up options are employed before the closure of the system.[10]

In the *first scenario* the most active participant could not submit payments to the system. In the initial setup the 45-minute stop sending rule was taken into account, then it was disregarded. In the *second scenario* the most active bank was affected by the technical problem and the debit authorisation was introduced (no stop sending rule was taken into account). Later, the debit authorisation was neglected. In the *third scenario* the three most active banks simultaneously could not submit payments to the system. At first, all three stricken banks granted debit authorisation to a number of other ARTIS participants. Secondly the simulations were re-run without the feature of debit authorisation (no stop sending rule was taken into account).

Schmitz et al. (2006) used several metrics to describe the impact of the technical default on the payment system as a whole and on individual banks. Among others, the indicators included the liquidity drain and sink effect, and the value and number of payments unsettled. In the study the lower and the upper bounds of additional liquidity that would be required to settle all transactions were also calculated. The authors concluded that the contagion effect in ARTIS was low, on condition that the existing business continuity arrangements prove effective. However, without the use or effective implementation of business continuity arrangements, the contagion effect on the smooth functioning of the payment system is significant. The stop sending rule reduced the disturbance in the payment system notably. The debit authorisation also attenuated the system's reaction to operational shocks, but to a much lesser extent.

2.4 THE CASE OF THE DANISH KRONOS (Bech and Soramäki, 2005)

The study of Bech and Soramäki (2005) evaluates the performance of *gridlock resolution algorithms* under both normal operating conditions and failure scenarios. The data used to test the effectiveness of the gridlock resolution mechanism under failure scenarios consists of actual payments settled in the Danish RTGS system. In the operational failure scenario the *largest bank became unable to send payments*. The connection *recovers only in the last opening hour of the system*. The liquidity available for banks equalled the upper bound of liquidity. In the first simulation setup the authors assumed that the banks were not aware of the failure and *continued sending* payments to the failing bank. In the second setup unaffected banks were *reluctant to keep on sending* payments and set lower priority to payments to the failing bank. In this way the payments between non-failing banks could be settled more smoothly.

Bech and Soramäki (2005) found that, in the absence of behavioural response, the recycling of liquidity in the system was severely damaged, which can be explained by the fact that a large proportion of liquidity is trapped on the failing bank's account until the last hour. When the banks took countermeasures, delay slightly decreased. When gridlock resolution algorithm was applied, settlement delays reduced significantly.

2.5 THE OPERATION OF THE NORWEGIAN NBO WITH DIFFERENT LIQUIDITY LEVELS (Enge and Øverli, 2006)

The study of Enge and Øverli (2006) measures the resilience of the NBO (the Norges Bank's real time large-value settlement system) by varying the liquidity levels. The settlement data covers a 10-day period from October 2005. In the simulations *actual and hypothetical liquidity levels* were used. The hypothetical levels of liquidity were obtained by reducing the actual level of liquidity step by step by 10%.

[9] If the stricken bank grants debit authorisation for a number of other participants, then many payments by the stricken bank could be submitted via the participants to whom debit authorisation was granted.

[10] In this case it was assumed that the internal systems of the stricken banks work properly and thus those banks have up-to-date information about their payment obligations.

Enge and Øverli (2006) addressed the question of how changes in actual liquidity available for participants influence the speed at which payments can be settled, or whether they can be settled at all. In the simulations the authors assumed that, despite the constrained liquidity, the transaction flows and the settlement behaviour are unchanged. The disturbance of the system caused by liquidity reduction is measured by three indicators on delays, unsettled transactions and settlement time. The authors found empirical evidence about the trade-off between the liquidity levels and payment delay in the Norwegian interbank settlement systems. It was shown that the shock-absorbing capacity of the system is high and that liquidity must be reduced substantially before considerable settlement delays occur.

3 Stylised facts

In this section some of the operational incidents occurring in VIBER in the recent past are outlined and briefly analysed. The aim of this section is twofold. Firstly, we would like to provide an insight into the disruption and regeneration of payment flows on problematic days. Secondly, we would like to partly support the formulation of our hypothetical operational incident scenarios (Subsection 5.2).

In the period January 2005 – October 2007 there were altogether *17 reported incidents* that affected one of the six systemically important banks.[11] (For definition of systemically important banks see Subsection 4.3.2.) Of the 17 incidents we explore only those which are relevant for this study. Consequently, we exclude from the analysis all incidents affecting participants with lower turnover, as we are interested in the disturbance of the payment system in the worst case. In addition, two incidents occurred on Saturdays which were official working days in Hungary, but not in Europe or in the United States. As a consequence, the turnover of VIBER was significantly lower than usual; the turnover on these Saturdays equalled around one fifth and one fourteenth of the average turnover of that month. Additionally, there were four incidents where we were not able to identify properly their beginning and their end. The banks reported technical problems on these days, but the maximum gaps in the time stamps of the settled transactions were around 30 minutes, and these occurred several times during the day. Finally, *we ended up with 11 incidents to be analysed in detail.*

The analysis of the operational incidents has several drawbacks. First of all, we do not have the receipt times (the actual times when the transactions were received by the system) at our disposal. As a second best solution we have used the time stamp of the transactions when they were settled. In this way our analysis is biased.[12] Secondly, in the majority of cases we do not have any exact information about the beginning and the end of the incidents (the reports of the participants usually contain many missing data). To overcome this problem, we looked for the maximum in the time gaps of settled transactions. The period with the maximum length in which there were no executed transactions was considered as the period of the incident.[13]

Mandated payments[14] were excluded from our analysis; these payments were submitted even in the case of the technical default of the participants. For the rest of the payments (bank-to-bank and customer payments, payments initiated via paper-based back-up and processed by the MNB) we cumulated the credit and the debit turnover of the bank under distress over a time period of five minutes, and we plotted these cumulative turnovers on a graph. To be able to compare the distribution of payments over time in the distressed period with the distribution of payments in normal times, we also created a benchmark period. The benchmark period included the working days of the month before and after the incident. For example, if the incident occurred on 14 March then the benchmark period corresponded to a period between 14 February and 14 April, excluding the day of the technical default. For the benchmark period the average turnover data were computed.[15]

From the 11 analysed incidents, five lasted for less then two hours. As the incidents were fairly short, they had no real impact on the process of the payment flows. Interestingly, on the day of the incidents the debit and the credit turnovers were generally (4 times out of the 5) higher than the average of the benchmark period. Chart 3 demonstrates the payments flows on a problematic day and in the benchmark period if a short incident occurred. As shown in the chart, on the day of the incident the turnover was higher than the average of the benchmark period. It is also observable that on the day of the incident the sending of payments proceeds in 'blocks', and when the bank manages to sort out the source of the problem there is a jump in the value of posted transactions. (It is important to note that in the benchmark period the sending of payments also

[11] Apart from reporting, another way of identifying the historical disruptions at participants would involve analysis of the time stamp gaps for sending (time between sequential payments). This would require the definition of the length of the time stamp gap (threshold), which might be already considered as 'a disruption'. This exercise is not easy, especially not for those participants who do not send payments continuously through the RTGS. For those participants whose sending is usually continuous, this exercise would be easier. Nevertheless, several complications might arise.

[12] It is obvious that there might be some delays between sending and settling times due to insufficient funds.

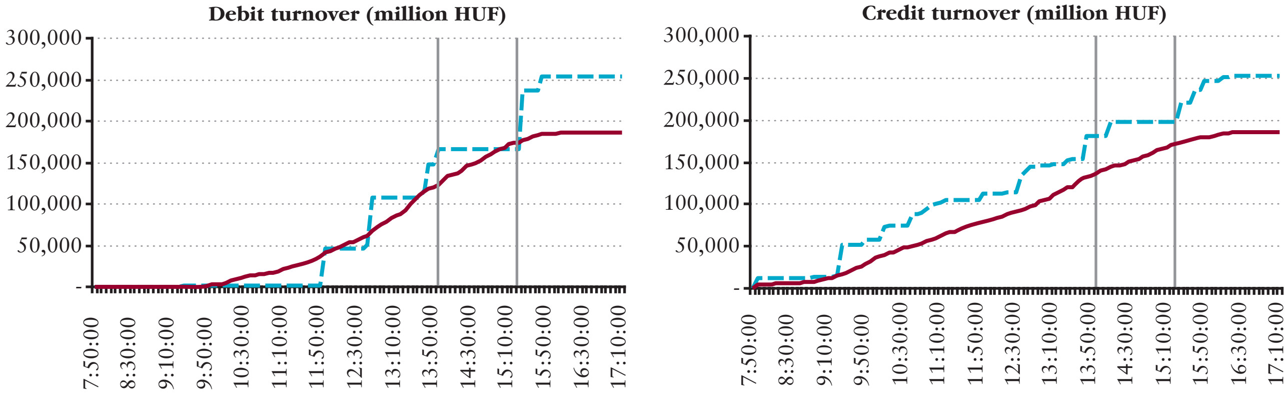
[13] Nevertheless, there were some cases where the exact timing of the incident could not have been identified even by this method. As was stated previously, these incidents were excluded from the analysis.

[14] For definition of mandated payments see Subsection 4.3.1.

[15] This method has some disadvantages as it assumes that the symmetric two-month period around the date of the incident can be considered as normal. However, there might be specific factors affecting the daily turnover (EU or US holidays, seasonality of certain types of payment, etc.). The optimal solution would be to estimate the potential daily turnover on the distressed day and then compare this estimation with the actual data.

Chart 3

Short incidents – payment flows on the day of the incident and in the benchmark period



proceeds in 'blocks'.[16] Nevertheless, we have constructed averages over two months and these blocks disappear.) Then the receipt of payments (credit turnover) is more balanced and we can observe only smaller jumps in the cumulative credit turnover balance.

Chart 4 shows the cumulative debit and credit turnover in the case of incidents affecting three different banks for a long period of time. In case A the incident lasted for 5 hours and 25 minutes; it started at 11:07 and ended at 16:32. Most probably the bank under distress sorted out the problem even later, as the bank submitted all its transactions at the end of the day by using the paper-based back-up facility. As shown in the chart, no transactions were booked for almost five and a half hours. Nevertheless, when the bank started to send its payment orders via fax, in less then one hour the debit turnover became even higher than the average of the benchmark period. By examining the cumulative incoming payment flows we might conclude that, despite the long incident, the payment habits of the counterparties were the same both on the day of the incident and in the benchmark period. The only difference is that on the day of the incident even more transactions are settled at the end of the day.[17]

Chart 4B demonstrates the cumulative debit and credit turnover in the case of an incident that lasted for 6 hours and 13 minutes. The bank was not able to send transactions after 10:14; after this point in time the first transaction was settled at 16:27, most probably by means of back-up options. As shown in Chart 4B, when the bank started to use its back-up facilities, there was a significant jump in the debit turnover, and finally the debit turnover became higher on the day of the incident than the average of the benchmark period. The cumulative credit turnover was more or less the same on the day of the incident as the average of the benchmark period. This may refer to the fact that, despite the disturbance in the payment flows from the side of the bank under distress, the counterparties did not change their settlement behaviour.

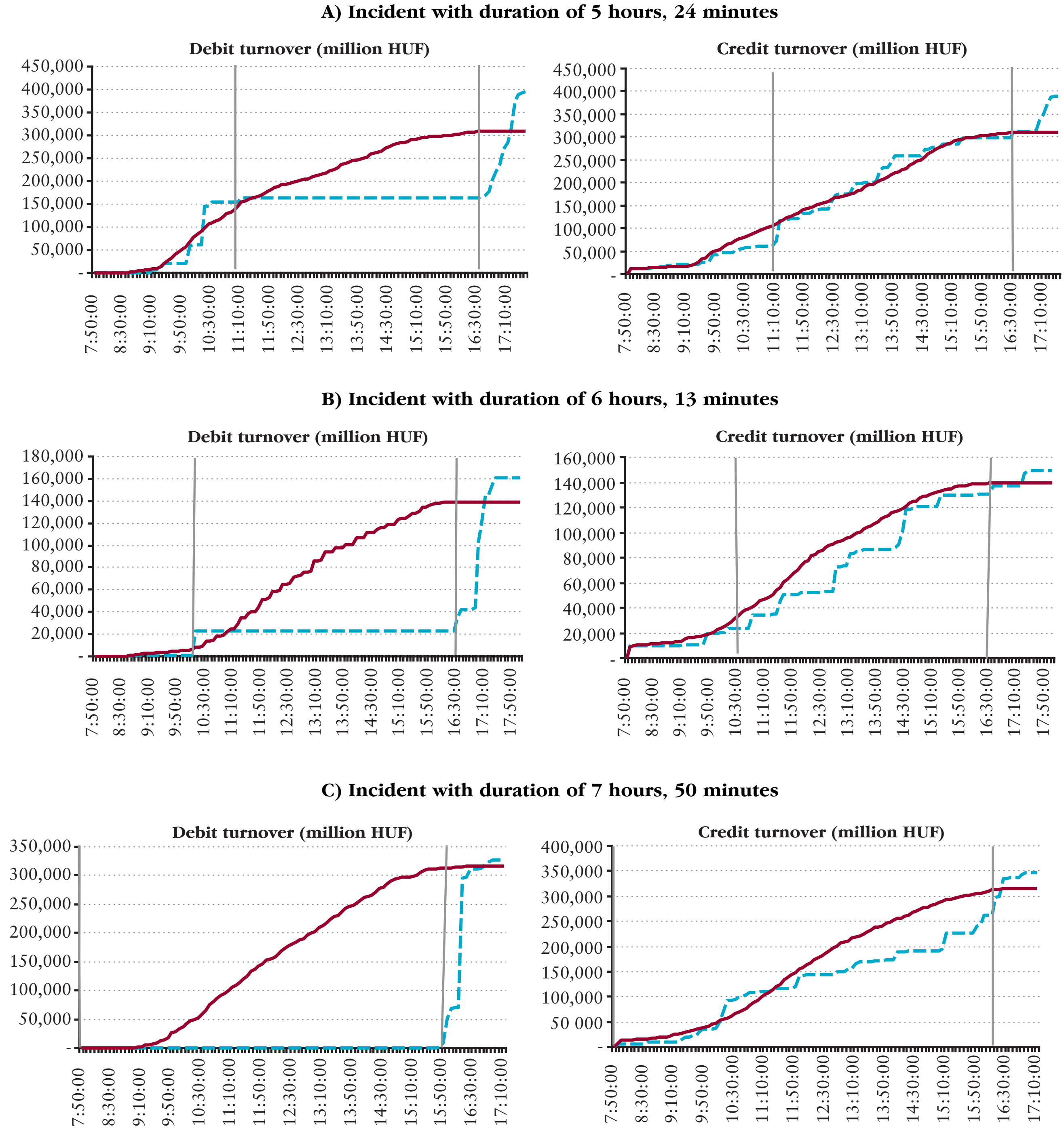
Chart 4C shows an almost entire-day incident; the length of the incident equalled 7 hours and 50 minutes. A couple of transactions were settled at the beginning of the day. Nevertheless, these transactions were mainly of smaller value, and most probably they were warehoused. On the day of the incident the first 'normal' transaction was booked at 15:43. Although the technical problem was sorted out very close to the end of the day, the bank finally managed to send and settle 235 transactions in around one hour. The value of transactions settled up to the closure of the system was slightly (3.35%) higher on the day of the incident than the average of the benchmark period. Looking at the chart giving cumulative credit turnover we might conclude that the counterparties send their payments continuously during the day; it seems that they do not withhold payments from the bank under distress. It is also observable that until 16:20 the turnover in the benchmark period is higher, which situation changes after 16:25.

[16] Sending is never perfectly continuous.

[17] This might be explained the fact that the incident occurred at the end of the minimum reserve requirement period, when achieving the required liquidity positions might result in more transactions at the end of the day. This again shows that it would be better to compare the incident data with an estimated turnover data, which could take into account several specific factors affecting the daily turnover.

Chart 4

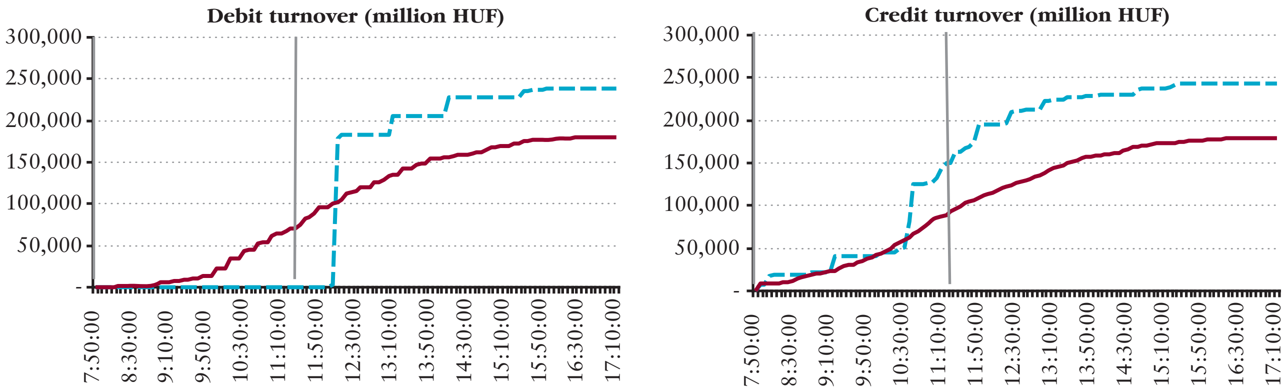
Long incidents – payment flows on the day of the incident and in the benchmark period



In the following an incident occurring during the forenoon is analysed in more detail. As demonstrated in Chart 5, the incident started at the beginning of the day and ended at 11:18. Thus, there was a morning incident, which lasted for 3 hours and 18 minutes. As shown by the chart, the debit turnover recovers in one hour after sorting out the technical problem. It is also shown that on the day of the incident the turnover is significantly higher (31.78%) than the average of the benchmark period. If we take a look at the cumulative credit turnover two important observations can be made. Firstly, on the day of the incident the counterparties send payment orders as they usually do, even at the beginning of the business day when the technical problem arose. Secondly, the credit turnover increases significantly at 10:35, forty minutes before the end of the incident.

Chart 5

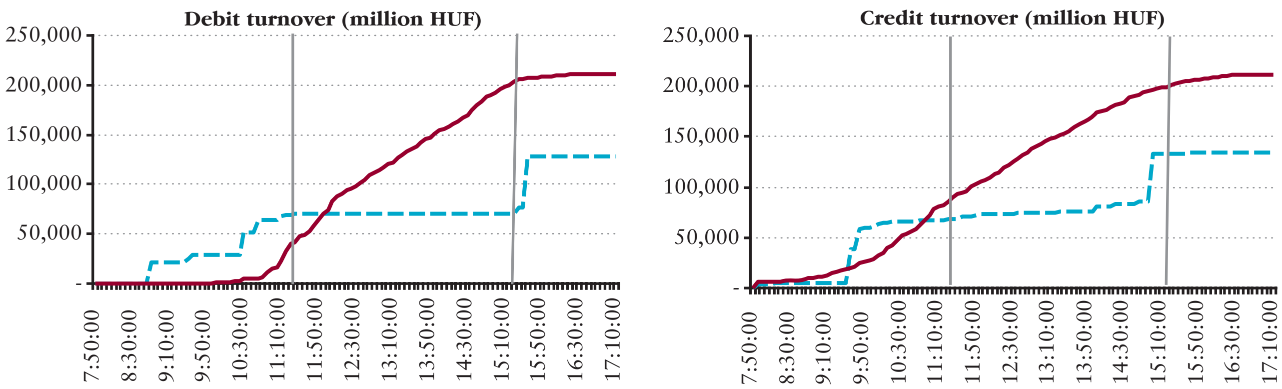
Morning incident – payment flows on the day of the incident and in the benchmark period



Finally, a four-hour incident is analysed in detail (Chart 6). The technical problem arose at 11:29 and ended at 15:22, thus it lasted for almost four hours (3 hours, 53 minutes). Both the credit and debit turnover was significantly (35-40%) lower than the benchmark average. Not surprisingly, there is a jump in the cumulative debit turnover after the problem was sorted out. There is also a jump in the cumulative credit turnover. Nevertheless, the jump occurs at 14:55, half an hour before the technical problem was solved.

Chart 6

4-hour incident – payment flows on the day of the incident and in the benchmark period



Though the above sample of examined incidents cannot be considered as comprehensive, it can be seen that the impact depends on many factors. In many cases we found that the turnover (both credit and debit) recovered after the incident, which was sometimes the result of applying paper-based back-up solutions. There was an example when the turnover did not recover at all (Chart 6). We defined 'recovery' in terms of whether the turnover (both debit and credit) reached the benchmark level after the disruption was sorted out. The benchmark was determined as the average daily turnover within a two-month period (which was symmetric around the date of the incident). This obviously has some drawbacks, just as other methods could have had (since we do not know exactly how the turnover would have evolved without the incident, we have to estimate it somehow). Nevertheless, by conducting this analysis it became clear that in real life entirely general assumptions cannot be drawn. There is usually a hump in the debit turnover after the incident was sorted out, but it is not that sudden ('recovery' requires some time, i.e. 30 minutes). It can be shown as well that in some cases a few transactions were stuck in the system somewhere, and when the problem is solved those overtake the payments initiated after the disruptions. When reality is replicated by means of assumptions, one has to pay attention not only to possible counterparty responses but also to the operation of the system elements.

4 Data and methodology

In this paper the operation of VIBER is analysed with the help of the simulator developed by the Bank of Finland (BoF-PSS). The simulations are conducted under normal (benchmark case or reference scenario) and distressed periods using actual data on payments and liquidity from the period December 2006 – January 2007 (equalling to 41 business days). The reference scenario replicates the actual functioning of VIBER. The institutional features of VIBER are reflected in the parameterization of the BoF-PSS2.

4.1 ABOUT RTGS SYSTEMS WITH SPECIAL FOCUS ON VIBER

Like CHAPS Sterling, ARTIS, KRONOS or NBO, the Hungarian VIBER is an RTGS system, in which the moments of clearing and settlement are not separated in time; booking is managed item by item continuously and in real time. The processing of payment orders and their final settlement takes place continuously, while the participants concerned are notified in real time. Each settlement takes place by examining whether the participant has provided sufficient liquidity. If so, the payment orders are settled immediately. If the participant does not have sufficient liquidity, the payment will be placed in the central *queue*. There is one queue per account that contains validated payments waiting for settlement. When entries are placed in the payment queue, they are inserted in *FIFO (first in first out) order* by priority, which latter is provided by the submitter. Payments with high priority are always queued nearer the front of the queue than those with lower priority. If the payment at the head of the queue cannot be settled due to insufficient cover, the queue is blocked. The situation is called gridlock if the queued payments could be settled by taking incoming payments in addition to the available liquidity into account. In the opposite case the situation is called deadlock. VIBER has a built-in feature (gridlock resolution algorithm) which solves gridlock situations on a multilateral basis. In VIBER *gridlock resolution* can be initiated manually by the central bank at the request of the submitter. At the same time it can be initiated automatically at a pre-defined frequency. In the current setup the gridlock resolution algorithm is initiated every 30 minutes. The algorithm works by selecting a set of payments and attempting to settle them together. Each attempt to settle either succeeds as a complete unit, or fails. If the attempt succeeds, the algorithm has completed successfully. If the attempt fails, a smaller set of payments is selected and the algorithm is repeated. The algorithm completes when either a settlement attempt succeeds, or no payments are selected for the next attempt to settle. Basically the algorithm corresponds to *multilateral partial offsetting* at a given interval of 30 minutes. During the business day the payments that have not been settled can be re-prioritised or deleted.

VIBER has direct and indirect membership. At the end of 2006 VIBER had 38 direct participants.[18] The *available* (or actual) *liquidity of direct participants* consists of the current account balance and the intraday credit line, which can be obtained from the central bank by providing collateral. The list of eligible collateral and the evaluation principles of those assets are determined by the central bank. Assets eligible as collateral to obtain intraday credit are the same as those accepted in monetary policy operations. Pledging additional collateral is possible continuously during VIBER business hours.

VIBER provides real time monitoring services. This facility is only used by some of the members. Participants can send inquiries for information about their payments and accounts via the messaging network. The messaging network of VIBER is SWIFT.

In order to be able to replicate the functioning of VIBER the following data have been collected:

a) the payments with
   – submission and value dates, time stamps and sequencing parameters that were essential to obtain the submission ranking,
   – the amounts,
   – the original priorities and the changes in priorities,
   – the debited and credited banks, and
   – the message types defined by the submitter,

[18] The number of the participants remained constant in January 2007.

b) the initial current account balances and intraday credit lines at the opening of the system and changes of the intraday credit lines during the day,

c) the system's open and closure time, and

d) the timing of the gridlock resolution algorithm.

4.2 SPECIFIC INDICATORS USED FOR DESCRIBING THE OPERATION OF AN RTGS SYSTEM

Besides the usual statistics (turnover and liquidity data, concentration indicators, timing indicators) more specific indicators were calculated to describe the operation of VIBER by employing the BoF-PSS. It is crucial to understand which kind of information the specific indicators might provide us. The indicators play an important role in comparing the outcome of the benchmark case and various stress scenarios.

a) Non-submitted, rejected and unsettled payments

An obvious indicator of the severity of the operational incident is the *number and value of payments initially not submitted* to the system. This direct effect is related to the fact that the operational failure of the settlement bank prevents the bank concerned sending payment orders.

The risk resulting from the technical default of a participant can be best captured by the *rejected payments indicator*. The indicator shows how significant the contagion effect is in terms of *number and value of rejected transactions*. We refer to *unsettled transactions* as the sum of the payments initially not submitted to the system and payments submitted, but due to insufficient funds rejected.

b) Hypothetical liquidity levels

Besides the actual level of liquidity, there are various hypothetical liquidity levels which could provide useful insight into the extent to which participants are able to withstand the liquidity risk resulting from an operational incident.

The *lower bound of liquidity* equals the minimum amount of liquidity required to settle all payments submitted during a day. The lower bound of liquidity corresponds to a very extreme case, in which the banks have just enough liquidity to settle their payments before the end of the day by applying multilateral offsetting as a gridlock resolution algorithm (BoF, 2005). The lower bound of liquidity corresponds either to the net amount of incoming and outgoing payments, or to zero. In the former case the value of payments sent exceeds the value of payments received, the difference has to be available at least at the end of the day. In the latter case the inflow of funds is higher than the outflow; the participant exclusively has to use the liquidity it receives to cover its outgoing payments. The lower bound *(LB_i)* of liquidity of participant *i* can be written formally as:

$$LB_i = \max\left(\sum_{j=1}^{n} p_{ij}^{out} - \sum_{k=1}^{n} p_{ik}^{in}\ ;0\right) \qquad \text{(Eq. 1)}$$

where - p_{ij}^{in} is the value of incoming payment *j* of participant *i* and

- p_{ik}^{out} is the value of outgoing payment *k* of participant *i*.

Thus, the first sum is the value of payments sent, while the second sum is the value of the payments received over the course of the business day by bank *i*. On system level the lower bound of liquidity is simply the sum of lower bounds of individual participants.

The *upper bound of liquidity* corresponds to a liquidity level that a settlement bank would need to obtain in order to settle its outgoing payments immediately upon their submission. Thus, the upper bound of liquidity is defined as the amount of liquidity needed to settle transactions without any queues.

Potential liquidity is equivalent to the sum of the current account balance and the hypothetical maximum of the intraday credit line. The hypothetical maximum of the intraday credit line is based on the data of eligible assets recorded on the participants' balance sheet.[19] Unfortunately these figures give only rough estimates as credit institutions can pledge their securities for other purposes, just like fulfilling collateralization obligations related to stock exchange transactions. Since in Hungary collaterals are pledged without transferring the title of the securities, we do not have information about how much of the eligible assets are not accessible if additional collateral would be needed for payment purposes.

c) Liquidity usage indicator

During the business day the outgoing payments are financed by incoming payments and by the available liquidity. The liquidity usage indicator measures the maximum share of the available liquidity used for financing outgoing payments.

d) Queue and delay statistics

To obtain better insight into the performance of the payment system it is worth analysing the evolution of the *queue statistics* (BoF, 2005). The *percentage of payments settled in real time* – both in volume and value terms – shows the fluidity of the system. The *number and total value of queued transactions* show the opposite. In our analysis we focus on the total value of queued transactions. It should be noted that the indicator is very rough; it does not take into account how large the queue was at certain points in time and for how long the payments were blocked due to insufficient funds.

The maximum queue and the average queue lengths are two indicators that can complement the total value of queued transactions. The *maximum queue* is the peak queue value during the business day. The *average queue length* is an indicator that captures the amount of time the payments spent in the queue. The average queue length shows the average queue duration of queued payments, namely the total queuing time of each payment divided by the total number of queued payments.

The fourth, fairly complex indicator of the queue statistic that was quantified and analysed is the *delay indicator*. As this indicator was quantified in many previous studies, it also serves as a good base for international comparison. The delay indicator quantifies the extent to which settlement of individual transactions is delayed; actual delay is compared to theoretic maximum delay at end of day. The delay indicator is a relative indicator ranging from 0 to 1. If no transactions are queued at all its value is 0. When all transactions are queued until the end of the day its value is 1. The indicator is calculated as the queuing time weighted value for all queued transactions (transaction value multiplied by the time in queue) divided by the time weighted value if all payments were delayed to the end of the day. The settlement delay for the entire system can be written formally as (BoF, 2005):

$$\frac{\sum_{i=1}^{n}\sum_{k=1}^{n}(t_{i,k}-s_{i,k})\,a_{i,k}}{\sum_{i=1}^{n}\sum_{k=1}^{n}(t_{end}-s_{i,k})\,a_{i,k}} \qquad \text{(Eq. 2)}$$

where – $a_{i,k}$ is the value of the payment *k* of participant *i*,

– $s_{i,k}$ is the submission time of payment *k* of participant *i*,

[19] In Hungary there is a detailed report on securities held in the portfolio of credit institutions at the end of the day. The report is submitted to the Hungarian central securities depository (KELER Ltd.) on a daily basis. In order to calculate the potential liquidity level, security holdings at the end of day were taken into account. It was assumed that only those assets could have been pledged as collateral during the business day which were at the credit institutions' own disposal at the end of the day. By calculating the potential liquidity level of participants, the evaluation policy of the central bank (pricing, haircuts, margins) was also considered.

– $t_{i,k}$ is the time for final settlement for payment *k* of participant *i*, and

– t_{end} is the closing time of the payment system.

The delay indicator can be also calculated for individual participants. In this case the first summing operators should be removed from Equation 2. The value of unsettled transactions is excluded from the queue statistics and thus from the indicator. The delay indicator shows only the delays for payments that could be settled.

4.3 DESCRIPTION OF NORMAL FUNCTIONING OF VIBER: THE BENCHMARK CASE

Analysis of the benchmark case, that is the normal functioning of VIBER in December 2006 and January 2007, is valuable for the following reasons:

1. The results of the stress scenarios can be compared with the benchmark case.

2. We can identify *critical period(s) of the business day(s)* when an incident with a pre-defined length might have the largest impact on the functioning of VIBER.

3. We can discover the *critical participants* based on proxies for liquidity risk and concentration indicators. The critical participants can be either systemically important participants or endangered participants. The technical default of the *systemically important participants* might have serious negative consequences on the functioning of VIBER. *Endangered participants* are institutions which might be heavily influenced by the operational incidents of the systemically important participants.

We will also analyse whether the systemically important and the endangered participants overlap. Identification of the systemically important and the endangered participants provides us with a list of potential institutions which might trigger contagion and which might suffer from the technical default. However, *the network structure* plays a pivotal role. In order to gain a proper insight into the interdependencies, simulation exercises are also needed.

4.3.1 General description and critical periods of the business day

Table 1 shows the descriptive statistics of VIBER for the months December 2006 and January 2007. All submitted payments were settled by the end of the day; there were no unsettled payments. As demonstrated by Table 1, in December 2006 and January 2007 on average 3,429 transactions were settled daily. The number of payments settled ranged from 2,098 to 4,963. The mean value of payments settled totalled 3,496 billion HUF.

VIBER opens at 8:00 a.m. CET and closes at 5:00 p.m. CET. During the analysed period prolongation of the operating hours occurred three times (once for 15 minutes and twice for 30 minutes). The credit institutions justified their request for prolongation with reference to technical problems. During the analysed period all the technical problems were sorted out by the end of the business day and there was no need for submitting payments via fax.[20] In fact these prolongations did not change the intraday pattern of payments' submission. Chart 7 shows the distribution of value of submitted payments according to the system's receipt time.

Table 1

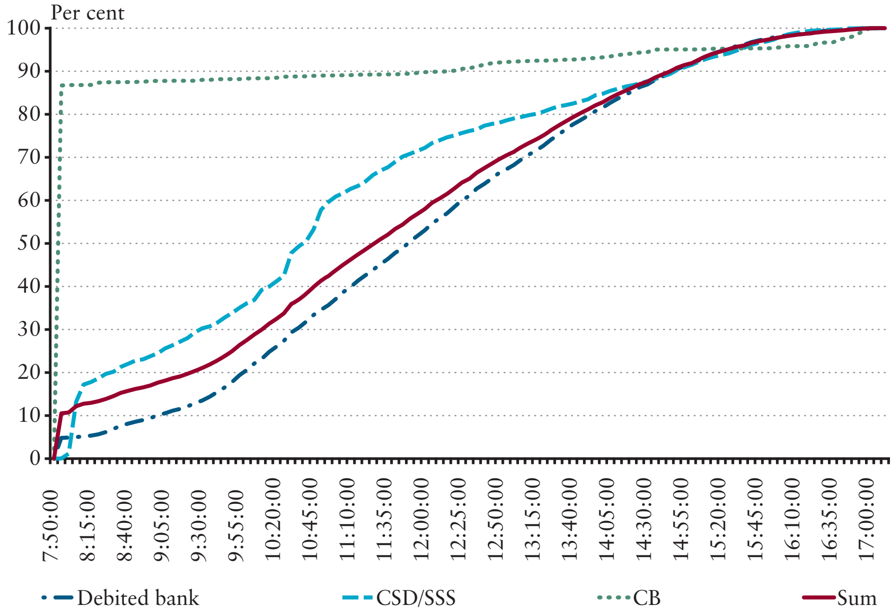
Descriptive statistics of VIBER (December 2006–January 2007)

	Minimum	Average	Maximum	St. dev.
Number settled	2,098	3,429	4,963	585
Number unsettled	-	-	-	-
Value settled (million HUF)	1,422,990	3,496,231	5,387,416	751,756
Value unsettled	-	-	-	-

[20] If there had been payments submitted via fax, those would have appeared in the underlying data as if they had been initiated by the central bank.

Chart 7

Distribution of value of payments (December 2006–January 2007)



Note that CSD stands for central securities depository, SSS for security settlement system and CB for central bank. In Hungary KELER Ltd. fulfils both the role of the CSD and the role of the SSS.

In Chart 7 it can be seen that at the beginning of the business day the slopes of the curves are steeper. This can be explained by the *warehoused payments*[21] which are channelled into the central accounting system right after the system is opened. The payments are submitted to VIBER via various channels. At default the transactions are initiated by the debited bank. However, there are cases when payments are initiated by someone else. These payments are know as *mandated payments* and are initiated, for instance, by the central bank (e.g. settlement of clearing positions of the ancillary systems) or by the CSD/SSS (e.g. DVP transactions).[22] Mandated payments include the START transfers, the DVP transactions initiated by KELER, the multinet settlement of stock exchange deals, the settlement of card transactions and cash withdrawals with the central bank, etc. The extremely steep slope of the curve for payments submitted by the central bank can be explained by the liquidity adjustment at the beginning of the day.[23] On the basis of Chart 7 we can also conclude that the *most active submission period for payments initiated by the debited banks is between 9:30 and 14:00.*

4.3.2 Systemically important participants

The systemically important institutions in VIBER are identified by means of concentration indicators of the debited banks.[24] The concentration ratios and the Herfindahl-Hirschman indices[25] showed *fairly high concentration in the last few years* (Table 2). The chosen reference period shows similar properties.

[21] Warehoused payments are payments submitted before the days of the value date. In VIBER it is possible to send payments five days before the value date. These warehoused payments are waiting in the internal queue of the central accounting system to be processed on the value date.

[22] DVP stands for Delivery versus Payment, which provides a link between a security transfer (settlement) and a funds transfer system to ensure that delivery occurs, if, and only if, payment occurs.

[23] After the closure of the system the final balances are stored in VIBER databases. However, after the closure payments related to, for example, monetary policy, operations are settled in the central bank's proprietary system (InFoRex). The business day ends with the closure of InFoRex. After this the retail payment system (Interbank Clearing System, ICS) settles payments using the liquidity of the credit institutions held at the central bank. Due to the settlement in InFoRex and ICS the final balances stored in VIBER databases at the end of the business day do not correspond to the real balances at the opening of the next day. The START items are booked right after the opening of VIBER; it synchronises the balances of VIBER participants in CAS with the balances in InFoRex.

[24] As bank-to-bank and customer payments make up the majority of the payments initiated in VIBER, the concentration indicator of the debited bank is a good proxy for the concentration indicator of the submitters.

[25] The Herfindahl-Hirschman index (HHI) shows the sum of the squares of the individual banks' market share expressed in percentage form. The maximum of the index is 10,000. In that case one market participant owns 100% of the market. According to the Horizontal Merger Guidelines of the United States, the market is highly concentrated if the Herfindahl-index is above 1800. The market is moderately concentrated if its HHI is between 1000 and 1800 and the market is not concentrated if its HHI is under 1000 (1997 Merger…,1997).

Table 2

Concentration of VIBER credit and debit turnover

		HI	CR(5)	CR(10)
Characteristics of VIBER				
Debit turnover	April of 2004	1,000	61%	85%
	Year of 2006	1,041	63%	85%
	Dec. 2006–Jan. 2007	1,002	62%	83%
Credit turnover	April of 2004	1,000	61%	86%
	Year of 2006	1,042	63%	84%
	Dec. 2006–Jan. 2007	1,042	63%	85%

In our analysis those participants are considered as systemically important institutions which dispose of more than 5% of the debit turnover in the reference period. In this way we have identified six participants whose technical default might have a serious impact on the functioning of VIBER.

Similarly to our findings, the study of Lublóy (2006) identified the same systemically important institutions according to certain network criteria. In the study a graph theoretical framework was applied that provided an ideal tool for identifying the most active nodes in the network. When the institutions most capable of generating contagion through the Hungarian large-value payment system were selected, it was taken into account that a liquidity crisis could arise if funds are not transferred to counterparties, although the counterparties might have expected it. Lublóy (2006) argued that the institutions most capable of generating contagion can be best captured by means of valued outdegree centrality and out-proximity centrality. Based on the centrality measures, a well-defined group of institutions was identified; the illiquidity of these institutions could cause the most serious disruption of the payment system.

4.3.3 Endangered participants

Participants endangered by the technical default of systemically important members can be identified by assessing the liquidity risk they face under normal conditions and in distressed periods. In this subsection, as a starting point, we examine various proxies for liquidity risk under *normal functioning* and, based on this information, we form clusters with common characteristics. Based on the clustering, we identify those whose members could be easily endangered in the case of a liquidity shock. *Secondly,* as a next step, the circle of these endangered participants is enlarged by means of a simple sensitivity analysis based on a stress indicator. *As a result, we arrive at an indicative list of participants who might be endangered if a systemically important member technically defaults.*

Nowadays it is widely accepted that RTGS systems eliminate credit risk, but introduce liquidity risk in the settlement procedure. In RTGS systems liquidity risk refers to a situation in which participants do not have enough funds to settle their payments *on time*. Liquidity risk in RTGS systems can be estimated by means of various rough proxies. The first indicator could be whether the members succeeded in settling their payments at least by the end of the day. In RTGS statistics this is shown by

• *the volume and value of unsettled payments, and by*

• *the relation of the lower bound of liquidity to the actual level of liquidity.*

Note that there might be transactions which stay in the banks' internal queue due to lack of funds. The central bank does not have information about these queues.

In addition, even if there are no unsettled payments in the system or in the banks' internal queues, liquidity risk can emerge as a result of settlement delays. It depends on the payment whether its urgency requires (almost) immediate settlement or a certain delay is tolerable. Immediate or almost immediate settlement has its own cost implications. Whether a delay is tolerable or not depends on the originator's preferences concerning immediacy. If the originator does not dispose of enough funds, the preference relating to the cost of immediacy might be important as well. In the function of these parameters the credit institutions should decide on timing and prioritizing of payments by having liquidity constraints at the same time. In RTGS systems it is important to see the trade off between available liquidity and delay. As intraday liquidity is costly for the member banks, queues and delays can be considered as typical features of RTGS systems. The costs of intraday liquidity include the opportunity cost of the collateral posted, the transaction cost of intraday credit changes and potential fees or interest rates related to intraday credit.[26] As we have no information about the time criticality of the payments, the following statistics can provide proxies for liquidity risk:

- Quantity of queuing in the system (queue indicators, liquidity usage indicator, relation of the upper bound of liquidity to the actual level of liquidity)

- Time required to clear the queues in the system (delay indicator, queue length indicator)

- Liquidity buffer of the participants under normal conditions (relation of the upper bound of liquidity to the potential level of liquidity).

Due to redundancy among the above listed indicators (e.g. between queues, liquidity usage indicator and the ratio of upper bound and actual level of liquidity) not all of them are analysed thoroughly.

All the indicators can be examined on a system level and on the level of each participant. It is important to stress that system-level indicators might be favourable, while individual indicators might show high variation. In the following we examine participant-level indicators and on the basis of these statistics we form groups and identify those clusters which are most prone to liquidity risk.

Previously it was noted that in the reference period there were *no payments rejected due to lack of funds.*[27]

The total value of *queued transactions* expressed as a percentage of value settled equalled 16.41% on average (Table 3); the maximum was 33.02%. The maximum queue value expressed as a percentage of value settled equalled 4.29% on average. However, there was a day when the maximum queue value was 11.08% of all the transactions settled. The mean of the average *queue duration* of queued payments was 41 minutes. On 19 January 2007, with more than two hours of average queuing time, the indicator reached its maximum.

In relation to the queue statistics there are significant variations across banks. If we look at the queue statistics in Table 4 in detail, we can see that five participants are responsible for 97% of the queues (both in number and value). Three out of the

Table 3

Queue and delay statistics (December 2006 – January 2007)

	Minimum	Average	Maximum
Value of payments initially not submitted	-	-	-
Value of unsettled payments	-	-	-
Total value of queued transactions (as % of value settled)	2.62%	16.41%	33.02%
Maximum queue value (as % of value settled)	1.35%	4.29%	11.08%
Average queue length (hh:mm:ss)	0:08:34	0:41:24	2:08:44
Settlement delay	0.01	0.07	0.16

[26] In U.S. the central bank applies fees, for example.

[27] In January, May and June 2006 there were some days during which the system had to reject payments at the end of the day due to lack of funds. Analysing the background of those unsettled payments, it often became clear that participants should have used the built-in functions of VIBER (e.g. gridlock resolution) more efficiently. In that case the majority of the rejected payments would not have been rejected at the end of the day.

Table 4

Concentration of queued transactions (December 2006 – January 2007)

	CR2	CR3	CR4	CR5
Number of queued transactions	76.22%	88.69%	96.11%	97.38%
Total value of queued payments	70.28%	85.35%	93.94%	97.17%

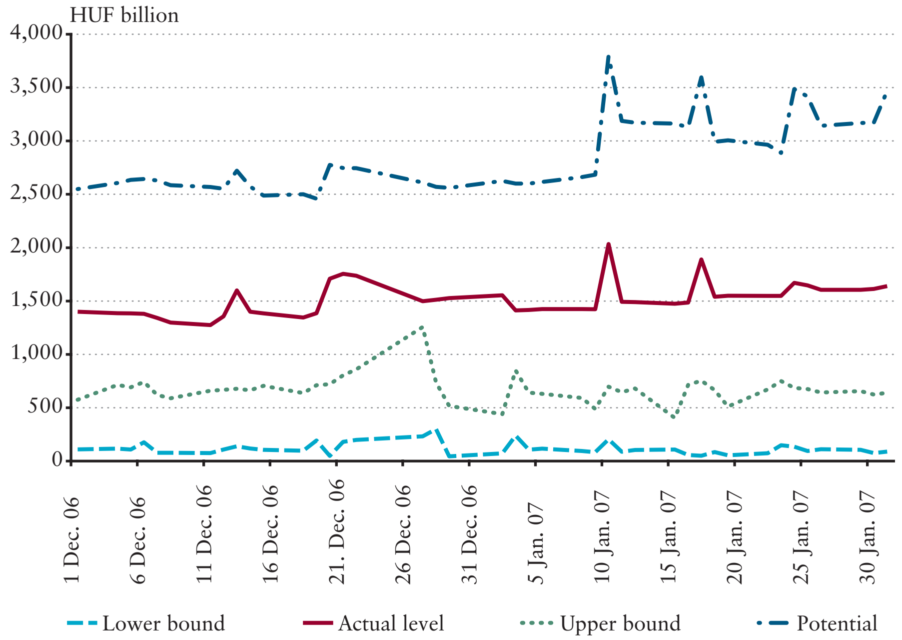
five participants dispose of the highest share in debit turnover. Two participants with the highest proportion of queued payments queued up 76.22% (number) and 70.28% (value) of their payment orders.

The *settlement delay* was 0.07 on average (Table 3), the maximum of the delay indicator equalled 0.16. The settlement delay also varies across banks. There is one small bank whose average settlement delay is outstandingly high compared to other system participants. The average settlement delay of this small bank equals 0.1895, which is almost 4 times higher than the average settlement delay of the bank with the second highest settlement delay (0.0478). This phenomenon can be explained by the specific timing behaviour of the small bank. Namely, the bank sends the majority of its payment orders at the beginning of the day and waits for the incoming payments. Meanwhile the payment orders are queued up; the average queue length of the bank is almost 2 hours.[28]

The settlement delay of another small bank, which is a subsidiary of a big bank, is nearly the same as the delay of the bank with the second highest delay which is the most active in the payment system. However, there are striking differences in the turnover and thus in the value of queued payments. There are five other banks at which the settlement delay is higher than the average. Two of them are among the most active participants in the payment system. Another two submit their payment orders to the system as usual, but on some days the banks have to wait fairly long for their incoming payments. If the incoming

Chart 8

Lower and upper bounds of liquidity, actual liquidity and potential liquidity (billion HUF)



Note: The data of the Hungarian State Treasury (Single Treasury Account, KESZ) were included in the liquidity levels. Filtering the data of the Hungarian State Treasury out induces changes mainly in the actual level of liquidity, but on the days when the actual level of liquidity is closer to the upper bound, this change is significantly smaller.

[28] It is an interesting observation that this small bank is one of the two institutions that changes priority of payments regularly. In Hungary the central bank and the CSD have dedicated the priority scale from 0 to 9 for their own purposes. The participants might prioritise their transactions from 10 to 98, but they do not make use of that. They usually use one priority as a default. From 1 December 2006 to 31 May 2006 there were 10 priority changes in the system. Seven out of the 10 priority changes were initiated by the above-mentioned small bank.

payments arrive later in the day, payments may stand in a queue for hours. As a consequence, the delay indicator is relatively high. The fifth bank can be characterised by almost the same payment pattern as that of the small bank which is a subsidiary of a big bank. As many banks do not have queues at all, or only a few transactions are queued up on certain days, the average settlement delay of these banks is either 0 or very close to 0.

At aggregate level the system had more than enough liquidity to settle all payments immediately, and the system as a whole had ample liquidity not posted as collateral. In Chart 8 it can be seen that on the system level the actual level of liquidity in VIBER is significantly higher than the lower bound. This means that on the system level the payments could be always settled at least by the end of the day. However, there are significant variations across banks. In distressed periods there might be institutions at which the liquidity buffer available might not be sufficient to mitigate the impact of a liquidity shock.

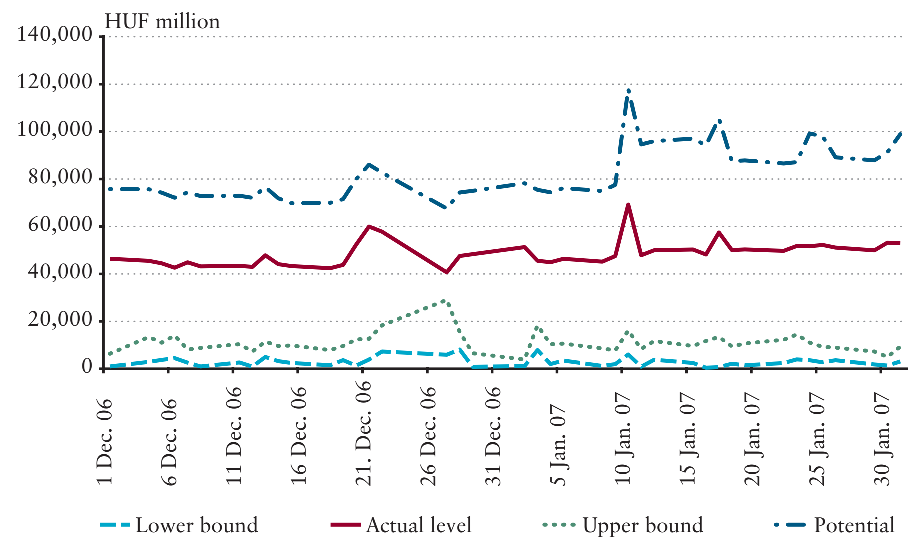
Based on the queue, delay and liquidity indicators, we have formed five clusters. Our results are summarised in Table 5.

Participants in *Group 'A'* have a higher actual level of liquidity than the upper bound of liquidity on most days. As we can conclude on the basis of Chart 9, participants in *Group 'A'* have recorded queues extremely rarely. The participants are not prone to liquidity risk, the actual liquidity level already ensures buffer against liquidity risk. Additionally, the participants have high liquidity buffer in their balance sheets, in case the actual liquidity proves to be insufficient. In *Group 'A'* there are five credit institutions among the 25 which use their available liquidity more efficiently than the others. This can be explained by the fact that their share in debit turnover is approximately 14%, which leads to economies of scale and stipulates the establishment of active payment and liquidity management functions inside the bank.

The remaining 20 institutions in *Group 'A'* have much more actual liquidity than they would need for their payment activity. This excess liquidity reflects inefficiency from the point of view of the payment system. Credit institutions might hold more liquidity than their working balances (defined as the liquidity needed for payment purposes) due to the binding nature of reserve requirements. In addition, the low opportunity cost of eligible assets might also be one reason why credit institutions post more collateral than they would need for their payment activity. Four out of the 20 institutions are specialised credit institutions with specific legal requirements concerning their asset holdings. Obviously there is an overlap between assets eligible in central bank operations and between those held by the specialised credit institutions in line with legal requirements. As the title of the securities is not transferred during pledging, regardless of the transaction fees, the opportunity cost of posting them as collateral is zero. Consequently, the share of the intraday credit line in available liquidity is high in the case of these institutions, even if they do not make use of it. Most probably there are some credit institutions where reserve

Chart 9

Lower and upper bounds of liquidity, actual liquidity and potential liquidity in Group 'A'
(average over 25 participants)



Note: The data of the Hungarian State Treasury (Single Treasury Account, KESZ) were included in the liquidity levels.

Table 5

Grouping of VIBER participants

The actual level of liquidity was less then the upper bound of liquidity (%, out of 41 days)			Other criteria applied for grouping direct VIBER participants		Number of participants	Share in debit turnover	Types of institutions in the group	Groups
Lower bound	<…<	Upper bound						
0%	<…<	10%	Liquidity usage is greater than 50% on at least half of the days		5	13.51%	banks (sometimes with special profile)	A
			Liquidity usage is less than 50% on at least half of the days	Ratio of intraday credit line to available liquidity is high	4	21.14%	specialised credit institutions	
				Ratio of intraday credit line to available liquidity is medium-sized	8		banks (sometimes with special profile)	
				Ratio of intraday credit line to available liquidity is low	8		universal and specialised banks, Hungarian State Treasury	
10%	<…<	50%	Balance sheet seems to contain enough liquidity buffer		3	0.25%	banks (often with special profile)	B
			Rarely can there be days when balance sheet does not contain enough liquidity buffer		3	3.74%	banks (sometimes with special profile)	C
50%	<…<	100%	Balance sheet seems to contain liquidity buffer, but there can be days when balance sheet does not contain enough liquidity buffer	Delay indicator is relatively high	0	55.43%	foreign owned banks highly exposed to FX settlement risk	D
				Delay indicator is medium-sized	3			
				Delay indicator is relatively low	0			
			It can easily happen that balance sheet does not contain enough liquidity buffer	Delay indicator is relatively high	1			E
				Delay indicator is medium-sized	1			
				Delay indicator is relatively low	0			
Sum					36	94.07%		

Please note that two participants (namely the central bank and the Hungarian Post) are not clustered.

requirements are binding and they cannot reduce their current balances. Identification of these institutions requires further research.

Participants in *Group 'B'* queue up transactions more often, but their balance sheet contains abundant liquidity buffer (Chart 10). In the reference period these institutions did not post any collateral. (Interestingly, in April 2006 one of them already posted collateral). Based on the debit turnover these members are the least active participants, so it might be worthless to develop sophisticated payment and liquidity management functions. The same holds for *Group 'C'*, though their share in debit turnover is slightly higher.

Group 'C' contains those participants which queue up payments more often than participants in *Group 'A'*. In the case of liquidity shocks there might be occasions when potential liquidity is not enough for immediate settlement of payments (Chart 11). We consider these credit institutions as endangered participants, as they might face problems if there are liquidity shocks.

Chart 10

Lower and upper bounds of liquidity, actual liquidity and potential liquidity in Group 'B'
(average over 3 participants)

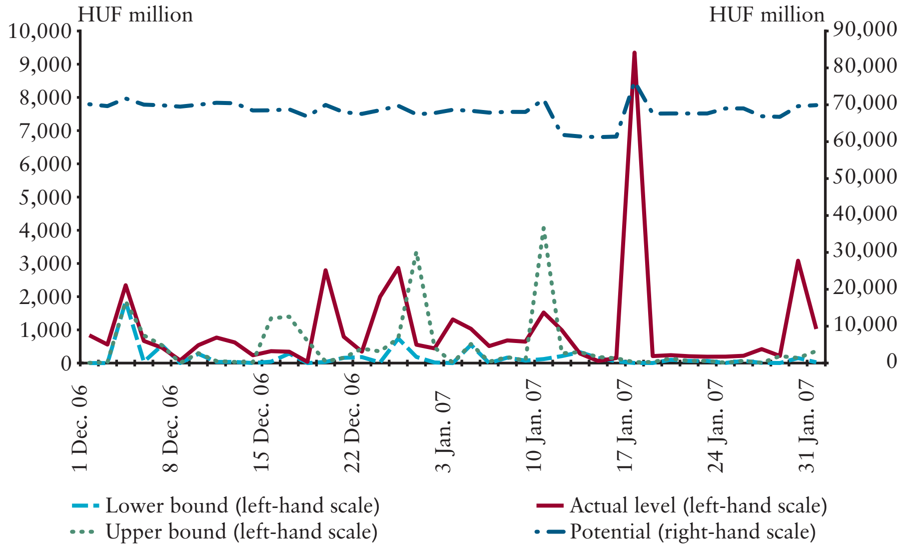
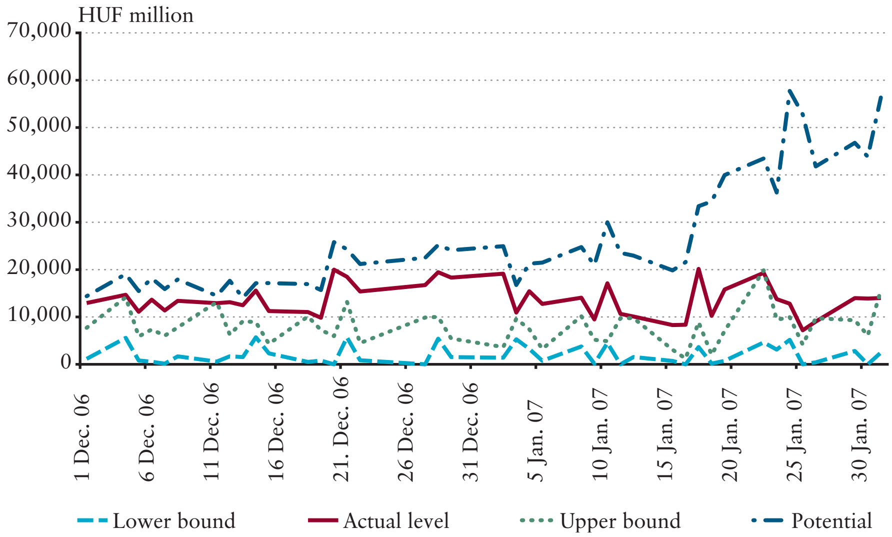


Chart 11

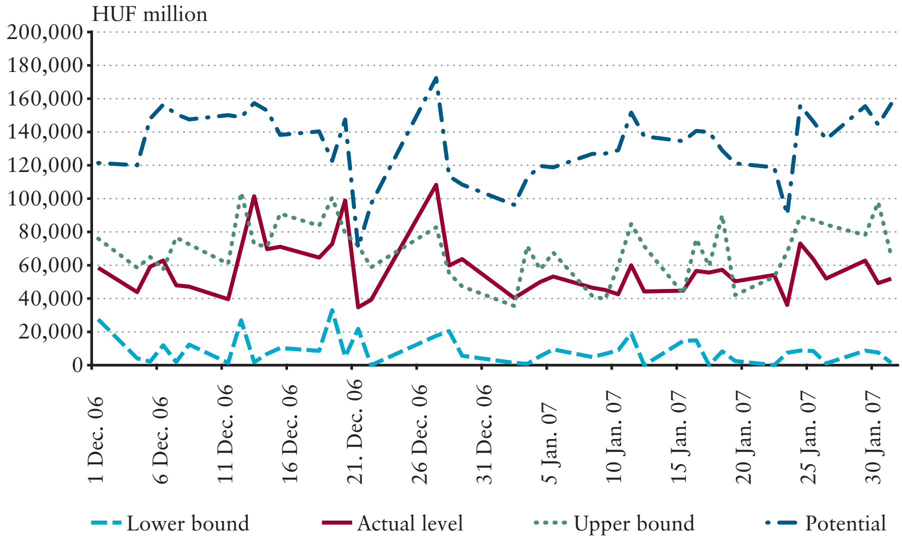
Lower and upper bounds of liquidity, actual liquidity and potential liquidity in Group 'C'
(average over 3 participants)



Participants in *Group 'D'* build up queues often and transactions spend quite some time in the queue. The delay indicator is medium-sized for them. Their balance sheet contains some liquidity buffer (Chart 12). Taking the uncertainty regarding the proper level of potential liquidity into account, these institutions might easily experience problems if there is a liquidity shock. We consider these credit institutions as endangered participants. Although two of these participants have high shares in the debit turnover and the usage of their intraday credit line is high, they do not manage intraday credit line that often. This might refer to a situation in which banks dispose of two asset portfolios: one is posted as collateral and the other is used for trading purposes.

Chart 12

Lower and upper bounds of liquidity, actual liquidity and potential liquidity in Group 'D'
(average over 3 participants)



The two participants in *Group 'E'* have no liquidity buffer in their balance sheets (Chart 13). Participants in this group dispose of the highest delay indicator. As was mentioned previously, one of the institutions has a significantly greater indicator. However, its share in debit turnover is low. The other credit institution is the most active one in VIBER. This institution is certainly pushed toward a more active payment and liquidity management. This participant manages its intraday credit line

Chart 13

Lower and upper bounds of liquidity, actual liquidity and potential liquidity in Group 'E'
(average over 2 participants)

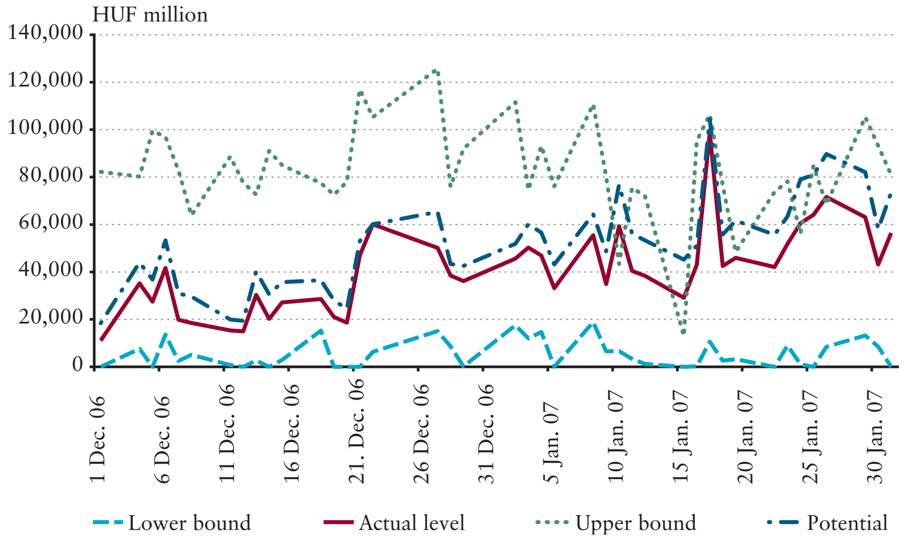


Table 6

Number of participants encountering problems

Share of loss of incoming payments	Number of participants	
100%	10	10
50%	4	11
30-40%	2	
10-20%	5	

actively. The relationship between the actual and potential liquidity might refer to the bank's special attitude toward asset management. The bank seems to pledge part of its trading portfolio as collateral and if there is a need for a specific asset which was posted before as collateral the bank releases it.

By means of a simple sensitivity analysis we have examined what happens to VIBER participants if they loose a pre-defined proportion of their incoming payments. We have measured whether the participants' eligible asset portfolio would be sufficient to fulfil the financing role of incoming funds. We varied the loss of incoming payments from 10% to 100%. The results are summarised in Table 6. The table shows the number of participants encountering problems on at least 25% of the days in the function of loss of incoming payments. The second row of Table 6 shows, for example, that if the participants do not receive 50% of their incoming payments scheduled for that day, then 4 additional participants will not be able to fulfil all of their payment obligations on at least 25% of the days. It is also shown in the table that in this case altogether 11 participants face liquidity problems on at least 25% of the days.

By varying the loss of incoming payments we found that 15 participants could easily cope with the loss of all incoming payments, as their balance sheets contain enough buffer of eligible assets. These 15 participants are excluded from Table 6. As shown in the first row of Table 6, 10 participants would face problems on at least 25% of the business days if they loose all their incoming transactions. Eleven institutions would face serious problems on at least 25% of the business days if they do not get at least 50% of their incoming payments. These participants rely heavily on the financing role of incoming payments. Interestingly, during the clustering we have classified 8 out of these 11 as endangered participants. In line with this simple sensitivity analysis, we enlarge the group of endangered participants with the three previously not identified institutions.

4.3.4 Overlap between the systemically important and the endangered institutions

If we have a look at the list of the systemically important and the endangered institutions there is an overlap between them. Only one of the systemically important participants is not identified as an endangered institution. This bank has a fairly large portfolio of eligible assets. The overlap corresponds to the findings on concentration ratios and rank correlation indicators. The indicators based on the debit and credit turnover showed high concentration. The rank correlation indicators shown in Table 7 highlight that members having the highest ranks according to their shares in debit turnover are the same as those having the highest ranks according to their shares in credit turnover. This is in line with the financing role of incoming payments, which is typical for an RTGS system. The rank correlation indicators demonstrate weaker relationship between the ranking of debit turnover and available liquidity. Thus, most active participants in VIBER are not necessarily the same as the institutions with the highest available liquidity.

In sum, the six most active players measured by the debit and credit turnover in VIBER could easily trigger a serious liquidity shock. On the other hand, these institutions could easily suffer from a liquidity shock if that is caused by a systemically important member.

These institutions and in many cases their important customers (e.g. large foreign financial institutions for whom domestic banks are forint correspondents) are active money market participants in the FX swap segment. The recent FX settlement survey of the central bank (Tanai, 2007) showed that these participants recorded the largest FX settlement risk in the domestic banking sector. These credit institutions initiate large amount of transactions in VIBER with a relatively small balance sheet.

Table 7

Rank correlation indicators

	April of 2004	Year of 2006	Dec. 2006–Jan. 2007
Between the following indicators			
Debit and credit turnover	0.9900	0.9955	0.9927
Debit turnover and average liqudity	0.8100	0.8773	0.8957

Should a liquidity shock arise in the system (e.g. due to improper functioning of financial markets or operational incidents), their balance sheets could easily be a bottleneck. On the one hand, the relatively high velocity of liquidity makes the institutions vulnerable to unexpected liquidity shocks, but, on the other, refers to extremely efficient payment and liquidity management practices.

4.4 ASSUMPTIONS BEING MADE IN DIFFERENT STRESS SCENARIOS

In the paper *operational failure* is defined as the technical problem of one or more system participant, excluding the MNB. The technically defaulted participants are unable to send and receive payment messages, that is, the participants are unable to access the SWIFT network. Inability of technically defaulted participants to send and receive payment messages would not hinder other non-defaulted participants to send payments to the problematic credit institutions.

The liquidity risk caused by operational disruptions is examined by means of several scenarios. The scenarios are hypothetical and based on stylised operational failures, though they might not be far from reality. The scenarios are based on different assumptions in relation to:

- the behavioural reactions of technically non-defaulted participants,
- the timing and length of the operational failures,
- the number and the list of technically defaulted participants, and
- application of existing back-up procedures.

4.4.1 Behavioural reactions of technically non-defaulted participants

In the simulations several behavioural assumptions are made. On the one hand, it is assumed that the behaviour and the payment pattern of the non-defaulted VIBER participants, regardless of the initial shock, are unaffected. This *behavioural assumption of no reaction* has several dimensions. Firstly, it is assumed that the settlement banks wish to settle the same volume and value of transactions (even to the technically defaulted participant) with the same priority as under normal business conditions. Secondly, in the model the settlement banks do not raise additional liquidity by borrowing funds from the mother bank or in the interbank market in order to ensure the settlement of all its payment orders. Based on enquiries with some Hungarian credit institutions, this behavioural assumption is not far from reality for (already) agreed obligations. There might be several reasons why banks do not stop sending payments to the stricken bank. Firstly, the technical infrastructure of the payment systems located in the back offices is very complex. Most of the payment orders are generated automatically from several internal back office systems as the last step of the straight through processing (STP). As a consequence, it is not easy to modify the list of payment orders waiting for transmission to the central settlement engine. Secondly, the banks cannot allow themselves to risk their reputation. If a bank wishes to maintain its high prestige, the bank should prove that it is able fulfil its contractual commitments, even when it experiences some problems. Thirdly, a contractual commitment is an obligation, if the bank does not fulfil it, then it should count with the legal and financial consequences.

On the other hand, in distinct scenarios we assume that the settlement banks are not passive economic agents. Instead they take actions aimed at preventing the bank under distress from becoming a liquidity sink and they stop sending payments to the bank experiencing the technical default *(stop sending rule)*. In Section 3 we have identified one out of the 11 analysed incidents when the turnover did not recover at all, as it did not reach the benchmark level after the disruption was sorted. In this case the evolution of the credit turnover (see Chart 6) might refer to the application of the stop sending rule. The stop sending rule implicitly assumes that there is no information asymmetry in relation to the operational incidents and unaffected participants are aware of the events affecting the technically defaulted member. However, in real life it usually takes time to get informed about participants' technical problems. Anecdotal evidence suggests that there is a time-lag between a VIBER participant experiencing an operational failure and the timing of phone calls in which the technically defaulted bank announces its problems to the MNB. After the announcement the central bank sends a free type SWIFT message to the other members. It can also happen that, even before the announcement, the intact settlement banks notice that they are not receiving the expected incoming payments and they wish to know whether the MNB has any information about the source of the problem at the settlement bank under distress. They usually call the central bank in order to obtain more information. Empirical evidence suggest that, even if the intact members get fully informed, they usually do not know whether they should stop sending payments or should continue with them. The central bank usually encourages them to submit their payments. There is high degree of uncertainty about how much time the elimination of information asymmetry requires. In our simulations we assume two hours reaction time. To examine scenarios with more efficient alarming systems would not be feasible. It should also be taken into account that international recommendations on recovery time define a two-hour interval, in which the institution should be able to sort out the operational problem (i.e. FED, 2003). As a result, the undamaged participants, even if they are aware of the operational problems in time, might wait two hours until they react by stopping outgoing payments to the damaged agent. In sum, in our paper the *stop sending rule applied in two hours* is simulated.

4.4.2 The timing and the length of the operational failures

The timing and length of operational incidents have a large impact on the system's performance. In one set of simulations the *worst-case* scenarios are considered. It is assumed that the operational incident occurs no later than the opening of VIBER and lasts until the end of the business day *(entire day incident)*. Thus, the technical problem arose no later than 8:00 a.m. CET and could not be sorted out until 5:00 p.m. CET.[29]

We also run simulations where the *starting point of the operational failure is not fixed in advance, however the length of the incident is set at a pre-defined level (part-time incidents)*. In this case the timing of the operational incident is the outcome of an optimization routine. We look for an appropriate algorithm to find the worst-case scenario; the operational failure should arise when it has the largest negative impact on the system.

However, there are some *constraints*. The severity of the disruption of the payment processing activity can only be large enough if the banks wish to settle many payments during the rest of the business day. As a consequence, it has no sense to analyse the impact of an incident that happens close to the end of the business day, as the number of transactions to be settled is low. The daily cumulative distribution of payment flows showed that in VIBER most payments (80-90% of the turnover) are settled by 2 p.m. CET (see Chart 7). Thus, it has no sense to let the operational incident occur later than that.

4.4.3 The number and list of technically defaulted participants

Initially it is assumed that a *single settlement bank* is unable to submit payments to VIBER owing to a failure of its internal back-office system. The technical problem is isolated; solely a single bank is hit by the shock. As we are interested in the disturbance of the payment system in the worst case, there is no point in choosing minor participants whose failure would have insignificant impact on the functioning of VIBER. Thus, we assume that *systemically important institutions,* which were identified by means of concentration indicators of the debited banks and certain network criteria, are affected by the technical problem.[30] In the paper, as we focus on the worst case, we quantify the *impact of the first six systemically most important institutions.*

By means of additional scenarios we also quantify the risk implications of operational disruption affecting the ability of *multiple settlement banks* to submit payments to VIBER. If we selected two banks randomly from the 38 participants, we would end up with 703 possible combinations. If we selected three banks randomly we would arrive at 8,436 various combinations. The modification of the input data and, in the case of a part-time incident, the optimization procedure would

[29] Prolongations mentioned in Subsection 4.3.1 have been taken into account.

[30] Note that occasionally it might happen that operational problems at a bank with a relatively lower debit turnover result in a severe disruption of the payment system. The connectedness of the bank and the unequal distribution of the liquidity might also play a crucial role. Nevertheless, the probability of a small bank generating a large shock is relatively low.

take too long for all of these combinations. As a result, we opted for analysing the worst cases and we assumed that the technical problems hit *two of the six systemically most important institutions.* This corresponds to 15 possible couples of banks that are suffering from a technical problem simultaneously. It is important to stress that the probability of this kind of incident is low.[31]

4.4.4 Possible contingency procedures

The functioning of the system in a distressed situation can be enhanced if back-up procedures are in place. In some countries these contingency procedures usually require time-consuming manual intervention. There exist quicker (mostly electronic) back-up facilities, but this is not the case in Hungary. We assume that one or more participants cannot submit their payments via SWIFT, but communicating via fax, which is the back-up for SWIFT, is feasible. The identification of the not-yet-sent payments, the production of the paper-based credit transfer with all the required data and the submission of the fax to the central bank requires some time, just like the processing of these fax-based transactions at the central bank.[32] It is important to note that, due to the fear of duplicating payments, participants hesitate to use back-up options. In order to re-channel the sunk liquidity from the bank under distress, some central banks apply the so-called stricken bank scheme. In our paper we do not deal with this possibility.

[31] At the same time it would be feasible to assume that *ELMA SWIFT* suffers from a technical incident. ELMA SWIFT is a concentrator which provides SWIFT connectivity services for VIBER participants. There are nine banks and savings co-operatives that do not have their own SWIFT interface, but join the interface of ELMA SWIFT and send payments through this single interface. If this interface is out of order, nine institutions could not submit payments. Nevertheless, the debit turnover of the nine institutions is very low. As this kind of operational incident would affect the operation of VIBER marginally, it is not analysed.

[32] The work at the central bank takes approximately five minutes per transaction. During the simulations we assumed four persons as an average number of staff members in the VIBER team of the central bank. This means that in one hour the VIBER team is able to process approximately 50 fax-based transactions.

5 Simulation results

5.1 GENERAL CONSIDERATIONS ON SIMULATION TECHNIQUES

The technical default of one or more VIBER participants has both *direct and indirect effects* on the performance of the system. The *direct effect* is obvious; the operational failure of the settlement bank prevents the bank concerned submitting payments to the system. If the problem is severe enough and cannot be fixed before the end of the business day, in the absence of contingency arrangements the settlement bank under distress will end up with many unsettled transactions. In addition to this direct effect, there might be significant indirect, so-called *network effects*. Namely, as the liquidity position of each VIBER participant is influenced by payment flows, if one settlement bank is not able to send payments, the liquidity position of the remaining participants is threatened. This, in turn, could force the initially unaffected settlement banks to queue, and thus delay payments. It might also happen that a large amount of liquidity is drained out of the system, as it is accumulated on the account of the bank experiencing the technical problem. As a consequence, there might be banks short of liquidity and thus they might end up with rejected payments at the end of the day. Both direct and indirect impacts are captured by the performance indicators.

For simulation purposes, on the day of the incident the *transactions initiated by the technically defaulted participants* should be removed or modified. The transactions should be removed if it is assumed that the operational problem cannot be solved before the end of the day. The transactions should be *modified* if it is assumed that the bank managed to solve the operational problem within the business day. In this latter case the time stamps (receipt times) of the transactions should be altered. The modified time stamps should reflect the point in time when the bank managed to sort out the technical problem.

Payment instructions initiated by technically functioning participants (including infrastructure like the CSD/SSS) to be debited or credited on the account of the defaulted participants are processed normally. Transactions processed normally include *mandated payments*. In addition, *warehoused outgoing payments* of technically defaulted participant are processed normally as well.

If it is assumed that the initially unaffected participants do not react to the shock, no modification in the initial dataset is needed. However, the participants may react to the liquidity shock. If the banks apply the stop sending rule, the time stamp of the transactions which are sent two hours after the beginning of the incident should be modified. The new time stamp of the transactions should reflect the time of the restoration of the SWIFT connection.

In the simulations it is implicitly assumed that the banks are able to solve the problem right after the official closing of VIBER and somehow the payments are settled.[33] We do not aim to simulate two- or three-day operational incidents. If this were the case, the disturbance in the payment system would be more significant and the entire economy would bear higher costs.

5.2 SIMULATED SCENARIOS

The simulations of operational failure scenarios are based on a combination of different assumptions (see Subsection 4.4). The assumptions applied in the simulations are summarised in Table 8. In the first simulation setup (Scenario 1 to 3) *entire-day incidents* were imitated. It was assumed that the operational failure starts at the beginning of the day and the bank under distress cannot sort out the problem until the end of the business day. In each scenario one of the six systemically most important banks became unable to send payment orders. In Scenario 1, shown in the first column of Table 8, no back-up facilities and behavioural reactions were assumed. In Scenario 2 we examine the shock-mitigating impact of back-up facilities. In Scenario 3 the disturbance of the payments system was assessed if technically non-defaulted participants took actions to prevent the bank under distress from becoming a liquidity sink, and stopped sending payments to the bank experiencing the technical default after two hours (stop sending rule).

[33] This could be achieved by prolongation of the official business hours and allowing VIBER to remain open until all the payments are settled. The use of InFoRex would be another possibility; however, it is highly unlikely that all the transactions can be settled as the procedure is paper-based.

Table 8

Various scenarios to be examined in simulation exercises

	Entire-day incident			Part-time incident		
Scenario	**1**	**2**	**3**	**4**	**5**	**6**
Number of technically defaulted participants	1	1	1	1	1	2
Duration of the incident (hours)	9	9	9	4	6	4
Contingency procedures: Back-up facilities	-	+	-	-	-	-
Behavioural reaction of technically non-defaulted participants	-	-	+	-	-	-

In the second simulation setup more realistic *part-time incidents* were simulated. We looked for worst-case scenarios in which operational failures of given length occurred when the *value weighted submission delay* for payment orders sent by one of the six systemically most important banks was the highest.[34] During the optimization procedure the value of payments postponed were weighted by the time lag between the submission time and the end of the operational incident. The weighing of payments by the time left until the end of the incident takes into account both the value of the payment and the delay in submission (consequently the delay in settlement). In this way, we suppose that each payment is time-critical, that is, it is important when the payment is submitted into the central queue via SWIFT and when it is settled. Other optimization procedures should have been used as well. In the future, by examining the behaviour of affected and unaffected participants, we plan to elaborate more on this.

For the optimization procedure only the length of the incident and the number of technically-defaulted banks were provided as input parameters (Table 8). It was assumed that the technical problem can be sorted out either in four or in six hours, but surely no later than the end of the business day.[35] In Scenario 4 and 5 one bank defaulted technically and the incident lasted for four or six hours respectively. Scenario 6 corresponds to a situation when an operational problem affected two banks simultaneously for four hours. It was assumed that the incidents began simultaneously, at the same moment. For the sake of simplicity, it was also assumed that the technical problems are sorted out within the same time period.

The output of the optimization provided us with the starting point of the operational failure and the list of technically defaulted participants. The timing and the technically defaulted bank(s) were not necessarily the same across the days.[36] They were highly dependent on the daily payments patterns. The stop sending rule was applied in none of the part-time incident scenarios. As the bank(s) averted the source of the operational problem within the business day, we did not analyse the effects of various contingency procedures and back-up facilities. Note that if the time-criticality of transactions were at our disposal we could apply back-up procedures for those. In such cases we would assume that technically defaulted banks are eager to settle those payments even if they are duplicated.

5.3 DISTURBANCE IN THE PAYMENT SYSTEM: ENTIRE-DAY INCIDENTS (SCENARIOS 1-3)

5.3.1 Scenario 1: Entire-day incidents – no back-up facilities and no behavioural reactions

The simulation results for the first scenario are summarised in Tables 9 and 10. As a first step it was assumed that the bank with the highest turnover suffers from an operational incident and is unable to submit payments during the entire business day. The counterparties did not change their behaviour and back-up facilities were not in place. Detailed results of the simulations accessing the impact of the other five technically defaulted participants on the payment system are presented in Appendix 1.

[34] We could have examined the impact of the timing of the incident as well; and similar to Ledrut (2007) we could have analysed the severity of disruption in the function of timing (e.g., incident occurs at 8:00, 8:30, 9:00, 9:30, etc.) We also could have analysed the consequences of the operational incidents at each bank separately. Nevertheless, our aim was to gain information about the worst-case scenario, which provides us both the timing and the location (name of the banks) of the incident as an output from the optimization procedure.

[35] Quantifying the effects of incidents lasting for three or five hours, for example, could also have been reasonable and realistic. However, in order to keep the number of simulated scenarios limited, we disregard these possibilities. Further research could be done in this direction as well.

[36] Note that the method highlights which participant should be chosen if we want to simulate the impact of the most dramatic operational incident.

Table 9

Disturbance in the payment system: operational incident at Bank 1

Bank 1 - Entire-day incident	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	4.62%	16.30%	21.72%
Value of rejected payments (as % of submitted payments)	0.00%	16.21%	34.72%
Value of unsettled payments (as % of the benchmark scenario)	1.96%	30.99%	50.94%
Total value of queued transactions (as % of submitted payments)	3.38%	38.37%	53.99%
Maximum queue value (as % of submitted payments)	2.69%	19.42%	41.98%
Average queue length (hh:mm:ss)	0:55:12	1:49:41	2:35:21
Settlement delay	0.13	0.29	0.50

As shown in Table 9, due to the technical default of Bank 1 an average 16.30% of the payments could not be submitted to the system. There were 6 out of the 41 days on which more than 20% of the payments sent in the benchmark scenario was not submitted at all. Meanwhile, there were no rejected payments in the benchmark scenario. In this scenario on average 16.21% of the submitted payments remained unsettled. As demonstrated by the last column of Table 9, in the very extreme worst-case scenario 21.72% of the payments were not submitted and 34.72% of the payments submitted were rejected. In comparison with the benchmark scenario, on average altogether 30.99% of the payments remained unsettled, while in the worst case 50.94% of the payments remained unsettled (either not submitted or rejected). If Bank 2 defaults technically, the corresponding figures are 26.67% and 54.96%.

In international comparison the proportion of unsettled transactions is outstandingly high. This can be explained by the high concentration of the debit and credit turnover and by the high rank correlations. The banks – being relatively badly endowed with liquidity – rely consciously on the financing role of the incoming payments. Thus, if there is a deficit in the incoming payments, outgoing payments cannot be settled due to lack of funds. Not surprisingly, the *five banks* disposing of the highest value of unsettled transactions include the banks *with the highest debit and credit turnover in VIBER.* They account for around 88% of unsettled payments. Due to the liquidity drain effect, these banks are left with 26% of rejected payments on average at the end of each day. *Four other, small banks* having strong relation to the banks active in the payment system suffer heavily from the liquidity drain effect as well. They cannot send 16% to 34% of their payment orders respectively. All of the nine banks can be found in the list of possibly endangered participants.

Compared to the benchmark case, the total value of queued transactions, measured as a percentage of submitted payments, became approximately 2.4 times higher.[37] In the worst case, more than half (53.99%) of the submitted payments were in the queue once, for either a shorter or longer period. Both the average and the maximum of the maximum queue value indicators increased significantly, becoming 4.52 and 3.79 times higher respectively. The average queue length increased drastically as well, it became 2.65 times higher an average. If Bank 1 suffered from an operational incident, the average of the settlement delay indicator equalled 0.29. This is more than 4 times higher than in the benchmark case. Note that the minimum of the delay indicator is 13 times higher than in the benchmark case.

Obviously, banks with the highest value of queued payments overlap with the banks disposing of the highest value of unsettled transactions. The five banks most active in the payment system are responsible for around 87% of the queued transactions. It is important to note that in the benchmark scenario only three of the five banks were among the banks with the most significant queues. While in the benchmark scenario these three banks queued up 10.52-21.14% of their payment orders, if Bank 1 defaults technically they queue up 65.74%-70.35% of their payments. At the end of the business day the three banks could not fulfil around 30% of their payment obligations. These payments were rejected due to lack of funds. In relative terms

[37] It is important to note that the initially not submitted payments were excluded from the indicator.

Table 10

Disturbance of the payment system according to technically defaulted banks in Scenario 1

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6
Value of payments initially not submitted (as % of the benchmark scenario)	16.30%	13.68%	10.27%	6.58%	5.84%	4.49%
Value of rejected payments (as % of submitted payments)	16.21%	13.77%	6.95%	3.09%	2.67%	0.49%
Value of unsettled payments (as % of the benchmark scenario)	30.99%	26.67%	17.18%	9.91%	8.62%	5.13%
Total value of queued transactions (as % of submitted payments)	38.37%	39.40%	34.17%	30.54%	25.41%	22.75%
Maximum queue value (as % of submitted payments)	19.42%	17.79%	13.08%	9.43%	7.64%	6.11%
Average queue length (hh:mm:ss)	1:49:41	2:07:23	1:27:39	1:07:35	0:59:17	0:43:51
Settlement delay	0.29	0.27	0.20	0.12	0.10	0.08

the other two banks were even more seriously affected by the operational incident; in the distressed situation they queue up an average 48.94% and 41.87% of their payments. The corresponding figures in the benchmark scenario equalled 0.70% and 0.09% respectively. At the same time, at the end of the day the banks were also left with significant amount of unsettled payments; 25.64% and 18.49% of their payment orders remained unsettled. In the case of the four (already mentioned) small banks, which also suffer heavily from the liquidity drain effect, the ratio of queued payments over submitted payments is higher than 30% (ranging from 30.63% to 80.78% and showing high variation).

Similarly to the benchmark scenario, the settlement delay greatly varies across banks. The five banks disposing of the highest average settlement delay (the average delay indicator exceeds 0.20) include four of the five most active banks and one of the four small banks.

Table 10 compares the outcomes of the simulations if one of the six systemically important participants suffers from an operational incident.

The values shown in Table 10 are averaged over 41 days. The minimum and the maximum of the corresponding indicators are shown in Appendix 1. Evidently, the lower the turnover of the participants in VIBER, the lower the value of payments initially not submitted to the system (measured as a percentage of value of payments of the benchmark scenario). The value of unsettled payments also decreases slightly. In the case of the bank with the highest turnover on average 16.21% of the submitted payments were rejected, while in the remainder of the cases the corresponding figure ranges from 0.49% to 13.77%.

The total value of queued transactions is almost the same for the first three banks. If an operational incident hits one of the three banks with the largest turnover in VIBER, one third of the transactions are queued up for some time during the business day. The corresponding figure is one fifth for the bank with the sixth largest turnover in VIBER. The maximum queue value, the average queue length and the settlement also decrease significantly in relation to turnover. In general, queue and delay indicators show a more favourable picture with the decreasing role of the shocked VIBER participants.

Table 11 focuses on the distribution of unsettled payments in the function of shocked banks, while Table 12 highlights the minimum, the average and the maximum of the settlement delay in the function of shocked banks.

Various factors might influence the severity of the shocks. The most important factors include the network structure, payment and liquidity management habits, and timing behaviour. The true mechanism concerning how these factors influence the disturbance of the payment system is so far undiscovered. However, the message from the simulation exercise is straightforward. *Regarding liquidity levels and unchanged timing behaviour, an operational incident at the most active players can lead to serious disturbances in VIBER.* The disturbance highly depends on the daily payment patterns; the severity caused by the incident changes from day to day. Analysing the figures in Table 11 it is obvious that in the case of Bank 1, Bank 2

Table 11

Distribution of unsettled payments

(as % of payments submitted in the benchmark scenario)

Scenario1	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Benchmark
Minimum	1.96%	1.79%	1.78%	0.83%	1.04%	2.26%	0.00%
Average	30.99%	26.67%	17.18%	9.91%	8.62%	5.13%	0.00%
Maximum	50.94%	54.96%	32.97%	22.45%	25.21%	12.89%	0.00%
Number of days when higher than 20%	37	29	11	1	4	0	0
Number of days when higher than 10%	40	39	35	15	10	2	0
Number of days when higher than 5%	40	40	40	36	30	18	0

The number of business days in the examined period was 41.

Table 12

Minimum, average and maximum of the settlement delay indicator

Scenario1	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Benchmark
Minimum	0.13	0.12	0.05	0.03	0.02	0.02	0.01
Average	0.29	0.27	0.20	0.12	0.10	0.08	0.07
Maximum	0.50	0.58	0.44	0.34	0.3	0.16	0.16

and Bank 3 the probability that their technical default would cause only minor effects in the system is very low. *Operational incidents at these banks require special attention, especially if their problem cannot be sorted out until the end of the day. There are several lines of defence which can mitigate the severity of such operational incidents.* The first includes (electronic) back-up facilities. If they work properly the incident might not even be noticed by other VIBER participants. In the next subsection we examine the impact of the time-consuming, paper-based back-up solution. The second factor which can provide some protection for the intact members lies in adapting to the situation. It is important to note that the technically non-defaulted banks most probably would trade with operationally viable counterparties more than with the bank in a distressed situation. If this is the case, the *payment pattern is changed as part of the intraday trade is adjusted.* Since the intraday financial market trades were not identified in the paper, we overestimate the consequences of operational incidents. *The expectations of operationally viable banks and information asymmetry between the technically defaulted and operationally viable banks are also of major importance.*

5.3.2 Scenario 2: Entire-day incidents – Back-up facilities without behavioural reactions

In this section we examine the shock-mitigating impact of back-up facilities. We assume that effective business continuity arrangements are in place and back-up options are employed one hour before the closure of the system. The processing of payments was supposed to be carried out manually. Thus, we do not count with the possibility that the back-up options allow the settlement of a very large number of payments before the closure of the system. In the simulations it was assumed that the banks under distress can submit altogether 50 payments. The payments were ranked initially by priority provided by the banks, secondly by the amount of the transactions and thirdly by the CAS receipt time. The first 50 transactions in this ranking were submitted to VIBER one hour before the closure of the system.[38] Note that implicitly it was assumed that the internal systems of the stricken banks work properly and thus the stricken banks have up-to-date information about their payment obligations. Another selection procedure could also have been followed to pick out the 50 manually processed payments. By the above detailed ranking mechanism we aimed at selecting the most time-critical transactions. On the one hand, we took the prioritization given by the submitter banks into account by assuming that the priority orders would remain unchanged in the event of the shocks. On the other, by taking the amount of the transactions into account, we assumed that submitters

[38] It would have been more realistic to distribute these payments uniformly in the last hour of VIBER. However, the modification of the receipt time stamps would require more effort. By uniformly distributing the time stamps of the payments in the last hour of VIBER, the delay indicator became lower.

Table 13

Disturbance of the payment system in Scenario 2

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6
Value of payments initially not submitted (as % of the benchmark scenario)	2.96%	8.16%	4.99%	3.08%	0.23%	0.10%
Value of rejected payments (as % of submitted payments)	0.08%	5.77%	2.25%	0.96%	0.00%	0.00%
Value of unsettled payments (as % of the benchmark scenario)	3.26%	14.54%	7.45%	4.40%	0.25%	0.11%
Total value of queued transactions (as % of submitted payments)	32.10%	36.66%	31.94%	29.54%	22.99%	21.64%
Maximum queue value (as % of submitted payments)	16.43%	16.49%	12.33%	9.07%	7.01%	5.84%
Average queue length (hh:mm:ss)	1:20:28	1:08:39	1:14:33	1:14:33	0:52:42	0:42:28
Settlement delay	0.24	0.18	0.18	0.11	0.09	0.08

minimise the value of unsettled payments. Other ranking procedure would have been feasible as well. The impact of the selection procedure is an interesting area for future research. The analysis of the participants' behaviour in this respect is also of crucial importance.

Table 13 summarises the disturbance in the payment system under Scenario 2. The values shown in Table 13 are averaged over 41 days. The minimum and the maximum values of the corresponding indicators are shown in Appendix 2. If Bank 1 submits 50 payments out of its daily 482 payments at the end of the business day, then only 2.96% of the payments were not submitted to the system instead of the 16.30% of the payments in Scenario 1. (For comparison see Table 10.) The value of rejected payments also decreased significantly, from 16.21% to 0.08%. There is no such significant decline in the value of the indicators relating to the queue statistics. The significant queues and delays in the system can be explained by the fact that the payments of the technically defaulted bank are channelled to the system in the last hour of the business day.

If Bank 2 or Bank 3 suffer from the operational incident, but make use of back-up facilities, then the decline in the proportion of not submitted and rejected payments is significantly lower than in the case of Bank 1. This can be explained by the fact that the 50 transactions that were booked manually are not of the largest value. On several days Bank 2 and Bank 3 had many customer payments with high priority. As the value of these payments is much lower than the value of the bank-to-bank payments (containing loro payments as well), it could happen that the payments with the far highest value were not submitted to the system. On these days the liquidity drain effect showed a very similar pattern to that of Scenario 1.

As shown in Table 13, if Bank 4 is under distress but uses the back-up facility, then the disturbance of the payments system is somehow similar to the disturbance caused by Bank 1. In the former case, 3.08% of the payments of the benchmark scenario was not submitted. Nevertheless, the proportion of rejected payments is higher, 0.96%. The total value of queued transactions and the average queue length were more or less the same, while the maximum queue value and the settlement delay were lower.

If Bank 5 and Bank 6 are technically defaulted but 50 of their transactions are booked manually at the end of the business day, there will be almost no rejected payments. More precisely, there were six days out of the 2 x 41 when one payment remained unsettled. Compared to the benchmark scenario, the queues became larger and lasted longer.

Table 14 shows the distribution of unsettled payments in the function of shocked banks, while Table 15 focuses on the minimum, the average and the maximum of the settlement delay in the function of shocked banks.

Finally, let us compare the results of the entire-day incident with and without back-up facilities. Even if the number of payments processed manually is limited, the effect of the submission into the system of the payments stuck in the internal queues of the technically defaulted banks is positive. This is obvious if we compare Table 14 with Table 11 and Table 15 with Table 12. The improvement depends heavily on the selection procedure of manually processed payments. We have chosen a

Table 14

Distribution of unsettled payments

(as % of payments submitted in the benchmark scenario)

Scenario 2	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Benchmark
Minimum	0.13%	0.96%	0.84%	0.39%	0.00%	0.00%	0.00%
Average	3.26%	14.54%	7.45%	4.40%	0.25%	0.11%	0.00%
Maximum	8.41%	51.60%	32.07%	22.19%	1.05%	0.52%	0.00%
Number of days when higher than 20%	0	12	4	1	0	0	0
Number of days when higher than 10%	0	22	7	5	0	0	0
Number of days when higher than 5%	4	31	20	14	0	0	0

Table 15

Minimum, average and maximum of the settlement delay indicator

Scenario 2	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Benchmark
Minimum	0.11	0.08	0.05	0.03	0.02	0.02	0.01
Average	0.24	0.18	0.18	0.11	0.09	0.08	0.07
Maximum	0.42	0.47	0.44	0.34	0.24	0.16	0.16

prioritization which leads to significant improvement if the incident happened at Bank 1, Bank 5 or Bank 6. The disruption of the payments system remained almost unchanged when operational failure occurred at Bank 2, Bank 3 or Bank 4. In sum, *the improvement achieved by back-up facilities is highly dependent on how the technically defaulted institution chooses its payments processed manually in a distressed situation.*

5.3.3 Scenario 3: Entire-day incidents – Behavioural reactions without back-up facilities

Table 16 shows the disturbance of the payments system if one of the banks is hit by an operational incident and the rest of the system reacts to it by blocking their payments to the stricken bank within two hours.[39] By comparing Table 16 with Table 10 we can conclude that by applying the stop sending rule the initially not submitted payments increased significantly and the value of rejected payments decreased drastically. The composition of unsettled payments is very different. In Scenario 1 a high proportion of payments is rejected due to insufficient liquidity. The liquidity drain effect is significant; many banks suffer from the impact of the technical default. In contrast, in Scenario 3 banks try to escape from the liquidity drain effect by not submitting their payments to the bank under distress. Many payments are withheld; the high disruption of the payment system can be explained by this behaviour. It is important to stress that, despite the higher proportion of unsettled payments in Scenario 3, the shock remains isolated. The disruption of the payment system is strongly connected to payments not submitted by the bank under distress and to payments not submitted to the bank under distress.

The value of payments that remained unsettled (either not submitted or rejected) is higher in Scenario 3 than in Scenario 1. This is the price of isolating the shock and privileging payments sent to other participants. The higher value of unsettled payments means that some kept-back payments could have been settled. If we compare the evolution of queues and delays in Scenario 1 and Scenario 3, it can be concluded that in Scenario 3 the transactions are settled more smoothly, the queues and the delays are lower. For a more detailed insight into the disturbance of the payment system under Scenario 3, see Appendix 3.

Table 17 highlights the distribution of unsettled payments in the function of shocked banks, while Table 18 shows the minimum, the average and the maximum of the settlement delay in the function of shocked banks.

[39] Note that a very high level of coordination is assumed among the banks, resulting in a rather improbable scenario.

Table 16

Disturbance of the payment system in Scenario 3

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6
Value of payments initially not submitted (as % of the benchmark scenario)	29.62%	25.47%	18.36%	12.11%	10.91%	7.99%
Value of rejected payments (as % of submitted payments)	2.55%	1.99%	1.59%	0.69%	0.45%	0.24%
Value of unsettled payments (as % of the benchmark scenario)	32.54%	28.16%	20.43%	13.30%	11.77%	8.48%
Total value of queued transactions (as % of submitted payments)	19.49%	23.53%	22.78%	20.80%	17.12%	18.04%
Maximum queue value (as % of submitted payments)	7.06%	7.75%	7.46%	5.87%	4.79%	4.93%
Average queue length (hh:mm:ss)	0:51:35	1:13:18	1:17:31	0:46:01	0:47:18	0:45:23
Settlement delay	0.11	0.13	0.11	0.08	0.07	0.07

Table 17

Distribution of unsettled payments

(as % of payments submitted in the benchmark scenario)

Scenario 3	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Benchmark
Minimum	3.12%	3.38%	3.17%	2.16%	1.73%	4.28%	0.00%
Average	32.54%	28.16%	20.43%	13.30%	11.77%	8.48%	0.00%
Maximum	49.04%	47.80%	37.93%	22.14%	23.45%	16.74%	0.00%
Number of days when higher than 20%	40	36	24	6	1	0	0
Number of days when higher than 10%	40	40	40	30	24	9	0
Number of days when higher than 5%	40	40	40	39	40	38	0

Table 18

Minimum, average and maximum of the settlement delay indicator

Scenario 3	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Benchmark
Minimum	0.04	0.04	0.02	0.02	0.01	0.01	0.01
Average	0.11	0.13	0.11	0.08	0.07	0.07	0.07
Maximum	0.20	0.32	0.26	0.18	0.23	0.21	0.16

As Scenario 3 relies on behavioural expectations, the results should be analysed with caution. We applied stop sending rules in the simulations without filtering out the intraday financial transactions (transactions agreed and settled on the day of the incident), which could be misleading. In order to see the influence of the stop sending rule, intraday financial transactions should be mapped. *In addition, we think that stop sending is very doubtful behaviour. It is more realistic to assume that operationally viable participants fulfil their agreed obligations in the course of the day and payments sent to the technically defaulted bank are placed to the end of the internal or external queues. It could also happen that transactions in question are only submitted at the end of the business day.* If in the absence incoming payments the participants face liquidity deficit and cannot finance all of their outgoing transactions, they would try to finance payments to the participant under distress from the payments to be received from the participant suffering from the shock. Consequently, management of the loss reallocation would be easier afterwards. Usually the loss reallocation works very smoothly between participants. Further research is required to map changes in intraday trading patterns and to assess how liquidity managers adapt to the situation. In order to gain more in-depth analysis we aim to interview critical VIBER participants and try to model those factors which cannot be forecasted (liquidity management, how information asymmetry ceases in the system, etc.). In Scenario 3 an oversimplified approach was applied, thus the results of the scenario should be considered as indicative. Further research is needed to identify intraday trades and the way in which participants would re-prioritise their payments.

5.4 GROSS AND NET LIQUIDITY DEFICITS IN SCENARIO 1 AND SCENARIO 2

It is important to have an idea of the *additional liquidity that would be required to settle all rejected transactions.* The value of rejected payments provides only an indication, as it does not take into account the liquidity circulation. Namely, the settlement of payments provides funds for the credited banks and from that liquidity other transactions could be settled. By considering liquidity circulation in the system and taking into account the set of unsettled transactions, the end-of-day balances and the intraday credit lines, the metric of *gross liquidity deficit* (GLD) of bank i is calculated:

$$GLD_i = \max\left\{\left[\left(\sum_{j=1}^{n} p_{ij}^{out} - \sum_{k=1}^{n} p_{ik}^{in}\right) - \left(IDCL_i^{end} + b_i^{end}\right)\right]; 0\right\} \qquad \text{(Eq. 3)}$$

where
- p_{ij}^{out} is the value of outgoing payments from participant *i* to participant *j* that was submitted by participant *i,* but due to insufficient funds became rejected,
- p_{ik}^{in} is the value of incoming payments from participant *k* to participant *i* that would have been received by participant *i,* if participant *k* would not be short of liquidity,
- b_i^{end} is the end-of-day balance of participant *i,* which can be positive, zero or negative,[40] and
- $IDCL_i^{end}$ is the amount of intraday credit line of participant *i* at the end of the business day.[41]

The first sum in Equation 3 refers to the value of payments sent, but rejected due to insufficient liquidity of participant *i.* The second sum in Equation 3 is the value of payments expected by participant *i* but not received over the course of the business day. The second part of Equation 3 equals the funds available for settlement. Note that if participant *i* has more credited than debited payment items, then the value of the gross liquidity deficit equals zero. This is also the case if the participant has more funds available for settlement $(IDCL_i^{end} + b_i^{end})$, than the value of net payments $(\sum_{j=1}^{n} p_{ij}^{out} - \sum_{k=1}^{n} p_{ik}^{in})$.

On a system level the gross liquidity deficit is simply the sum of the GLDs of individual participants. The metric calculated in this way shows the minimum amount of money needed to enable all participants to clear transactions in the queues and to avoid rejections at the end of the day.

The required liquidity could be injected into the system in various ways. Technically non-defaulted participants hit by the operational incident are not passive agents. They can raise additional funds in several ways. For instance, participants short of liquidity can transact with their counterparties in the money market in order to gain funds for their queued payments.[42] There are countries in which the money market deal is enhanced by the central bank itself. For example, the 'stricken bank scheme' in the United Kingdom (Bedford et al., 2004) requires the settlement bank that is unable to resume normal payment processing operations by 4 p.m. to extend uncollateralised overnight loans (settled manually by the Bank of England) to any unaffected settlement bank requiring additional liquidity.

The liquidity assistance required might also be provided by the central bank in the framework of monetary policy operations. By pledging eligible assets as collateral, VIBER participants can always get higher intraday credit lines. If the overdraft is not eliminated until the end of the business day, the intraday credit is transformed into overnight credit. The interest paid on the overnight credit is determined by the ceiling of the interest rate corridor. At their discretion central banks might provide the liquidity required under favourable terms and conditions by means of open market operations. For example, the FED did this

[40] Negative end-of-day balances refer to overdrafts. Note that a bank might have a positive end-of-day balance even if it has rejected payments. In this case the positive balance of the participant is too small to settle any of the queued outgoing payments.

[41] Note that a bank might have an unexploited intraday credit line (overdraft is less than the maximum allowed) even if it has rejected payments. In this case the unexploited credit line is already too small to settle any of the queued outgoing payments.

[42] If the market conditions are favourable, the participants might eliminate their overdraft positions.

in September 2001. However, the participants might run out of eligible collateral. In this case the gross liquidity deficit cannot be financed in the framework of monetary policy operations. It is the role of the central bank to decide whether it is ready to accept additional, non-eligible collateral and intervene in its lender of last resort role. Due to moral hazard, the central bank policies on lender of last resort are not disclosed. In general, central banks should consider the systemic implications of the disruption of the payment system. If it large enough and the incident might threaten the financial stability of the entire banking system, a central bank might intervene.

To gain a more comprehensive picture about the crystallization of the liquidity risk caused by operational incidents, *the net liquidity deficit* (NLD) of bank *i* is computed in the following way:

$$NLD_i = \max\left\{\left[GLD_i - \left(POT_i^{end} - IDCL_i^{end}\right)\right]; 0\right\} \quad \text{(Eq. 4)}$$

where – GLD_i is the gross liquidity deficit participant *i* faces,

– POT_i^{end} is the value of eligible assets possessed by participant *i* at the end of the business day, and

– $IDCL_i^{end}$ is the amount of intraday credit line of participant *i* at the end of the business day.

NLD gives some indication whether the eligible asset portfolios in the participants' balance sheets would be enough to obtain the required liquidity in the framework of monetary policy operations. Note that we overestimate the volume of potential liquidity, as the banks also have to post collateral to other systems (e.g. bankcard settlement).

In the following we have calculated gross and net liquidity deficits for each day and for the technical default of each participant under Scenarios 1 and 2. Table 19 shows the gross liquidity deficit as a percentage of rejected payments in Scenario 1. Table 20 also demonstrates the gross liquidity deficit; however, as a percentage of initially not submitted payments in Scenario 1. According to Table 19, taking the offsetting role of incoming payments and the residual liquidity into account, on average 35-50% of the rejected payments would be required to settle all the submitted transactions. Figures lower than 100% mean that banks partially queue payments against each other, but due to insufficient funds they are in a deadlock situation. In the worst cases this offsetting is significantly lower. The figures depend on the systemic importance of the bank suffering from the initial shock.

If we compare the gross liquidity deficit figures with the value of initially not submitted payments (Table 20) we can conclude that, depending on the technically defaulted bank, on average 5-39% of the initially not submitted payments would have been sufficient to avoid end of day rejections.

Table 21 shows the net liquidity deficit as a percentage of the turnover of the benchmark case for a typical day, for the worst-case scenario and for the least problematic business day in Scenario 1. As the role played by VIBER participants in the payment system increases, the lack of liquidity buffer in the participants' balance sheets on a typical day usually increases. However, in line with the findings on performance indicators when Bank 2 defaulted technically, the net liquidity deficit was higher than in the case of Bank 1. The net liquidity deficit that would be required on average above the eligible assets in the

Table 19

Gross liquidity deficit – Scenario 1

(percentage of rejected payments)

Scenario 1: GLD/Rejected	Bank1	Bank2	Bank3	Bank4	Bank5	Bank6
Minimum	0.00%	24.57%	12.67%	0.00%	0.00%	0.00%
Average	46.42%	52.40%	49.08%	55.19%	48.49%	36.83%
Maximum	75.89%	88.53%	99.88%	96.29%	100.00%	97.40%
Percentile (25%)	39.80%	41.83%	32.87%	39.57%	17.64%	0.00%

Table 20

Gross liquidity deficit – Scenario 1

(percentage of initially not submitted payments)

Scenario 1: GLD/Not submitted	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6
Minimum	0.00%	1.24%	1.08%	0.00%	0.00%	0.00%
Average	36.19%	38.86%	23.02%	15.36%	15.54%	5.32%
Maximum	67.31%	68.94%	57.58%	44.88%	44.60%	38.24%
Percentile (25%)	27.55%	30.47%	10.46%	4.30%	0.77%	0.00%

Table 21

Net liquidity deficit – Scenario 1

(percentage of the turnover of the benchmark scenario)

Scenario 1: NLD/Benchmark turnover	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6
Minimum	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Average	2.09%	3.64%	1.66%	0.55%	0.64%	0.14%
Maximum	5.90%	7.94%	6.25%	2.91%	2.88%	2.28%
Percentile (25%)	0.87%	1.46%	0.01%	0.00%	0.00%	0.00%

participants' balance sheets to settle all transactions ranges from 0.14% to 3.64% of the turnover of the benchmark scenario. In the worst-case scenario, depending on the systemic importance of the bank suffering from the initial shock, the additional liquidity required ranges from 2.28% to 7.94% of the turnover of VIBER.

Table 22 displays the individual data on net liquidity deficits. The first column of the table refers to the bank which experienced the operational incident. The first row of the table shows those banks that require additional liquidity. As show by Table 22, there is high variation across banks suffering from the operational incident. In Scenario 1 the daily net liquidity deficit at system level ranges from 0.1 to 316 billion HUF on average. The range of the interval strongly depends on the technically defaulted bank and on the business day.

The results presented in Table 22 are in line with the clustering (Subsection 4.3.3). Almost all banks encountering liquidity problems were identified as endangered participants. Nevertheless, not all the endangered participants suffered from the liquidity shock. At least three of the five technically not defaulted banks with the highest VIBER turnover and two small banks always appear in Table 22. The banks with highest turnover account for the majority of the net liquidity deficit.

Table 22 also shows the number of days (out of the maximum 41) on which the value of the eligible collateral of the participants (in the column) does not cover the liquidity needed to settle all payment obligations if the bank shown in the row becomes technically defaulted. The following conclusions can be drawn from the table:

- If Bank 1, Bank 2, Bank 3 or Bank 6 are unable to submit payment obligations, seven banks are more or less seriously affected. They are not able to fulfil their payment obligations, even if all their eligible securities are posted as collateral. Four participants could have had problems on more than half of the days if Bank 1 or Bank 2 had defaulted technically. The empirical probability of liquidity problems decreases when an operational incident at Bank 3 or Bank 6 was simulated.

- If Bank 4 suffers from an operational incident eight banks are affected, as their eligible assets do not cover their payment obligations. In the case of the eight participants, the number of days with net liquidity deficit ranges between 1 and 12.

- If Bank 5 defaults technically most probably two out of the six banks would require additional liquidity to fulfil their payment obligations.

Table 22

Individual data on banks encountering liquidity problems – Scenario 1

Scenario1 - NLD		Sum	Banks encountering liquidity problems (NLD>0)							
Technically defaulted banks	Indicators		Bank A	Bank B	Bank C	Bank D	Bank E	Bank F	Bank G	Bank H
Bank 1	Number of days when a participant encountered liquidity problems	37	24	23	21	20	12	6	1	-
	Minimum of NLD across the days (million HUF)	5,590	543	4,540	2,533	556	44	3,997	1,084	-
	Average of NLD across the days (million HUF)	82,723	11,894	32,794	52,491	22,097	23,278	32,723	1,084	-
	Maximum of NLD across the days (million HUF)	192,031	31,326	112,824	132,511	72,361	78,399	66,604	1,084	-
Bank 2	Number of days when a participant encountered liquidity problems	39	36	24	22	16	8	8	3	-
	Minimum of NLD across the days (million HUF)	9,165	255	66	4,753	1,922	2,258	1,346	8,947	-
	Average of NLD across the days (million HUF)	136,400	99,434	23,104	32,139	14,069	21,490	5,763	11,767	-
	Maximum of NLD across the days (million HUF)	315,637	225,396	77,198	79,313	33,302	90,877	10,150	14,380	-
Bank 3	Number of days when a participant encountered liquidity problems	30	25	16	16	7	6	3	2	-
	Minimum of NLD across the days (million HUF)	2,070	2,136	2,774	287	108	3,792	29	4,550	-
	Average of NLD across the days (million HUF)	78,197	59,594	22,946	18,310	16,607	11,325	72	5,770	-
	Maximum of NLD across the days (million HUF)	220,703	140,540	67,454	62,674	49,612	16,532	156	6,990	-
Bank 4	Number of days when a participant encountered liquidity problems	24	12	12	10	6	3	2	2	1
	Minimum of NLD across the days (million HUF)	525	1,643	946	525	568	1,546	857	239	8,337
	Average of NLD across the days (million HUF)	32,568	30,229	14,893	6,810	9,193	29,310	8,744	1,582	8,337
	Maximum of NLD across the days (million HUF)	99,258	82,828	40,922	19,411	25,322	46,573	16,630	2,925	8,337
Bank 5	Number of days when a participant encountered liquidity problems	21	11	9	5	2	2	1	-	-
	Minimum of NLD across the days (million HUF)	3,407	4,356	3,407	8,260	18,460	3,484	1,692	-	-
	Average of NLD across the days (million HUF)	43,197	51,268	16,194	23,898	29,445	8,688	1,692	-	-
	Maximum of NLD across the days (million HUF)	104,008	104,008	37,166	44,775	40,431	13,892	1,692	-	-
Bank 6	Number of days when a participant encountered liquidity problems	9	3	2	2	2	1	1	1	-
	Minimum of NLD across the days (million HUF)	111	1,845	7,504	7,196	254	40,725	111	85,849	-
	Average of NLD across the days (million HUF)	26,386	4,354	10,931	34,876	3,057	40,725	111	85,849	-
	Maximum of NLD across the days (million HUF)	93,353	8,349	14,358	62,556	5,860	40,725	111	85,849	-

The Hungarian Post was excluded from the analysis.

Banks encountering problems were ranked on the basis of the number of days when they faced net liquidity deficit. Consequently, Bank A in the case of the technical default of Bank 1 is not necessarily the same as Bank A in the case of the technical default of Bank 2.

Table 23

Gross liquidity deficit – Scenario 2

(percentage of rejected payments)

Scenario 2: GLD/Rejected	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6
Minimum	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Average	12.63%	36.56%	32.93%	23.25%	0.00%	0.06%
Maximum	96.17%	95.61%	97.24%	85.08%	0.00%	1.00%
Percentile (25%)	0.00%	20.71%	0.00%	0.00%	0.00%	0.00%

Table 24

Gross liquidity deficit – Scenario 2

(percentage of initially not submitted payments)

Scenario 2: GLD/Not submitted	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6
Minimum	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Average	0.92%	18.17%	9.66%	5.52%	0.00%	0.05%
Maximum	19.55%	63.23%	52.51%	42.43%	0.00%	1.65%
Percentile (25%)	0.00%	1.47%	0.00%	0.00%	0.00%	0.00%

We have calculated the gross and liquidity deficits in Scenario 2 as well. The results are displayed in Table 23 and 24. The overall picture has improved significantly if back-up facilities were in place.

Table 25 shows that the net liquidity deficit as a percentage of the turnover of the benchmark scenario is lower if back-up facilities are in place. The decrement is less significant in the cases of Bank 2, Bank 3 and Bank 4. This can be explained by the lower effectiveness of the procedure on the basis of which the critical payments to be processed manually are selected. On average the net liquidity deficit varies from 0% to 1.14% of turnover of the benchmark scenario. In the worst-case scenario, depending on the systemic importance of the bank suffering from the initial shock and the efficacy of the back-up facility, the net liquidity deficit ranges from 0% to 6.29% of the turnover of VIBER.

Table 26 demonstrates indicators on net liquidity deficit at participant level. Banks with net liquidity deficits include the same institutions (both in the worst-case and on typical days) that encountered problems in Scenario 1. However, the net liquidity deficit was notably lower.

Table 25

Net liquidity deficit – Scenario 2

(percentage of the turnover of the benchmark scenario)

Scenario 2: NLD/Benchmark turnover	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6
Minimum	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Average	0.01%	1.14%	0.53%	0.16%	0.00%	0.00%
Maximum	0.39%	6.29%	4.57%	2.16%	0.00%	0.00%
Percentile (25%)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Table 26

Individual data on banks encountering liquidity problems – Scenario 2

Scenario1 - NLD		Sum	Banks encountering liquidity problems (NLD>0)								
Technically defaulted banks	Indicators		Bank A	Bank B	Bank C	Bank D	Bank E	Bank F	Bank G	Bank G	Bank H
Bank 1	Number of days when a participant encountered liquidity problems	3	2	1	1	-	-	-	-	-	-
	Minimum of NLD across the days (million HUF)	2,391	2,391	4,461	4,130	-	-	-	-	-	-
	Average of NLD across the days (million HUF)	9,103	9,359	4,461	4,130	-	-	-	-	-	-
	Maximum of NLD across the days (million HUF)	20,787	16,327	4,461	4,130	-	-	-	-	-	-
Bank 2	Number of days when a participant encountered liquidity problems	22	16	11	9	7	6	4	3	2	1
	Minimum of NLD across the days (million HUF)	2,983	588	58	8,711	2,366	1,346	2,983	8,947	18,890	17,564
	Average of NLD across the days (million HUF)	83,636	58,941	21,903	32,630	12,106	4,503	19,322	15,879	54,033	17,564
	Maximum of NLD across the days (million HUF)	309,028	174,544	77,040	78,488	22,021	8,366	42,605	24,388	89,176	17,564
Bank 3	Number of days when a participant encountered liquidity problems	18	9	7	6	5	4	2	-	-	-
	Minimum of NLD across the days (million HUF)	30	2,484	2,871	1,874	2,622	4,527	30	-	-	-
	Average of NLD across the days (million HUF)	44,887	45,296	20,569	9,428	9,428	30,381	93	-	-	-
	Maximum of NLD across the days (million HUF)	193,492	119,919	67,454	16,532	36,024	62,674	156	-	-	-
Bank 4	Number of days when a participant encountered liquidity problems	10	5	5	4	2	1	1	-	-	-
	Minimum of NLD across the days (million HUF)	315	1,807	315	6,771	2,812	16,495	2,925	-	-	-
	Average of NLD across the days (million HUF)	22,836	6,558	11,822	24,715	9,093	16,495	2,925	-	-	-
	Maximum of NLD across the days (million HUF)	74,742	19,411	22,553	49,377	15,374	16,495	2,925	-	-	-

The Hungarian Post was excluded from the analysis.

Banks encountering problems were ranked on the basis of the number of days when they faced net liquidity deficit. Consequently, Bank A in the case of the technical default of Bank 1 is not necessarily the same as Bank A in the case of the technical default of Bank 2.

5.5 DISTURBANCE IN THE PAYMENT SYSTEM: PART-TIME INCIDENTS (SCENARIOS 4-6)

In Scenarios 4 and 5 it was assumed that one bank suffers from an operational incident and it is unable to send payment orders to its counterparties for four and six hours respectively. The beginning and the end of the four- and six-hour intervals were calculated by means of an optimization procedure detailed in Subsection 5.2. In Scenario 4 in 35, while in Scenario 5 in 32 out of the analysed 41 days the bank most active in the payment system would have to suffer from on operational incident in order to cause the most severe disturbance in the payment system. On the other the days the second, third and fourth participants most active in the payment system would have to suffer form the operational incident in order to have the most serious impact on the payment system. In Scenario 6 in most of the cases the joint technical default of Bank 1 and Bank 2 (20 cases) vs. Bank 1 and Bank 3 (17 cases) generated the highest value of payments not submitted on time.

Table 27

The value of transactions not submitted on time

(million HUF)

	Mimimum	Average	Maximum
Scenario 4	75,040	466,334	650,003
Scenario 5	98,459	540,828	773,256
Scenario 6	124,417	806,287	1,186,135

Table 28

The timing of the incidents

	Mimimum	Average	Maximum
Scenario 4	8:52:16	9:54:56	12:36:05
Scenario 5	8:01:22	9:25:48	10:16:16
Scenario 6	8:23:46	9:47:25	11:12:05

Table 27 shows the value of transactions not submitted on time across Scenarios 4 to 6. The maximum, the average and the minimum of the value of payments with delayed submission are displayed. Obviously, if the incident lasts longer or two banks defaults technically, the value of transactions not submitted on time increases. In Scenario 4, 5 and 6 the average value of transactions not submitted on time equals 466 billion, 541 billion and 806 billion HUF respectively.

Table 28 provides some information about the timing of the incidents. The beginning of the operational incidents occurring the earliest, on average and the latest are highlighted. If the incident lasts six hours, it should start earlier compared to an incident lasting for four hours.

Table 29 illustrates the simulation results of the part-time incidents. Note that, as the values of payments initially not submitted to the system and the value of unsettled payments equals zero, they are excluded from the table. By comparing the simulation result to the benchmark scenario (see Table 3) we can conclude that, in line with our expectations, more queues and longer delays show up in the system. The average of the total value of queued transactions increased by almost 50% in Scenario 4 and 6, and by 75% in Scenario 5. The two extremes (minimum and maximum) almost remained unchanged. The average of the maximum queue value also increased notably. Compared to the benchmark case it became 2.66, 3.55 and 3.85 times higher in Scenarios 5, 6 and 7 respectively. The maximum queue value is more than two times higher in each part-time incident scenario than in the benchmark. The average queue length increased by 12 minutes in Scenario 4, by 27 minutes in Scenario 5, and by 21 minutes in Scenario 6. In the benchmark case the average of the settlement delay equalled 0.07. The average of the delay indicator increased by around 75% in Scenarios 4 and 6, and tripled in Scenario 5.

Table 29

Simulation results of the part-time incidents

	Scenario 4			Scenario 5			Scenario 6		
	Minimum	Average	Maximum	Minimum	Average	Maximum	Minimum	Average	Maximum
Total value of queued transactions (as % of submitted payments)	2.43%	24.48%	37.92%	0.84%	28.73%	40.80%	2.96%	23.54%	37.71%
Maximum queue value (as % of submitted payments)	1.98%	11.41%	24.77%	0.44%	14.39%	31.11%	1.98%	12.22%	24.68%
Average queue length (hh:mm:ss)	0:23:48	0:52:58	1:21:04	0:46:16	1:07:56	1:59:37	0:16:52	1:01:57	1:27:19
Settlement delay	0.05	0.12	0.23	0.07	0.2	0.35	0.03	0.12	0.21

If we compare the part-time incident scenarios with each other it is interesting that Scenarios 4 and 6 show very similar properties. In both cases the incidents lasted for four hours; nevertheless in Scenario 4 one, while in Scenario 6 two banks suffered from the operational incidents. The similar queue and delay properties can be explained by two adverse effects. On one hand, the value of payments submitted later is higher in Scenario 6. This obviously should result in larger queues and longer delays. On the other, the banks suffering from the operational incidents also transact intensively with each other. If both of them send their payments as soon as the incidents are sorted out, their payments will not stand in the queue or only for a very short period. This is why it could happen that we do not experience more significant queues and delays in Scenario 6 than in Scenario 4. In Scenario 5 the operational incident lasted for six hours. The simulation results are in line with our expectation – there are longer and larger queues and more significant delays.

6 International comparison

Numerous central banks have assessed the operational resilience of their large-value payment systems in a similar way as we did in our study. It is an interesting question whether the disruption of the Hungarian payment system is more or less serious than those experienced in other countries. It is important to note that the comparison of simulations is hindered by the diversity of assumptions the authors made and by the variation of measures used to describe the severity of disruption in the payment system. In the following we compare the simulation results obtained for the large-value payment systems of the United Kingdom, France, Austria, the Netherlands, Belgium and Switzerland with the Hungarian outcomes.[43]

The analysis of Bedford et al. (2004) showed that CHAPS Sterling is well placed to withstand a variety of operational disruptions. The scenario constructed by the authors is mostly in line with Scenario 3 of our study, the simulation results of which were presented in Table 16. Bedford et al. (2004) found that at the upper bound of liquidity the operational disruption did not prevent settlement of any payments. The delay indicator was very close to zero if one bank defaulted technically, and increased only up to 0.03 if three banks defaulted simultaneously. As in practice the total amount of intraday credit obtained by the CHAPS Sterling settlement banks typically exceeds significantly the upper bound (by about half), the shock-absorbing capacity of CHAPS Sterling might be considered as outstandingly high.

In the French case Mazars and Woefel (2005) simulated the technical default of the largest debtor in the PNS system. The authors found that in the event of an entire-day default, almost 10% of payments (in value terms) between non-defaulting participants could be rejected. At the same time the queues became larger and longer; on average 63.15% of the total payments were queued up for 45 minutes. In the benchmark case the respective figures equalled 42.90% and 30 minutes, thus both indicators increased by 50%. The delay indicator also increased significantly; compared to the benchmark case it doubled (0.09 vs. 0.2). The simulation setup of Mazars and Woefel (2005) is basically equivalent to Scenario 1 formulated in our paper. By comparing the French results with the Hungarian ones, we might conclude that the disruption is more sever in VIBER than in PNS. In Hungary, in Scenario 1 the total value of queued payments became 2.33 times higher and the average queue length became 2.68 times longer, while the delay indicator almost quadrupled in comparison with the benchmark case.

Schmitz et al. (2006) constructed nine distinct scenarios to assess the shock-absorbing capacity of Austria's ARTIS. One of the scenarios captures the technical default of the top bank account for an entire day, without back-up options and behavioural reactions.[44] This scenario is in line with Scenario 1 worked out to assess the shock-absorbing capacity of VIBER. The payments initially not submitted by the banks suffering from the operational incidents, expressed as a percentage of total turnover, were very similar in the two systems: 16.30% in VIBER and 15.96% in ARTIS. Nevertheless, the proportion of unsettled payments is much higher in Hungary than in Austria. In VIBER an average 30.99%, while in the worst case 50.94% of the payments remained unsettled if the systemically most important bank defaulted technically. In contrast, in Austria an average 2.92%, while in the worst case 8.39% of the payments were not fulfilled if the top bank account suffered from an operational incident. The figures presented above refer to a more sever disruption of the Hungarian payment processing activity in the case of an operational incident.

As a next step the simulation results of Ledrut (2007) for the Dutch interbank payment system, known as TOP, are compared with the disruption experienced in VIBER. The author assesses the impact of an operational failure at one of the biggest participants, varying the time at which the disruption takes place. For comparison purposes we focus exclusively on the scenarios in which payments from the technically defaulted participant to the other banks are removed at the opening of the system. In this case, on average 18.75% of the payments are not submitted initially by the defaulter. As a consequence, 16 of the submitted payments remained unsettled on average, representing more than EUR 1 billion in value terms. In the worst

[43] We do not aim to compare the simulation results obtained, for example, for the Danish RTGS (Bech and Soramäki, 2005) or for the Norwegian NBO (Enge and Øverli, 2006) systems with the Hungarian results. In both cases the scenarios analysed by the authors are not at all comparable with the scenarios formulated to assess the shock-absorbing capacity of the Hungarian VIBER.

[44] The remainder of the scenarios are not comparable with the scenarios formulated in our study, as they are related to the analysis of special functions of ARTIS or TARGET, to the analysis of the impact of debit authorisation or to the assessment of the impact of simultaneous failure of the three most active accounts.

case 45 payments remained unsettled, corresponding to more than EUR 2.2 billion in value terms. In the worst case the proportion of unsettled payments (in value terms) might be around 1.35% of the payments submitted.[45] The delay indicator equalled 0.13; in the benchmark case the indicator had a value of 0.08. In further scenarios Ledrud (2007) introduces the reaction from other payment system participants. The scenario in which the banks cease to pay to the stricken bank within two hours is in line with the assumptions made in Scenario 3 in our study. In this case in the Dutch system the average number of unsettled payments equalled 5, corresponding to EUR 330 million. The average of the settlement delay equalled 0.14. If we look at the simulation results of Scenario 1 (Table 10) and Scenario 3 (Table 16), we might conclude that in a case of an operational incident the disruption of the Hungarian payment processing activity is more sever than the disruption of the Dutch TOP system.

In the Financial Stability Review of the National Bank of Belgium (2007) the operational resilience of ELLIPS, the Belgian RTGS, was assessed. One of the four different types of scenarios that was tested to simulate exogenous shocks included the technical unavailability of a single participant during the whole day. This scenario is comparable with Scenario 1 of our paper.[46] In the Belgian case the severity of disruption was measured if problems arose at the level of one of the 5 major ELLIPS participants. According to the article, even in the worst case the value and volume of the unsettled payment instructions (10 payments in a value of €2.7 billion) are quite low compared to the value and number of submitted payment instructions (11,000 payments with a total value of €120 billion). In the report it is argued that the limited contagion effect is related to the abundance of assets eligible as collateral and to the relatively limited importance of national payment instructions compared to international payment instructions in ELLIPS.

Finally, Glaser and Haene (2007) simulated participant level operational disruption in the Swiss Interbank Clearing, which is an RTGS used for both large and small-value payments. The authors formulated a scenario in which one of the SIC members is assumed to fail at the moment when the largest potential liquidity sink develops during the day. The SIC member experiencing a problem cannot enter payments during the rest of the day after the disruption, while other members stop making payments to the disrupted member only 2 hours after the disruption. The scenario formulated by Glaser and Haene (2007) is more or less comparable with our Scenario 3. In Switzerland, in the worst case, if one of the two largest SIC participants defaulted technically, 32% of the payments were not submitted from and to the failing bank, while another 30% of the payments remained unsettled due to systemic effects. Thus, less than 40% of payments were settled correctly. In contrast, In Hungary 29.62% of the payments were initially not submitted, and 2.55% were rejected, thus even in the worst case 67.46% of the payments were settled correctly (see Table 16). In Switzerland the serious disruption of the payment flows can be explained by the high concentration of payments (the two largest members dispose of more than 50% of the payments in value terms) and by the relatively low liquidity levels in SIC (the effective liquidity to upper bound is 28%), which makes this very liquidity efficient system vulnerable.

[45] The figure was estimated as a ratio of EUR 2.2 billion over the value of payments settled on average in June 2004.

[46] The remainder of the scenarios covered the bankruptcy of a single participant and the technical unavailability of the interlinking component.

7 Conclusions

The simulations carried out can be considered as a first step in evaluating the ability of the Hungarian payment system to withstand certain types of operational shocks. We quantified the capacity of the system to function smoothly in the event of operational incidents by simulating the technical default of VIBER participants. We set up hypothetical scenarios for operational incidents by making various assumptions about the behavioural reactions of technically non-defaulted participants, the timing and length of the operational failures, the number and list of technically defaulted participants, and the application of existing back-up procedures. Altogether six hypothetical scenarios were formed, three entire-day incidents and three part-time incidents. In the future it would be useful to simulate more plausible scenarios.

The impact of the technical default of one of the VIBER participants, thus the disturbance in the payment system was measured by several indicators developed to describe the operation of an RTGS system. Among others, these indicators include the value of initially not submitted payments, the value of rejected payments, the total value of queued payments, the maximum queue value, the average queue length and the settlement delay. When entire-day incidents without back-up options and behavioural reactions were simulated, the disturbance of the payment system was severe. By international comparison the proportion of unsettled transactions is outstandingly high. As a consequence of the technical default of the systemically most important participant, 16.21% of the submitted payments were rejected. In the worst case 34.72% of the payments submitted were rejected. In comparison with the benchmark scenario, on average altogether 30.99% of the payments remained unsettled, while in the worst case 50.94% of the payments remained unsettled (either not submitted or rejected). If the bank with the second largest debit turnover defaulted technically, the corresponding figures were 26.67% and 54.96%. Queues and delays were also higher than in the simulation exercises of other countries. This can be explained by the high concentration of the debit turnover in VIBER and by the fact that the most active participants are mainly not those that are well equipped with liquidity. Another important explanation might be linked to the structure and size of the money markets. In the euro zone the largest market participants might be considered as 'small', at least compared to the size of the market. In contrast, in Hungary those market participants – getting involved in some Forint deals through their correspondent banks – might be considered as large, especially compared to the size of the market.

If back-up options are employed and fifty transactions of the technically defaulted participants are settled manually before the closure of the system, then the disturbance of the payment system was significantly lower. If the systemically most important bank experiences operational problems and submits fifty payments at the end of the business day, then only 2.96% of the payments were not submitted to the system instead of the previously experienced 16.30%. The value of rejected payments also decreased significantly, from 16.21% to 0.08%. However, the shock-absorbing capacity of the system depends heavily on the selection procedure of manually processed payments. We have chosen a selection procedure which leads to an almost smoothly functioning payment system in the case of three banks, while the processing of payments was highly disrupted when operational failure occurred at the other three banks. On the one hand, this stresses the importance and the potential efficacy of back-up options. On the other, it highlights that the way in which the technically defaulted institution chooses its payments processed manually in a distressed situation is of crucial importance. Thus, in the case of operational incidents the MNB should stipulate that the banks select not only the transactions with the highest priority but also those with the highest value.

Behavioural reactions were also taken into account; the initially unaffected participants reacted to the operational incident by blocking payments to the stricken bank within two hours. By overcoming information asymmetry and applying the stop sending rule, the initially not submitted payments increased significantly and the value of rejected payments decreased drastically. By withholding many payments the value of payments remaining unsettled (either not submitted or rejected) became higher. This is the price of isolating the shock and privileging payments sent to other participants. The higher value of unsettled payments means that some of the kept-back payments could have been settled. By building behavioural reaction into the model, several assumptions were made. In the absence of real entire-day incidents, it is hard to judge what would happen with the information flow, how high the coordination among banks would be and when the information asymmetry would be eliminated totally. We do not have proper knowledge about the potential changes in payment patterns (blocking of payments, modifying time stamps or re-prioritizing payments) and modifications of intraday trade (trading altogether less and trading more with operationally viable participants). Regarding our limited knowledge about the behaviour of participants in shock situations, our simulation results should be considered as indicative. Further research is needed to map the behaviour of banks in distressed situations.

In two scenarios involving entire-day incidents, by means of the indicators of gross and net liquidity deficit, we calculated the additional liquidity that would be required to settle all rejected transactions. By taking the residual liquidity of the participants, the offsetting role of incoming payments and the liquidity circulation into account, on average 35-50% of the rejected payments would be required to settle all submitted transactions. If the gross liquidity deficit is expressed in the value of initially not submitted payments then, depending on the technically defaulted bank, on average 5-39% of the initially not submitted payments would have been sufficient to avoid end-of-day rejections of transactions. The metric of net liquidity deficit gives some indication whether the eligible asset portfolios in the participants' balance sheets would be sufficient to obtain the missing liquidity in the framework of monetary policy operations. We could see that an average 0.14% to 3.64% of turnover of the benchmark scenario would be required above the eligible assets in the participants' balance sheets to settle all transactions. In the worst-case scenario, depending on the systemic importance of the bank suffering from the initial shock, the additional liquidity required ranged from 2.28% to 7.94% of the turnover of VIBER. Analysing the individual data about net liquidity deficit figures, we found that the daily net liquidity deficit at system level ranges from 0.1 to 316 billion HUF on average. The range of the interval strongly depended on the technically defaulted bank and on the business day. The overall picture improved significantly if back-up facilities were in place.

By analysing the impact of scenarios involving part-time incidents, we concluded that, similarly to the benchmark scenario, the values of payments initially not submitted to the system and the value of unsettled payments equalled zero. Nevertheless, more queues and longer delays showed up in the system. By comparing the part-time incident scenarios with each other, we experienced similar settlement patterns in both four-hour scenarios, regardless of the number of defaulting banks. The similar queue and delay properties can be explained in this case by the mutual interdependence of the two shocked banks – they trade very actively with each other.

The simulation exercise has several *drawbacks,* which lead to the *overestimation* of liquidity risk. First of all, we assume that the participants do not raise *additional* funds. However, participants short of liquidity can transact with their counterparties in the money market, can obtain collateralised or uncollateralised credit from the mother bank or can agree upon a credit with the central bank in the framework of its monetary policy operations. We tried to overcome this problem by examining whether the participants have sufficient level of liquidity buffer. This was done by comparing the value of unsettled transactions with the value of eligible assets in the balance sheet. Note that we overestimated the value of eligible assets, as banks might pledge securities as collateral for other than payment purposes.

The weakest point of the research lies in the *behavioural assumptions* of the study. We assumed *unchanged trading patterns* during the entire business day, the banks planned to settle the same volume and value of transactions, with the same counterparties and with the same priority as under normal business conditions. In this way we overestimate the severity of disruption again. Most probably this type of behaviour would not be the case, as banks are not passive economic agents and would adjust their trading patterns to the shock situation. Banks short of liquidity might postpone some of their transactions and would make efforts to settle fewer transactions on the day of the shock. Moreover, the banks would surely favour participants with operating infrastructure and with abundant liquidity. Thus, not only the value and volume of intraday transactions would be lower, but also the counterparties to trade with would be reset.

Moreover, not only the trading patterns, but (excepting the scenario of applying the stop sending rule) the *settlement behaviour* was also assumed to be constant. Banks initially not affected by the operational incident did not place the payments to the technically defaulted bank to the end of the internal or external queues (for example, by giving a lower priority to them), or did not alter the timing of the payments (for example, by submitting the transaction to the defaulter at the end of the business day). In this way the severity of disruption might be overestimated again. In reality, in the absence of incoming payments those participants that face liquidity shortage and cannot finance all of their outgoing transactions would change their settlement pattern. Most probably they would try to finance payments to the participant under distress from the payments to be received from the participant suffering from the shock by re-prioritizing or altering the time stamp of the transactions. From this point of view the scenario with the behaviour of automatic stop sending is also improbable. As we have argued previously, there are several reasons why banks do not stop sending certain payments to the stricken bank. First of all, it is a very complex exercise to modify the list of payment orders waiting for transmission to the central settlement engine, and it contains the risk of duplicating the settlement of transactions. Secondly, the banks cannot allow themselves to risk their reputation. If a bank wishes to maintain its high prestige, the bank should fulfil its contractual commitments, even when it experiences some problems. Thirdly, a contractual commitment is an obligation, if the bank does not fulfil it, than it should count with the legal and financial consequences. The simulation results of the stop sending scenario should be considered indicative.

As we had no information concerning how the trading patterns and the settlement behaviour of the banks would change in distressed periods, we tried to keep the simulations as simple as possible and avoided making further, more speculative assumptions. Obviously, more research is needed to be able to answer all these questions. As a next step, by means of qualitative and quantitative research methods, more investigation is needed to model precisely the behaviour of the banks in shock situations.

As for *policy implications,* the role of the MNB in a crisis situation is of crucial importance. The MNB is the one that communicates with the participants and might have an influence on the settlement behaviour by providing up-to-date information about the nature of the operational incident. In addition, there seems to be a small number of VIBER participants whose operational failure can affect heavily the functioning of the system. In the future, in the central bank oversight more attention should be paid to the back-up facilities and procedures of (at least) these critical participants. In order to judge the sufficiency of potential liquidity of the critical participants more precisely, assets not eligible as collateral should be also mapped.

In sum, we would like to stress that the research should be considered as a first step towards mapping the operational resilience of VIBER participants. We addressed several 'what if' types of question, mostly focusing on what would happen with the payment system if one of the participants were unable to send payment messages. We made several assumptions; in some cases we modelled real life more closely, while in others we formed a hypothetical world. We addressed many research questions, some of which remain open and require further research.

Appendix

APPENDIX 1

Disturbance in the payment system

Scenario 1: Entire-day incidents – no back-up facilities and no behavioural reactions

Table 1

Disturbance in the payment system: operational incident at Bank 2

Bank 2 – Entire-day incident	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	4.15%	13.68%	21.21%
Value of rejected payments (as % of submitted payments)	0.08%	13.77%	43.89%
Value of unsettled payments (as % of the benchmark scenario)	1.79%	26.67%	54.96%
Total value of queued transactions (as % of submitted payments)	3.57%	39.40%	62.01%
Maximum queue value (as % of submitted payments)	2.73%	17.79%	43.89%
Average queue length (hh:mm:ss)	00:11:10	2:07:23	2:53:58
Settlement delay	0.12	0.27	0.58

Table 2

Disturbance in the payment system: operational incident at Bank 3

Bank 3 – Entire-day incident	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	3.77%	10.27%	13.76%
Value of rejected payments (as % of submitted payments)	0.20%	6.95%	24.73%
Value of unsettled payments (as % of the benchmark scenario)	1.78%	17.18%	32.97%
Total value of queued transactions (as % of submitted payments)	3.45%	34.17%	56.95%
Maximum queue value (as % of submitted payments)	2.58%	13.08%	34.99%
Average queue length (hh:mm:ss)	0:30:58	1:27:39	2:48:12
Settlement delay	0.05	0.20	0.44

Table 3

Disturbance in the payment system: operational incident at Bank 4

Bank 4 – Entire-day incident	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	1.95%	6.58%	10.47%
Value of rejected payments (as % of submitted payments)	0.00%	3.09%	14.05%
Value of unsettled payments (as % of the benchmark scenario)	0.83%	9.91%	22.45%
Total value of queued transactions (as % of submitted payments)	2.76%	30.54%	53.45%
Maximum queue value (as % of submitted payments)	1.90%	9.43%	22.72%
Average queue length (hh:mm:ss)	00:11:04	1:07:35	1:50:32
Settlement delay	0.03	0.12	0.34

Table 4

Disturbance in the payment system: operational incident at Bank 5

Bank 5 – Entire-day incident	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	2.45%	5.84%	10.07%
Value of rejected payments (as % of submitted payments)	0.00%	2.67%	20.43%
Value of unsettled payments (as % of the benchmark scenario)	1.04%	8.62%	25.21%
Total value of queued transactions (as % of submitted payments)	2.76%	25.41%	63.11%
Maximum queue value (as % of submitted payments)	1.88%	7.64%	22.32%
Average queue length (hh:mm:ss)	0:11:02	0:59:17	1:51:25
Settlement delay	0.02	0.10	0.30

Table 5

Disturbance in the payment system: operational incident at Bank 6

Bank 6 – Entire-day incident	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	2.25%	4.49%	7.58%
Value of rejected payments (as % of submitted payments)	0.00%	0.49%	4.35%
Value of unsettled payments (as % of the benchmark scenario)	2.26%	5.13%	12.89%
Total value of queued transactions (as % of submitted payments)	0.91%	22.75%	40.17%
Maximum queue value (as % of submitted payments)	0.48%	6.11%	14.14%
Average queue length (hh:mm:ss)	0:15:20	0:43:51	1:29:45
Settlement delay	0.02	0.08	0.16

APPENDIX 2

Disturbance in the payment system

Scenario 2: Entire-day incidents – back-up facilities without behavioural reactions

Table 1

Disturbance in the payment system: operational incident at Bank 1

Bank 1 – Back-up options	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	0.32%	2.96%	6.19%
Value of rejected payments (as % of submitted payments)	0.00%	0.08%	1.51%
Value of unsettled payments (as % of the benchmark scenario)	0.13%	3.26%	8.41%
Total value of queued transactions (as % of submitted payments)	3.23%	32.10%	47.07%
Maximum queue value (as % of submitted payments)	2.57%	16.43%	32.94%
Average queue length (hh:mm:ss)	0:47:32	1:20:28	2:05:36
Settlement delay	0.11	0.24	0.42

Table 2

Disturbance in the payment system: operational incident at Bank 2

Bank 2 – Back-up options	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	2.08%	8.16%	16.53%
Value of rejected payments (as % of submitted payments)	0.02%	5.77%	28.03%
Value of unsettled payments (as % of the benchmark scenario)	0.96%	14.54%	51.60%
Total value of queued transactions (as % of submitted payments)	3.50%	36.66%	55.09%
Maximum queue value (as % of submitted payments)	2.68%	16.49%	37.93%
Average queue length (hh:mm:ss)	0:24:59	1:08:39	2:20:25
Settlement delay	0.08	0.18	0.47

Table 3

Disturbance in the payment system: operational incident at Bank 3

Bank 3 – Back-up options	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	1.35%	4.99%	11.22%
Value of rejected payments (as % of submitted payments)	0.00%	2.25%	24.68%
Value of unsettled payments (as % of the benchmark scenario)	0.84%	7.45%	32.07%
Total value of queued transactions (as % of submitted payments)	3.39%	31.94%	56.91%
Maximum queue value (as % of submitted payments)	2.46%	12.33%	34.94%
Average queue length (hh:mm:ss)	0:33:42	1:14:33	2:24:54
Settlement delay	0.05	0.18	0.44

Table 4

Disturbance in the payment system: operational incident at Bank 4

Bank 4 – Back-up options	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	0.62%	3.08%	8.85%
Value of rejected payments (as % of submitted payments)	0.00%	0.96%	13.99%
Value of unsettled payments (as % of the benchmark scenario)	0.39%	4.40%	22.19%
Total value of queued transactions (as % of submitted payments)	2.73%	29.54%	61.98%
Maximum queue value (as % of submitted payments)	1.80%	9.07%	22.66%
Average queue length (hh:mm:ss)	0:33:42	1:14:33	2:24:54
Settlement delay	0.03	0.11	0.34

Table 5

Disturbance in the payment system: operational incident at Bank 5

Bank 5 – Back-up options	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	0.00%	0.23%	0.87%
Value of rejected payments (as % of submitted payments)	0.00%	0.00%	0.00%
Value of unsettled payments (as % of the benchmark scenario)	0.00%	0.25%	1.05%
Total value of queued transactions (as % of submitted payments)	2.69%	22.99%	40.61%
Maximum queue value (as % of submitted payments)	1.78%	7.01%	20.61%
Average queue length (hh:mm:ss)	0:09:54	0:52:42	1:51:25
Settlement delay	0.02	0.09	0.24

Table 6

Disturbance in the payment system: operational incident at Bank 6

Bank 6 – Back-up options	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	0.00%	0.10%	0.48%
Value of rejected payments (as % of submitted payments)	0.00%	0.00%	0.06%
Value of unsettled payments (as % of the benchmark scenario)	0.00%	0.11%	0.52%
Total value of queued transactions (as % of submitted payments)	0.84%	21.64%	37.43%
Maximum queue value (as % of submitted payments)	0.44%	5.84%	13.75%
Average queue length (hh:mm:ss)	0:14:56	0:42:28	1:21:45
Settlement delay	0.02	0.08	0.16

APPENDIX 3

Disturbance in the payment system

Scenario 3: Entire-day incidents – behavioural reactions without back-up facilities

Table 1

Disturbance in the payment system: operational incident at Bank 1

Bank 1 – Stop-sending	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	7.35%	29.62%	42.29%
Value of rejected payments (as % of submitted payments)	0.00%	2.55%	10.07%
Value of unsettled payments (as % of the benchmark scenario)	3.12%	32.54%	49.04%
Total value of queued transactions (as % of submitted payments)	2.72%	19.49%	35.80%
Maximum queue value (as % of submitted payments)	1.56%	7.06%	15.91%
Average queue length (hh:mm:ss)	0:21:59	0:51:35	1:41:20
Settlement delay	0.04	0.11	0.20

Table 2

Disturbance in the payment system: operational incident at Bank 2

Bank 2 – Stop-sending	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	7.90%	25.47%	37.27%
Value of rejected payments (as % of submitted payments)	0.00%	1.99%	8.07%
Value of unsettled payments (as % of the benchmark scenario)	3.38%	28.16%	47.80%
Total value of queued transactions (as % of submitted payments)	2.23%	23.53%	46.56%
Maximum queue value (as % of submitted payments)	1.36%	7.75%	17.33%
Average queue length (hh:mm:ss)	0:20:32	1:13:18	1:49:26
Settlement delay	0.04	0.13	0.32

Table 3

Disturbance in the payment system: operational incident at Bank 3

Bank 3 - Stop-sending	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	7.46%	18.36%	26.20%
Value of rejected payments (as % of submitted payments)	0.00%	1.59%	8.92%
Value of unsettled payments (as % of the benchmark scenario)	3.17%	20.43%	37.93%
Total value of queued transactions (as % of submitted payments)	2.21%	22.78%	50.72%
Maximum queue value (as % of submitted payments)	1.44%	7.46%	22.33%
Average queue length (hh:mm:ss)	0:14:21	1:17:31	2:36:54
Settlement delay	0.02	0.11	0.26

Table 4

Disturbance in the payment system: operational incident at Bank 4

Bank 4 – Stop-sending	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	5.08%	12.11%	20.01%
Value of rejected payments (as % of submitted payments)	0.00%	0.69%	5.38%
Value of unsettled payments (as % of the benchmark scenario)	2.16%	13.30%	22.14%
Total value of queued transactions (as % of submitted payments)	1.61%	20.80%	38.63%
Maximum queue value (as % of submitted payments)	0.53%	5.87%	13.67%
Average queue length (hh:mm:ss)	0:11:04	0:46:01	2:12:17
Settlement delay	0.02	0.08	0.18

Table 5

Disturbance in the payment system: operational incident at Bank 5

Bank 5 – Stop-sending	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	4.08%	10.91%	18.35%
Value of rejected payments (as % of submitted payments)	0.00%	0.45%	4.36%
Value of unsettled payments (as % of the benchmark scenario)	1.73%	11.77%	23.45%
Total value of queued transactions (as % of submitted payments)	2.66%	17.12%	34.97%
Maximum queue value (as % of submitted payments)	1.34%	4.79%	11.58%
Average queue length (hh:mm:ss)	0:10:35	0:47:18	1:57:13
Settlement delay	0.01	0.07	0.23

Table 6

Disturbance in the payment system: operational incident at Bank 6

Bank 6 – Stop-sending	Minimum	Average	Maximum
Value of payments initially not submitted (as % of the benchmark scenario)	4.33%	7.99%	14.37%
Value of rejected payments (as % of submitted payments)	0.00%	0.24%	2.15%
Value of unsettled payments (as % of the benchmark scenario)	4.28%	8.48%	16.74%
Total value of queued transactions (as % of submitted payments)	0.91%	18.04%	33.66%
Maximum queue value (as % of submitted payments)	0.46%	4.93%	11.15%
Average queue length (hh:mm:ss)	0:08:04	0:45:23	2:11:15
Settlement delay	0.01	0.07	0.21

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